

MASTER

Evaluating business process model understandability a user's perspective

van de Wouw, S.G.

Award date:
2010

[Link to publication](#)

Disclaimer

This document contains a student thesis (bachelor's or master's), as authored by a student at Eindhoven University of Technology. Student theses are made available in the TU/e repository upon obtaining the required degree. The grade received is not published on the document as presented in the repository. The required complexity or quality of research of student theses may vary by program, and the required minimum study period may vary in duration.

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain

Eindhoven, April 2010

**Evaluating Business Process Model
Understandability:
a user's perspective**

by
MA Sander Gos van de Wouw

Student identity number 0622165

in partial fulfilment of the requirements for the degree of

**Master of Science
in Innovation Management**

Supervisors:
dr.ir. H.A. Reijers, TU/e, IS
dr. A. de Jong, TU/e, ITEM

TUE. Department Technology Management.
Series Master Theses Innovation Management

Subject headings: process modelling, understandability, user characteristics

Evaluating Process Model Quality

A user's perspective

Quality is not a benchmark, it is a perception.



Norman Percevel Rockwell, Girl at the mirror (1954)

Abstract

This research inquires into the effect of user characteristics on business process model understanding. Conceptualising understanding as a result of learning, four quality dimensions and three learning concepts were translated into user characteristics assessing the relation between them through quantitative analysis. The results indicated significant prediction effects for conception ability and self-efficacy validating the approach taken in this research. Based on these results, recommendations were made to improve both process model understandability and (future) user training.

Acknowledgements

“It’s the journey that makes us happy, not the destination.”
(Socrates, The Peaceful Warrior)

And quite the journey it’s been.
(Sander)

Quite the journey indeed, although I must admit the destination is a pretty happy place to be at. I look back with amazement, realising how far I’ve come. Graduating at the TU/e has for long been nothing short of a dream to me, to now be living it is simply *Bon Perignon*.

I would firstly like to thank my inspirator Hajo for his guidance, patience, and positive attitude throughout the whole trajectory; down under and back up again. Thank you so much for giving me the opportunity to work with such a brilliant and good spirited mind as yourself. Secondly, my thanks goes to Ad de Jong for his advice and sharp feedback, challenging me to walk that extra mile. My gratitude also goes to Jan Recker and the other experts willing to share their thoughts with me and help me attain this wonderful result.

My special thanks goes out to Tonia de Bruin. I could not have done this without you. Thanks for your support and for being such an optimist; I guess you were right about kuku’s, they always come in pairs.

Last but not least, I would like to thank my parents, my brother and my sunniqueen for their undying support and for just always believing in me (can you believe I actually did it?). I love you all very much, please don’t ever forget that.
Jaap and Eef, cheers for the coffee; Boer, wagwaan for the Fernandes.

Two down, nill to go.
With great pride, I close this chapter of my life, it has been both fantastic and very real.

“I, like many, define the real world as stuff that happens after graduation. But I was wrong.”
(Van Wilder)

Sander Gos van de Wouw
Eindhoven
26 april 2010

Management Summary

Exposition

This research is situated in the area of business process modelling. Business process modelling denominates the act of analysing business processes, defining them and creating business process models accordingly. Defining the purpose of a process model as communicating with stakeholders, process models should foremost be understandable. The problem is that little is known about what makes an understandable model. Part of this problem is caused by existing research mainly taking a model-centric perspective thereby attributing little attention to the role of the user.

The purpose of this research is to complement the mainly model-centric research programme on process model understandability with a user-centric perspective. By defining understandability as an emergent property the interdependency between model, task and user is centralised in the understandability debate. By doing so, the aim is to identify those characteristics that allow some users to attain a higher level of understanding and propose ways to improve user-model interaction accordingly. The main question can thus be formulated as:

How do user characteristics explain differences in user understanding of business process models?

Theory

Building on cognitive theory, creating process model understanding was defined as the outcome of a learning process. Understanding was theorised to be created in three stages, being the presage, process and product stage of learning. Isolating the learning context, model content and model content presentation, these three stages of learning comprise the constructs user characteristics, learning and understanding respectively.

User Characteristics

Existing process modelling literature has mainly reviewed the impact of model characteristics on model understanding and has defined a rather one-sided set of user characteristics when assessing the impact of user characteristics on model understanding. This research builds on existing process model quality literature to compose a more integrative set of user characteristics. The table below depicts the four types of quality included in this research, the formal means available to improve a process model along a certain quality type and the translation into user characteristics.

Quality Type	Model-Oriented Means (MOM)	User-Oriented Means (UOM)
Syntactic quality	Completeness, Validity, Structuredness	Syntactic knowledge
Semantic quality	Completeness, consistency	Semantic knowledge
Pragmatic quality	Size reduction Object-relevance Nesting	Abstraction ability Selection ability Conception ability
Empirical quality	Lay-out: Object presentation	Intuitive learning style

Syntactic knowledge refers to the knowledge about the language's grammar, i.e., notation, of a process model (e.g., Recker & Dreiling, 2007); semantic knowledge refers to the knowledge about the real world domain that is depicted in the process model (Lindland et al., 1994); abstraction ability refers to being able to establish an abstract concept by eliciting information of its common and qualitative/quantitative properties in order to mentally process it (Wang et al., 2006); selection ability refers to being able to engage in trial-and-error explorations to find a set of correlated objects, attributes, or relations for a given object or concept (Wang et al., 2006); conception ability refers to being able to create a representation by drawing up relations between new objects and existing objects to concept 'to be' relations (Wang et al., 2006); an intuitive learning style refers to discovering new relations and grasping new concepts in a holistic way (Felder & Soloman, 2010).

Learning

Existing process modelling literature has mainly looked at the impact of either model or user characteristics on process model understanding, thereby implying that no factors are present mediating their relationship. Building on learning theory and existing IS literature, motives, goals, strategies and self-efficacy are identified. Motives relate to desire representing the affective component of learning; goals relate to intention assessing a motive for its feasibility; strategies relate to behavioural intention bridging to action; and self-efficacy relates to the user's beliefs about the sufficiency of its skills and abilities.

Understanding

Three types of learning outcomes are identified based on recall and transfer, being no learning, memorisation and understanding. This thesis focuses on memorisation, rating no learning as an insufficient result, memorisation and understanding as adequate results.

Methodology

The research design can be categorised as empirical confirmatory quantitative research using an electronic survey design. The research was classified empirical due to the collection of primary data, confirmatory due to the objective to estimate the user-understanding relation according to the hypotheses posed in chapter six and quantitative due to numeric scales being used for data collection. The survey included introductory texts, multiple questions and two process models. In addition to the variables identified in the theoretical chapters, four control variables were included being age, education, domain experience and modelling experience. The process of data collection comprised four stages, being:

Stage	Activity	Purpose
Initium	Panel study	Validate the instrument and procedure qualitatively
Ex-ante	Pilot testing	Validate the instrument and procedure quantitatively
Survey	Empirical survey	Gather the actual data
Ex-post	Panel discussion	Discuss the research findings

Conclusions

The conclusions were drawn based on eleven hypotheses:

Hypotheses	Supported?
H1: <i>Semantic knowledge positively affects understanding process models.</i>	no
H2: <i>Syntactic knowledge positively affects understanding process models.</i>	no
H3: <i>Abstraction ability positively affects understanding process models.</i>	no
H4: <i>Selection ability positively affects understanding process models.</i>	no
H5: <i>Conception ability positively affects understanding process models.</i>	yes
H6: <i>Sensing learning positively affects understanding process models.</i>	no
H7: <i>Learning style influences the effect of user characteristics on understanding process models</i>	no
H8: <i>Self-efficacy affects understanding process models.</i>	yes
H9: <i>Self-efficacy influences the effect of user characteristics on understanding process models.</i>	no
H10: <i>A deep learning approach positively mediates the user-understanding relation.</i>	no
H11: <i>A surface learning approach positively mediates the user-understanding relation.</i>	no

Given the delineations of this research, the findings suggest that user characteristics indeed matter and can therefore be utilised to contribute to more understandable business process models. Consistent to defining understandability as an emergent property, a fit perspective was taken on process model understanding aiming to improve the compatibility between user, task and model (e.g., Goodhue, 2006; Topi & Ramesh, 2002). The significance of conception ability illustrated the importance of the user-technology relation in the creation of understanding while self-efficacy illustrated the importance of the interaction between the three. The latter is still poorly understood due to the absence of the learning process stage in the most dominant process model understandability literature. This research therefore proposes opening that black box in future endeavours.

Model understandability

Using the taxonomy by Van Bommel et al. (2007) pragmatic quality was the most dominant factor with a strong prediction effect for conception ability and multiple significant relations for selection ability. These results illustrate that complex process model understandability mainly relates to nesting depth and the ease with which users can chunk information in the model. From an analyst's perspective modularisation and a lower nesting depth makes a model easier to enact (Gruhn & Laue, 2006; Reijers & Mendling, 2008) while these model features, through reduced size, are associated with less error-proneness from a modeller's perspective (Vanderfeesten et al., 2007). Future research should therefore aim to optimise understandability using the other quality dimensions (Siau & Tan, 2005) as means to realise low perceived nesting depth and high chunkability. Following this recommendation some examples of such conduct are proposed.

User training

Firstly, in accordance with Moores and Chang (2009) performance self-efficacy was found to be the strongest negative predictor for process model understandability. This was most plausibly explained by overconfidence mainly coinciding with domain expertise and domain experts experiencing higher cognitive load due to having to integrate the new information with existing knowledge. This conclusion was consistent to the positive effect of achievement self-efficacy beliefs for domain experts and complete novices relying heavily on conception ability and some little modelling expertise. These results indicate that training should emphasise the importance of inference in process model ontology and creating understanding (Wand & Weber, 1995; Wang et al., 2006). Secondly, the significance of conception and selection ability indicated that if the learning goal is end-to-end flow understanding then object-by-object browsing while scanning for object-relevance is the most effective learning strategy whereas if the learning goal is attaining more integrative understanding then chunking is paramount. These findings are synthesised into a conceptualisation of the process model user containing the variables IQ, conception ability, modelling experience and performance self-efficacy. Consistent to this model, this research proposes user training to focus on making inferences between process models and the real world as well as making an assessment about which strategy being most relevant to use, end-to-end scanning, i.e. mentally following one path in the state space, or conceiving process-wide overview, i.e. mental conception. The proposed way to do so is through the use of worked examples (Chandler & Sweller, 1991).

Fin

In conclusion, the legitimacy of user-centred design has been proven by 1) identifying and testing some essential user characteristics, 2) generating significant and meaningful results and 3) being able to rank causes and come up with advice to improve model understandability as well as user training based on these findings. More such endeavours on single model improvement can be accumulated into the creation of a set of user-validated guidelines to ultimately make complex process models more understandable.

Table of Contents	
Title	Page
I. Exposition	12
1. Introduction	12
II. Theoretical Framework	16
2. Understanding Business Process Models	16
3. Learning from Business Process Models: user characteristics	19
3.1 <i>User characteristics and business process model understanding</i>	19
3.2 <i>An introduction to process model quality</i>	21
3.3 <i>Model-oriented means to realise process model quality</i>	22
4. Learning from Business Process Models: learning	25
4.1 <i>Conceptualising the process of learning</i>	25
4.2 <i>The process stage of process model learning</i>	27
5. Learning from Business Process Models: understanding	29
5.1 <i>Understanding as a product of learning</i>	29
5.2 <i>Understanding as a product of process model learning</i>	30
6. Hypotheses	31
III. Methodology	34
7. Research Design	34
7.1 <i>Research goal</i>	34
7.2 <i>Research type</i>	34
7.3 <i>Variables</i>	35
7.4 <i>Objects</i>	36
7.5 <i>Subjects</i>	37
8. Operationalisation	39
8.1 <i>Instrumentation</i>	39
8.2 <i>Data analysis</i>	41
IV. Results	42
9. Initium	42
9.1 <i>General remarks</i>	42
9.2 <i>Specific variables</i>	42
10. Pilot	43
10.1 <i>General Questionnaire Contents</i>	43
10.2 <i>Specific questions</i>	43

11. Survey	44
11.1 <i>Missing data, outlier analysis & data preparation</i>	44
11.2 <i>Factor Analysis</i>	45
11.3 <i>Reliability analysis</i>	46
11.4 <i>Correlation Analysis</i>	47
11.5 <i>Linear Regression Analysis</i>	48
11.6 <i>Logistic regression analysis</i>	50
12. Ex-Post	52

V. Conclusion and Discussion **54**


13. Conclusion	54
13.1 <i>Hypotheses</i>	54
13.2 <i>General conclusions</i>	58
13.3 <i>Fin</i>	62
14. Discussion	63


References **66**

Appendices **73**

Appendix A	Philosophical Approach	73
Appendix B	User Characteristics in the learning process	73
Appendix C	A Layered Reference Model of the Brain	74
Appendix D	Language-Domain Appropriateness	74
Appendix E	Measurement Model	75
Appendix F	SSA Process Models	76
Appendix G	Survey	78
Appendix H	Demographics	99
Appendix I	Assumptions for factor analysis	100
Appendix J	Factor analysis	102
Appendix K	Assumptions for regression analysis	104
Appendix L	SPSS Syntax	106



Figures		
Title		Page
Figure 1	<i>Three examples of a business process model notated in EPC, BPMN and Petri</i>	12
Figure 2	<i>Research project outline</i>	15
Figure 3	<i>Research scope (after: Mayer, 1989)</i>	18
Figure 4	<i>Approach to identify user characteristics</i>	20
Figure 5	<i>Different types of Quality (Siau & Tan, 2005)</i>	21
Figure 6	<i>Theory of meaningful learning: the presage stage (after: Mayer, 1989)</i>	24
Figure 7	<i>Theory of meaningful learning: the process stage (after: Mayer, 1989)</i>	28
Figure 8	<i>Theory of meaningful learning: the product stage (after: Mayer, 1989)</i>	30
Figure 9	<i>Conclusions visualised in measurement model</i>	57
Figure 10	<i>Black box in User-Process Model interaction</i>	59
Figure 11	<i>The process model user conceptualised</i>	61

Tables		
Title		Page
Table 1	<i>Concepts from the theory of meaningful learning (Mayer, 1989)</i>	16
Table 2	<i>Three stages of learning (Biggs, 1987)</i>	18
Table 3	<i>Quality types and means</i>	24
Table 4	<i>Learning Strategies & Motives (Kember et al., 2004, p.268)</i>	27
Table 5	<i>Different types of learning (after: Mayer, 2001)</i>	29
Table 6	<i>Stages in the research design</i>	34
Table 7	<i>Measurement variables and their typology</i>	35
Table 8	<i>Respondent groups by syntactic and semantic knowledge</i>	37
Table 9	<i>Reliability analysis; variables, computation and alphas</i>	46
Table 10	<i>Correlation analysis by stage of learning</i>	47
Table 11	<i>Multiple linear regression analysis testing for main prediction, moderation and mediation</i>	48
Table 12	<i>Multiple linear regression analysis testing the user-learning process relationship</i>	49
Table 13	<i>Logistic regression analysis testing the user-process-understanding relationship</i>	51
Table 14	<i>11 hypotheses and their results</i>	54

I. Exposition

1. Introduction

"It is the east, and Juliet is the sun"
(Shakespeare, *Romeo & Juliet*, Act II: Scene II)

But those who have read *Romeo and Juliet* know how the story is to end: "O, how may I ... Thy drug are quick. Thus with a kiss I die." The quote preludes Romeo's suicide after perceiving Juliet had gone before him. His understanding of this real-world situation did not match the situation itself, yet still triggered the according events. The story thus illustrates that people do not always act based on facts, but more so on their perception of it. Similarly, this thesis discusses people's perception of situations, be it not in the real-world but captured in business process models (in short: process models). The central assumption in this thesis is that to improve the understandability of process models, understandability should be defined as a result of user-model interaction rather than as a static attribute of a process model.

Analysts and designers of information systems (IS) need to form an understanding of the domain in which the system has to operate to determine its functionality (Maes & Poels, 2007). An important tool in this practice is business process modelling (in short: process modelling) which is used to articulate business processes being executed in the real-world. Based on these process models, business processes can be documented and IS requirements can be specified. So what then constitutes a process model? A process model can be defined as "an abstract description of an actual or proposed process that represents selected process elements that are considered important to the purpose of the model and can be enacted by a human or machine" (Curtis et al., 1992, p.76). Process models thus describe real-world situations which are expressed in a certain modelling language or notation. Figure 1 features examples of process models notated in EPC (left), BPMN (centre) and Petri (right).

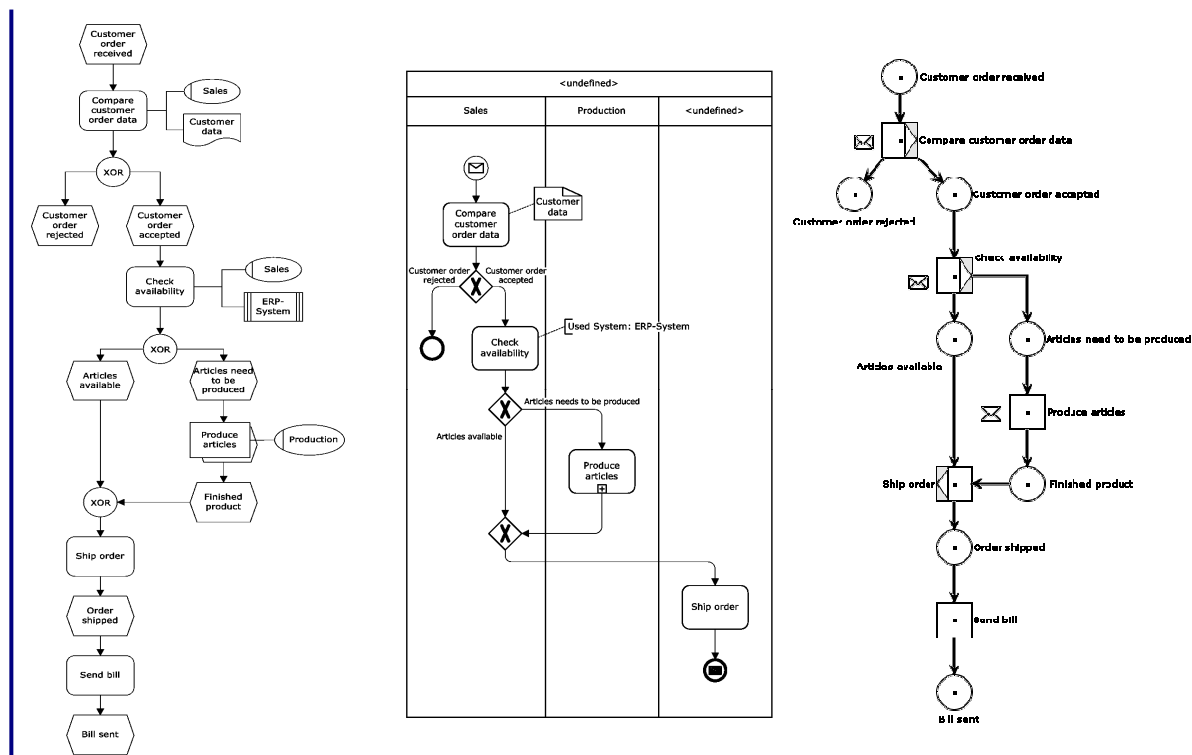


Figure 1 Three examples of a business process model notated in EPC, BPMN and Petri

Like visible in Figure 1, notations allow the definition of activities and states and offer rules on how to draw relations between these activities and states. Process models thus graphically articulate at least activities, events/states and control flow logic that constitute an actual business process (Recker, 2008). The challenge of process modelling is to make the graphical articulation of a business process in an accurate way so that it conforms to its purpose. Curtis et al. (1992) identify five such purposes, being: Facilitate human understanding and communication, support process improvement, support process management, automated guidance in performing process and automated execution support. This research focuses on the first purpose being to reach common understanding on how a process is executed (as-is) or how a process should be executed in the future (to-be).

The challenge of graphically articulating a business process conforming to the purpose of human understanding is to create an understandable model (Recker and Mendling, 2007). This challenge has been acknowledged by process model quality literature which defines understandability as one of the main determinants of process model quality (Moody, 1998). Existing research defines understandability as “the ease with which the model can be understood” (Moody, 1998, p.217). In the quality debate, understandability is predominantly approached from a model-centric perspective defining it as an intrinsic property of a process model (e.g., Cardoso et al., 2006; Vanderfeesten et al., 2007). This means that understandability is perceived as a consequence of a process model’s design, for example its complexity or its correctness. However, anecdotal evidence reveals that although process models are often designed with great care they are not always understood by all its users.

Such evidence has been confirmed by explaining differences in user performance by differences in their personal characteristics. Examples are high domain knowledge (Khatri et al., 2006) and high experience (Batra & Kirs, 1993) having been linked to better (modelling) task performance. It can be expected that the influence of user characteristics on performance is likely to manifest itself in the user-understanding relation as well, i.e. presence of domain knowledge can also be expected to lead to higher understanding. The validity of this assumption is proven in other disciplines by, e.g., showing that perceived ease-of-use impacts technology acceptance (Davis, 1989) or explaining how perceived relative advantage serves as a predictor to technology adoption (Rogers, 1995). When assuming a relation between user characteristics and understanding, the question can be raised whether understandability can indeed be defined as an intrinsic property of a process model? Rather, this research contends that understandability should be defined as an emergent property of a process model, i.e. as something that is created in user-model interaction. Accordingly, understandability is therefore also created during decoding by the receiver rather than only during encoding by the sender.

Some past endeavours exist that look into the creation of a set of guidelines for process model encoding (e.g., Becker et al., 2000; Mendling et al., 2009) yet no consensus exists on what comprises an understandable model. Defining understandability as an emergent property, this research examines the interaction between user and process model to assess the possibility to work towards such guidelines taking a user-centric perspective. This research therefore focuses on how a model is understood by a user. The aim within this focus is to assess the impact of specific user characteristics on process model understanding.

Problem Statement and purpose

This research is situated in the area of business process modelling. Business process modelling denominates the act of analysing business processes, defining them and creating business process models accordingly. Defining the purpose of a process model as communicating with stakeholders, process models should foremost be understandable. The problem is that little is known about what makes an understandable model. Part of this problem is caused by existing research mainly taking a model-centric perspective thereby attributing less attention to the role of the user.

The purpose of this research is to complement the mainly model-centric research programme on process model understandability with a user-centric perspective. By defining understandability as an emergent property the interdependency between model, task and user is centralised in the

understandability debate. This interaction can be described as: The user tries to understand a process model according to a task s/he is aiming to fulfil. This research focuses on this dependency by looking at the relation between user characteristics and process model understanding. By doing so, the aim is to identify those characteristics that allow some users to attain a higher level of understanding and propose ways to improve the user-model interaction accordingly.

The main question can thus be formulated as:

How do user characteristics explain differences in user understanding^ of business process models†?*

Four sub questions can directly be derived from this main question, being:

- ^ Ch.2 How do users attempt to understand a business process model?
- * Ch.3 Which user characteristics are pertinent to understanding business process models?
- Ch.4 How are these characteristics used to realise understanding?
- † Ch.5 When is a business process model understood?

By answering these four sub questions, conclusions can be drawn that bridge the gap between theory and empirical observation. The necessity for such research is guided by the earlier identified lack of normative guidelines in the formal research programme as well as an arbitrary selection of user characteristics in the empirical research programme. The relevance for this research can therefore be considered threefold (after: Topi & Ramesh, 2002).

- a) Firstly, to provide insight into the nature of the relation between user characteristics and process model understanding.
- b) Secondly, understanding the impact of user characteristics on process model understanding may allow for more effective education. This could have possible beneficial impact on training in both academia and practice.
- c) Thirdly, understanding the impact of user characteristics on process model understanding may allow for process model improvement. In other words, by making a direct connection between user characteristics and aspects of the modelling artifact, the artifact design can be adapted by translating the user characteristics back to these aspects thereby improving its understandability.

Research approach and assumptions

In accordance with Zmud and Boynton (1991), this research is opinionated that new instruments should only be developed as a last resort. Seconding this notion, this research roots itself in process model quality literature. As an aspect of general process model quality, understandability is focused on. The approach to understandability is consistent to Recker's (2006) description of socio-pragmatic constructionism, i.e. knowledge creation is subjective, yet can be analysed by studying human action. He describes the implications for process modelling to be threefold, concluding proposing usage of semiotic theory in the process model quality debate. In accordance with Recker (2006), semiotic theory is used to look at quality embracing the idea of meaning creation to realise understanding (Pask, 1988). (For further elaboration on the philosophical context of this research, see Appendix A)

Assumptions

- Goal attainment will be defined as a one-dimensional process, i.e. the learner will only pursue one goal at a time.
- Model quality is inherently complex and cannot completely be appreciated via a correspondence theory in a factual or objectivist sense but rather needs to incorporate social contextual and pragmatic variables (Recker, 2006).

Remark

- Gender-specific personal nouns and pronouns should be interpreted as neutral.

Thesis outline

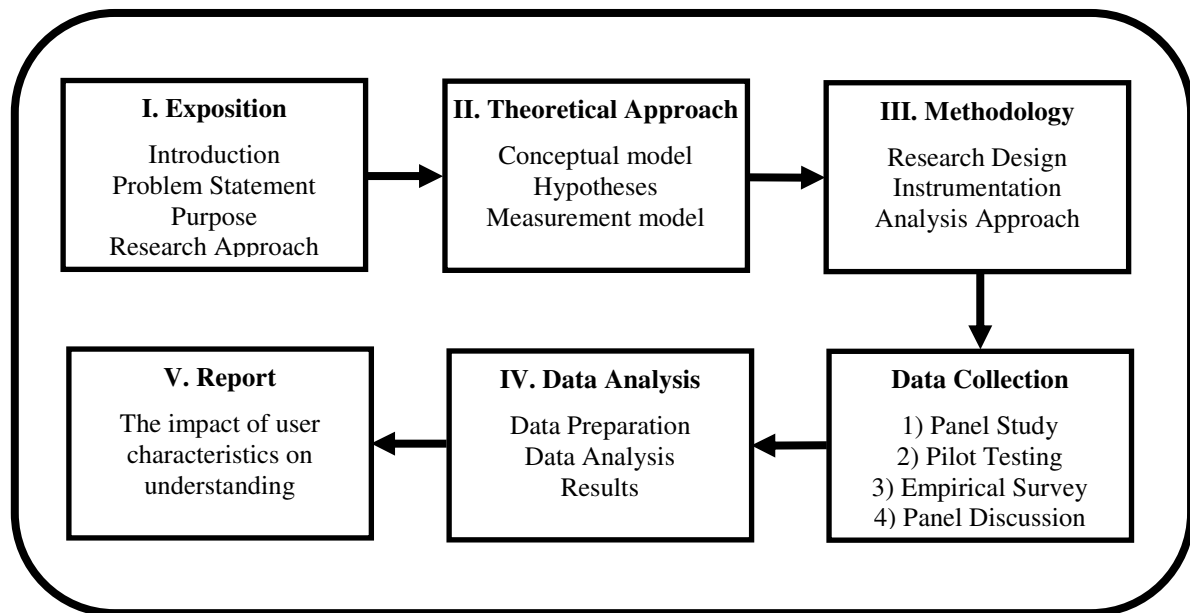


Figure 2 *Research project outline*

The outline in Figure 2 illustrates the six steps that were taken in this research project. The following summation briefly elaborates on the activities in each step.

- I. During the exposition step, the topic of process model understanding was formulated and the problem statement, purpose and research approach were set.
- II. In the theoretical step, the conceptual model was designed based on cognitive theory and existing process modelling literature. After drawing up the conceptual model, hypotheses were formed which led to the proposition of a measurement model.
- III. In the methodological step, the four stages of data collection were designed. Accordingly, the research approach, objects, variables, instrument and subjects of this research were specified. In addition, a preview was taken on the statistical analyses that would be required to generate the results.
 - In the data collection step, data was gathered conform to the four steps illustrated in the methodological section.
- IV. After data collection, the data was (statistically) interpreted consistent to the research design.
- V. Finally, the hypotheses were verified followed by the general conclusions and discussion section.

The five steps that are preceded by a Roman numeral are incorporated in this thesis report as sections. The fourth step, of data collection, has merely been an activity in the project and is not explicitly reported on in this thesis. This project outline is part of the first section introducing this research. The four consecutive sections each contain multiple chapters and elaborate on the theory, methodology, results and conclusions respectively.

II. Theoretical Framework

2. Understanding Business Process Models

How do users attempt to understand a business process model?

This chapter focuses on how to describe the process of creating understanding of a process model. Consistent to the introduction, understandability is defined as an emergent property which necessitates a process of meaning creating. By using meaningful learning theory (Mayer, 1989) and the three stages of learning by Biggs (1987) a general theoretical model is formed. This model assumes isolation of model characteristics (content and content presentation) and of the learning context. The model comprises user characteristics presage to the learning process, knowledge creation during the learning process and understanding as a product of the learning process. These three stages (presage, process and product) serve as the outline of the remainder of the theoretical framework, representing chapters three, four and five respectively.

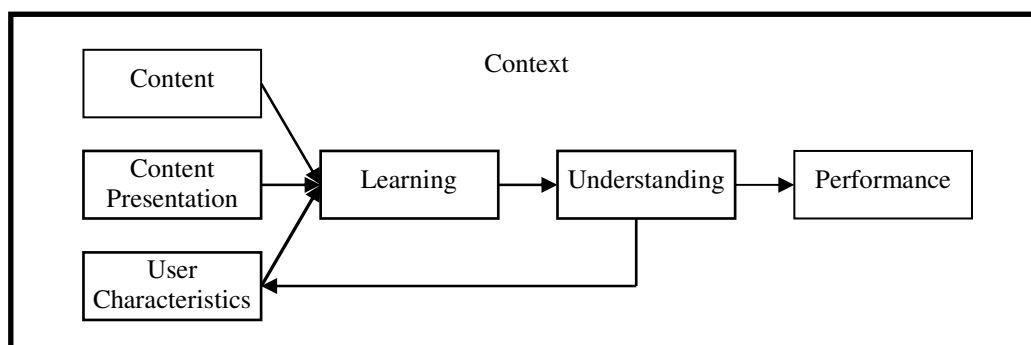
An introduction to learning theory

In the introduction, the interdependency between user, model and task in the process of understanding process models was discussed. Rather than a static concept understandability thus refers to interaction. Consistent to this notion of interaction, understanding can be regarded an outcome of a preceding process. To conceptualise this process, the theory of meaningful learning by Mayer (1989) is chosen. This theory explains how users create understanding of explanative material that is presented to them. This theory is utilised because it explicitly recognises the impact of content and content presentation on the learning process which are central concepts for process model learning having them contain both auditory and visual aspects. In addition, this perspective on constructing understanding has been successfully deployed in existing empirical (process) modelling literature (e.g., Gemino & Wand, 2003; Recker & Dreiling, 2007) illustrating its fit for this research purpose.

The theory of meaningful learning identifies five independent factors, of which two are mediating ones, and one dependent factor (Mayer, 1989; see Table 1).

Table 1 *Concepts from the theory of meaningful learning (Mayer, 1989)*

Concept	Explanation
Content	the subject-matter that is presented for the learner to acquire
Content presentation	the way in which the material is presented to the learner
User characteristics	the differences between individual learners
Learning	the process of selecting, organising and integrating knowledge
Understanding	the knowledge that the learner acquires as a result of learning
Performance	the behavioural possibilities as a result of the acquired knowledge



The theory depicts learning as a process which is influenced by all three of the independent variables. Learning leads to understanding, whereby understanding influences performance and user characteristics through a feedback loop. This description thus illustrates that a learning process is more complex than merely comprising a user creating meaning. This complexity is discussed below based on cognitive load theory and the learning context.

Cognitive Load Theory

According to Chandler and Sweller (1991), the concept of knowledge construction is an activity that presumes cognitive load. Cognitive load is the amount of effort that is needed to enact a part of the message. Three types of load exist, (1) related to the content and (2) content presentation of the message and (3) related to the necessity for problem-solving. Their premise is that the utilisation of human cognitive resources is limited in capacity and duration. Because of these limitations, high cumulative cognitive load, i.e. a 'difficult message', inhibits a person from understanding the message. This theory thus reinforces the perspective of user-model interaction (Goodhue & Thompson, 1995; Vessey & Galletta, 1991), i.e. model features can facilitate or inhibit user understanding through the effort they require from the user. In addition, the principle of cognitive load is used to express model complexity, comprehensiveness (Gruhn & Laue, 2006) and effectiveness (Huang et al., 2009). Cognitive load theory therefore explains how content and content presentation play a role in understanding process models.

Learning context

Besides the learning process being dependent on cognitive load, it can also be considered contextually dependent (Biggs, 1987). In collaboration with co-authors, Biggs argues that differences between users manifest themselves dependent on, and within a given context (Biggs et al., 2001, p.137). Consistently, users are theorised to set their goals according to (a) past learning experience and (b) expected utility of the current learning outcome. Not only does the user need to anticipate a desired learning outcome, it also requires the learning context to anticipate the user (e.g. through training methods or teachers tailoring their approach to suit specific users). A responsive environment or situational factors can therefore be labelled a crucial determinant of achieving a desired learning outcome (Ford, 1992). This proposition is confirmed by Mendling et al. (2007) finding differences amongst a rather homogeneous set of respondents explained by the type of training they enjoyed.

The cognitive load theory and learning context thus indicate that the complexity of the interaction stretches beyond user characteristics and process model understanding. Researching the effect of user characteristics in a valid way therefore necessitates minimisation of the effects of task, model and context.

Using learning theory to explain business process model understanding

As this research desires to measure one specific relation theorised in the model, i.e. user characteristics-understanding, the other factors need to be isolated. This necessitates delineation of the model. Four delineations are made to the model of meaningful learning and are presented below.

- I. Consistent to Mayer's recommendation (1989) only one of the three independent variables is reviewed. As the focus lies on the impact of user characteristics on understanding, content and content presentation are isolated through object similarity, i.e. having the whole sample learn from the same process models.
- II. In order to isolate the effect of specific user characteristics, some level of sample homogeneity was realised in order to prevent noise due to contextual factors. This resulted in a low variety of nationalities represented in the sample group and the control group mainly consisting of students. In addition, age, education, domain experience and modelling experience were incorporated as control variables to further reduce the chance of noise due to contextual factors.
- III. Understanding is defined as a learning outcome which facilitates learning performance (Mayer, 1989, p.47). Although existing process modelling literature has mostly focused on performance, e.g. usage and continuation (see: Bandara et al., 2007), this research labels performance as

irrelevant to the theoretical discussion. Mind that this research does aim to contribute to the user-performance relation, viz. improve model understandability and user training, yet perceives this to be the next step in the programme building on the output of this research. Hence the concept of learning performance is dropped from the conceptual model.

- IV. The timeframe considered in this research is limited to one learning episode. This makes the process one-dimensional and makes the incorporation of a feedback-loop redundant.

Figure 3 illustrates the delineations.

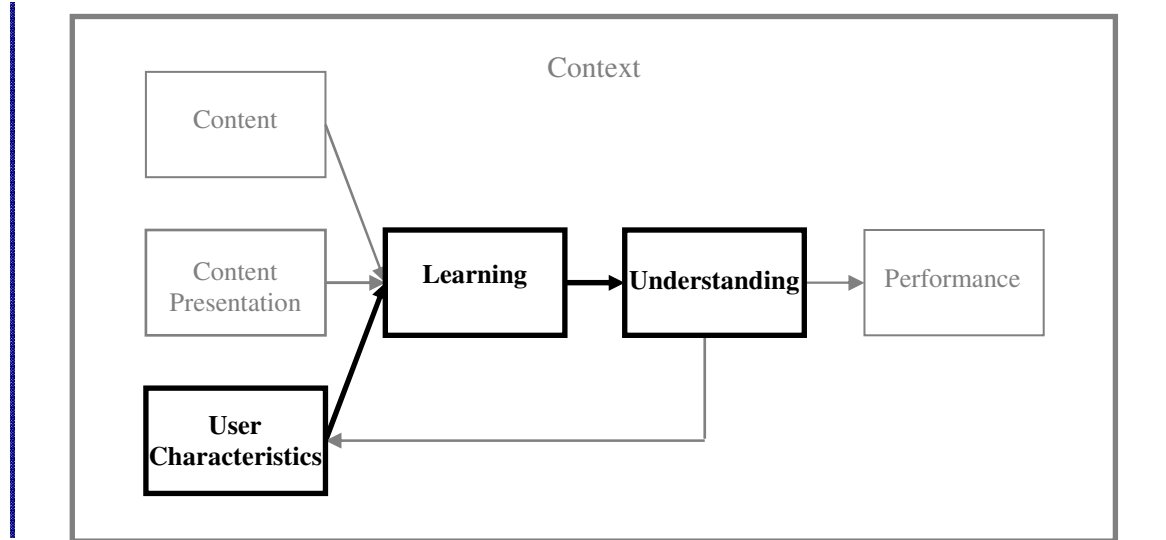


Figure 3 Research scope (after: Mayer, 1989)

The delineated model depicted in Figure 3 is compatible with the 3P model of learning by Biggs (1987). The 3P model is rooted in the theory of “student approaches to learning” (Marton & Säljö, 1976) and has become accepted due to its simplicity (i.e. comprising merely four factors), its comprehensiveness and parsimoniousness of measurement. The model has mainly been applied to teaching enhancement by means of student learning analysis. The model identifies three stages, being presage, process and product (hence 3P) which fit the three concepts in Figure 3.

Table 2

Three stages of learning (Biggs, 1987)

Stage	Concept	Explanation
presage	user characteristics	what exists prior to the learning process
process	learning	the learning process itself
product	understanding	the result of the learning process

In the next three chapters these three stages of one learning episode are discussed according to the central concepts they comprise.

Summary Ch.2

The main question in this chapter was: *How do users attempt to understand a business process model?* This chapter illustrated that understanding is created in three stages, being prior to, during and after learning. In this research learning context, content and content presentation are isolated. The three stages therefore comprise the constructs user characteristics, learning and understanding respectively.

3. Learning from Business Process Models: user characteristics



Which user characteristics are pertinent to understanding business process models?

This chapter introduces the first of the three learning stages, viz. the presage stage describing what exists prior to learning. This stage comprises the concept of user characteristics and accordingly this chapter is dedicated to selecting the pertinent ones. Firstly, existing user-oriented process modelling research is briefly discussed. The conclusion drawn from this discussion is that no suitable and/or integrative framework on user characteristics yet exists. In order to compensate for this lack, the concept of user characteristics is linked to literature on process model quality. By analysing different types of quality, an integrative overview is given of the factors affecting understandability of process models. Four of these quality types are considered relevant to this research, being syntactic, semantic, pragmatic and empirical quality. Based on these four, six user characteristics are identified that are pertinent to understanding process models due to their conceptual closeness to model quality. Therefore, §3.1 reviews existing user-oriented process model literature, §3.2 reviews existing process model quality literature and §3.3 proposes a framework of user characteristics.

3.1 User characteristics and business process model understanding

In order to answer the question *which user characteristics are most appropriate to process modelling* firstly past research is consulted. By reviewing existing process modelling research on user characteristics, frequently used concepts can be benchmarked to this research. This review includes research that (a) aims to improve the formal quality of process models and (b) incorporates understanding as a dependent variable.

a) User characteristics as a moderator for model quality

Existing process model quality literature has mainly discussed the impact of user characteristics on understanding when testing the intrinsic understandability of process models through the effect of structural parameters. An illustrative example is the assessment of the impact of modularity on user understanding, controlling for such user characteristics as company experience and domain knowledge (Reijers & Mendling, 2008). This research programme therefore aims to improve formal process model understandability while attributing a moderating effect to user characteristics. Topics which have been covered in this programme include usage of different property types (Gemino & Wand, 2005), structural cognitive load (Huang et al., 2009), labels and icons (Mendling et al., 2009) and cross-connectivity (Vanderfeesten et al., 2007). General results in this programme do indicate existence of relations between formal quality metrics and understanding (e.g., through cognitive load or modularity).

b) User characteristics as a predictor for understanding

Existing process model literature includes exploration of the direct impact of user characteristics on process model understanding aiming to improve user training. Most often has the impact of a single user characteristic been isolated, using two groups differing on a specific parameter. Examples being Khatri et al. (2006) investigating the impact of domain knowledge; Recker and Dreiling (2007) testing the impact of process modelling language familiarity; and Mendling et al. (2007) testing the effect of both practical experience and theoretical knowledge. These three examples are illustrative for the focus in this research programme, favouring the impact of expertise, experience and knowledge over such characteristics as distal variables (e.g. personality), affective variables (e.g. anticipated emotions), psychosocial variables (e.g. self-confidence) and skills (e.g. mathematical ability) (for a

more exhaustive overview of user characteristics see Appendix B [Van de Wouw et al., forthcoming]). General results about the impacts of experience, expertise and knowledge are rather equivocal, sustaining ambiguity in this research programme. Although experience and knowledge are considered in this research, expertise is excluded from analysis based on its vast scope and evasiveness. (For a more integrative discussion of expertise see Jackson-Kokkonen et al. [in press].)

Based on this review, no definitive set of user characteristics can be proposed. Research programme a) has successfully identified some metrics related to understanding, yet lacks empirical evidence of its relation to user characteristics. Research programme b) has assessed the direct impact of some user characteristics on understanding, yet lacks unequivocal results and an integrative framework. When these two research programmes are combined, the frameworks used in a) can be used to more integratively follow the approach proposed in b).

This research aims to do so by translating existing formal literature on understandability, i.e. quality metrics, into user characteristics. By doing so, the latter can be used to improve both process model understandability and user training. Due to the lack of an integrative framework for user characteristics, this translation is made using the layered reference model of the brain by Wang and co-authors (2006; see Appendix C). This model is rooted in cognitive informatics (the interface between cognitive psychology and information science) and describes the execution of human activity as a function of lower level cognitive capabilities. This model is not used as an initial concept, but moreover as a frame of reference to guarantee compatibility and originality of the user characteristics identified. This conduct can be visualised in Figure 4.

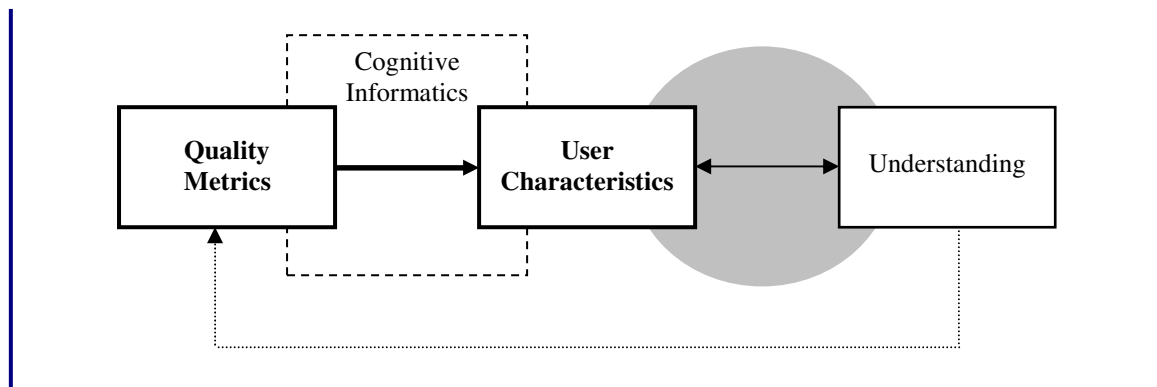


Figure 4 *Approach to identify user characteristics*

Figure 4 thus shows that quality metrics are translated into user characteristics referenced by cognitive informatics. By doing so, the grey area, which signifies the user characteristics-understanding relation, can be investigated in a structured manner. Insight in this relation can be directly linked to the impact of user characteristics and indirectly to quality metrics. In §3.2 formal quality literature is discussed identifying different types of quality. In §3.3, these types are translated into user characteristics using the quality taxonomy by Siau and Tan (2005).

Summary §3.1

User characteristics have been researched as moderator to process model quality and as predictor for process model understanding. Because neither programme proved suitable as an initial concept, this research combines both approaches and explores the impact of user characteristics as a predictor for process model quality.

3.2 An introduction to process model quality

In order to make the translation between understandability and user characteristics, usage of quality literature was proposed. In order to identify some appropriate quality metrics, firstly the choice for quality literature is highlighted followed by the proposition of a quality framework.

Rationale for using quality literature

Like mentioned in chapter one, the concept of understandability can be related to the question: What makes an understandable business process model? (Recker, 2006). This question is one of the main drivers in the process model quality-debate, which still is to reach maturity (e.g., Becker et al., 2000; Lindland et al., 1996; Moody, 1998). Although understandability is but one attribute of process model quality, general quality literature is used to look at understandability. Such conduct is legitimised by the relation between understandability and quality being theoretically reciprocal, i.e. the dimensions that quality is broken down into equally apply for understandability. It should be noted though that the reciprocity only pertains to the sub dimensions of both constructs rather than their contents being interchangeable. Besides legitimate, using quality literature is also very desirable due to the systematic approach and level of agreement by which this programme is characterised.

A taxonomy of types of quality

Looking at quality from an understandability perspective requires the selection of a quality framework grounded in semiotic theory. Lindland et al.'s SEQUAL framework (1994) meets this prerequisite and is used as the initial concept of the quality-debate. The SEQUAL identifies three basic quality types, being syntactic, semantic and pragmatic, plus according goals and means. Building on these three, other authors have identified complementary quality types (e.g. Krogstie 2003; Krogstie et al., 2006; Pohl, 1994; Shanks & Darke, 1995). Siau and Tan (2005) have realised synthesis in the debate by mapping the different types of quality (visualised in Figure 5).

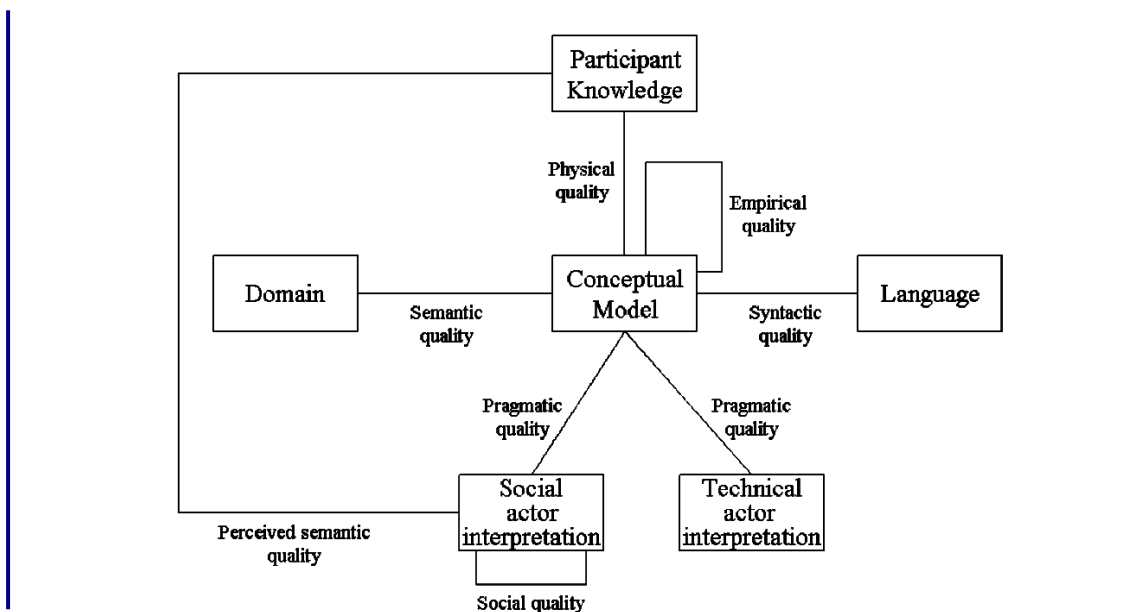


Figure 5 *Different types of Quality (Siau & Tan, 2005)*

All seven quality types identified in the model are briefly explained below:

- Syntactic quality relates to the modelling language
- Semantic quality relates to the modelling domain
- Pragmatic quality relates to the interpretation by the user (Lindland et al., 1994, p.44)
- Empirical quality refers to the cognitive ergonomics of the process model (Van Bommel et al., 2007) which relates to the user identified error-frequency. It is therefore textually related to structure and readability, and visually related to the aesthetics of the model (Krogstie, 2003, p.8).

- Perceived semantic quality refers to the correspondence between a user's interpretation of the model and a user's existing domain knowledge. The concept thus builds on the discrepancies between a desired and current level of knowledge and an optimal and actual domain.
- Physical quality relates to externalisation (being able to update the model according to the users' knowledge) and internalisability (being able to obtain knowledge based on the model).
- Social quality is the agreement amongst user, making it an interpersonal type of quality.

Because this research considers the learning process of a single user in a single learning episode, physical quality (related to the longer term) and social quality (considering multiple users) are left out of the review. In addition, the concept of perceived semantic quality is excluded from further discussion due to its lack of formal evaluation techniques (Krogstie et al., 2006, p.98) and its resemblance to semantic quality when approached from a user's perspective. The other four quality types are included and are defined as facilitating conditions for creating model understanding. In §3.3, the means to realise these four types of quality are discussed and translated into user characteristics.

Summary §3.2

Seven types of process model quality can be identified of which four are included in this research, being syntactic, semantic, pragmatic and empirical quality.

3.3 Model-oriented means to realise process model quality

In accordance with the discussion of Siau and Tan's quality taxonomy (2005), four quality types are considered in the conceptualisation of a user's perspective on process model understandability. In the summation below existing model-oriented means are listed and translated into user-oriented means. All means and their relations are catalogued in Table 3.

1. Syntactic quality has been defined in a rather unambiguous way as process model correctness. Means to realise process model correctness are identified as syntactic validity, syntactic completeness and well-structuredness (Krogstie, 2003, p.8; Recker & Mendling, 2007, p.5). These means guarantee the model to adhere to the language's grammar, to only include modules in that language and to be sound and nested correctly. Yet even if an artifact conforms to these syntactic rules, i.e. is encoded perfectly, the user is required to have the syntactic knowledge to decode the message. It can even be argued that poor codification can be compensated by superior knowledge of decodification. Syntactic quality is therefore coupled to syntactic knowledge.
2. Semantic quality has mostly been defined in terms of semantic completeness and semantic validity (Krogstie, 2003; Lindland et al., 1994). These goals relate to the extent to which all relevant real-world concepts can be found in the process model in a consistent way. It thus describes the extent to which the externalised model reflects the user's knowledge of the real-world (Van Bommel et al., 2007, p.3). It means the user compares her relevant knowledge of the real-world to the model, whereby the information in the model complements her existing knowledge. Yet if the latter exceeds the former, be it due to superior semantic knowledge or poor semantic quality, semantic quality becomes obsolete for attaining the goal of understanding the business process. Semantic quality is therefore coupled to semantic knowledge.
3. Pragmatic quality has been defined quite ambiguously in existing research, hence requiring the identification of common denominators. This resulted in a selection of means related to simplicity, absence of overload and language-domain appropriateness (Becker et al., 2000; Lindland et al., 1994; Moody, 1998). Of these three, only simplicity is included in this debate. Absence of overload is excluded due to its scope, intangibility and difficulty to operationalise in an unequivocal way. Language domain-appropriateness is excluded due its overlap with syntactic (language) and semantic (domain) knowledge, and level of abstraction (e.g., captured in the criteria by Nyssetvold and Krogstie [2005, p.6; see Appendix D]). In the next paragraphs, the user characteristics mapping to simplicity are discussed. Simplicity is defined as the inverse of complexity, which is assumed to make a modelling artifact more difficult to enact. Existing

literature tends to break complexity down into sub measures claiming one general measure of complexity is unrealistic. Two of the most common measures of computational complexity are size and structure, which are discussed below.

Size

Firstly, simplicity relates to size or the amount of constructs in a process model, where less constructs lead to a more understandable model (Moody, 1998, p.220; Lindland et al., 1994, p.48). This can either be realised by (a) reducing the amount of operators and operands in the main process model, or (b) by adapting each model to fit a specific purpose or audience (Becker et al., 2000, p.45).

- 3a Model size is theorised to negatively correlate with understandability emphasising the importance of an abstracted external representation (Cardoso et al., 2006; Lindland et al., 1994; Moody, 1998; Vanderfeesten et al., 2007). A fully expanded model thus requires the user to make the abstraction herself. Constructing an abstraction can be defined as a “process of the brain .. that establishes an abstract model (or concept) for an entity of external world by eliciting the information of its common and qualitative/quantitative attributes or properties in order to mentally process it” (Wang et al., 2006, p.7). Abstraction ability thus refers to being able to make an accurate representation based on systematic information reduction. Hence size reduction is coupled to abstraction ability.
- 3b Object relevance is an inherently subjective concept because it expresses complexity based on whether the objects in a model are relevant to a user. More specifically, it describes the amount of mental states that have to be evaluated, captured as McCabe’s CFC, to distil the user-relevant information from a model. The fewer states a user has to consider, the less complex a model is perceived to be (bounded by relevance and given well-structuredness [Gruhn & Laue, 2006]). A lack of relevance thus requires the user to evaluate a large amount of information and make a relevant selection herself. This process is related to the cognitive process of search. Search can be defined as a “process of the brain ... that is based on trial-and-error explorations to find a set of correlated objects, attributes, or relations for a given object or concept; or to find useful solutions for a given problem” (Wang et al., 2006, p.7). This implies search impacts understanding expressed in speed, the success of the exploration strategy, and accuracy, the output expressed in correlated objects (Chiew & Wang, 2004). The ability associated with search is selection ability, hence coupling object-relevance to search or selection ability.

Structure

Secondly, simplicity relates to the structuredness of the model, where a well-structured model is easier to understand (Gruhn & Laue, 2006). A well-structured model is one that is (c) properly nested (Van der Aalst, 1998), i.e. features no intervening usage of splits and joins. Additionally, structuredness also considers modularisation and uniqueness. Although relevant, the user characteristics related to the latter two concepts are theoretically too intertwined with learning to incorporate them in an unequivocal way, i.e. they are regarded as much a predictor, as a part of the learning process, as a result of learning. Hence, only nesting is included in this debate.

- 3c Nesting relates to the joins and splits in a model. It is measured in nesting depth and jumps for structured and unstructured loops respectively (Van der Aalst, 1998). Together they consider the amount of choices on a process path that need to be considered in order to reach an end state. Thereby more choices, i.e. a higher nesting depth, mean a more complex model. Yet, users that are able to pick the relevant bits of information, make a mental conception of these choices and relate them to the other objects are presumably less susceptible to a higher level of depth. Such conduct is referred to as concept establishment, by which concepts “are used to construct propositional thought, to interpret our current experience by classifying it as being of a particular kind relating to prior knowledge, and to be a means of understanding the world” (Wang et al., 2006, p.6). It thus considers creating a representation by drawing up relations between new objects, e.g. splits, and existing objects, e.g. the objects prior to the split, to concept ‘to be’ relations. The ability to construct these concepts is referred to as conception ability, hence coupling nesting to conception ability.

Pragmatic quality is thus coupled to abstraction, selection and conception ability. Note that abstraction and conception ability refer to the construction of a mental representation of the information, whereas selection ability refers to the accuracy and speed with which a user can extract information from the existing representation.

- Empirical quality's aesthetic dimension refers to the way textual and visual aspects influence understandability. Consistent to these two aspects roughly two types of means exist to improve the empirical quality. Textual means focus on improving the readability of an artifact through naming conventions and consistency (e.g. Mendling & Recker, 2008). Aesthetic means concern object placement, usage of colour, usage of icons or pictorials and object size & form (Becker et al., 2000, p.43). This research only focuses on object presentation, which considers the way the layout assists the user in enacting the process model. Ideally, the layout of a process model makes it vivid, lifelike and intuitive to the user (after: Moody, 1996). However, presentation faces a trade-off with simplicity whereby more visual aids increase the cognitive load of the model due to its size. It is assumed that users trying to grasp the feel of a model benefit from an intuitive look, while users learning a model bit by bit suffer from having to enact more information. The division between sensing and intuitive learning covers this difference, where intuitive learners prefer discovering new relations and grasping new concepts in a holistic way whereas sensing learners prefer learning and memorising facts bit-by-bit to engage in problem-solving (Felder & Soloman, 2010). Hence, empirical quality is coupled to the difference between sensing and intuitive learning.

Summary §3.3

Table 3 *Quality types and means*

Quality Type	Model-Oriented Means (MOM)	User-Oriented Means (UOM)
Syntactic quality	Completeness, Validity, Structuredness	Syntactic knowledge
Semantic quality	Completeness, Consistency	Semantic knowledge
Pragmatic quality	Size reduction Object-relevance Nesting	Abstraction ability Selection ability Conception ability
Empirical quality	Lay-out: Object presentation	Intuitive learning style

Summary Ch.3

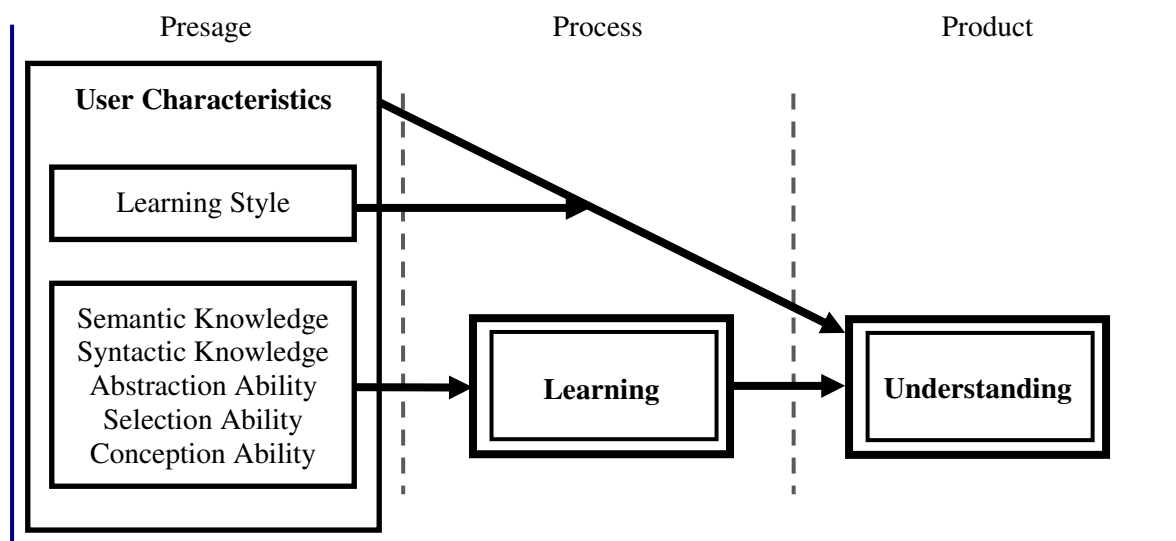


Figure 6 *Theory of meaningful learning: the presage stage (after: Mayer, 1989)*

4. Learning from Business Process Models: learning



How are these characteristics used to realise understanding?

This chapter discusses the process stage of learning, viz. actual learning. Learning thus links the user characteristics in the presage stage to process model understanding in the product stage and provides insight into how understanding is created. In existing IS literature, the process stage is often regarded a mere link between input and output implying its insignificance. This is reflected by its absence in some of the most accepted frameworks in modelling literature (e.g. Davis, 1989; Goodhue & Thompson, 1995; Topi & Ramesh, 2002). Using general learning theory to complement the isolated concepts identified in existing modelling literature, a conceptualisation is proposed for the process stage. Learning is theorised to include setting a learning approach and developing beliefs of self-efficacy. A learning approach reflects the level of understanding that the user desires to attain expressed in motives, goals and strategies. Self-efficacy is an evaluation of the user's ability to realise a desirable learning outcome. §4.1 proposes a conceptualisation for the process stage while §4.2 elaborates on the concepts it comprises.

4.1 Conceptualising the process of learning

Little process modelling research has been conducted into the role of the process stage. This is mainly attributable to the dominantly static view on process model understandability focusing on the direct relation between user characteristics and performance. This implies the process stage to be regarded as a full mediator rather than itself a predictor of understandability. Other explanations are the ambiguity of the composition of the process stage and the absence of this stage in accepted perspectives such as Davis' utilisation perspective (1989), Burton-Jones and Grange's representational perspective (2008) and Goodhue and Thompson's (1995) fit-in-use perspective.

Existing modelling research that does incorporate the process stage has mainly focused on the operationalisation of learning as an activity. Examples are monitoring chunking and tracing activity in creating understanding (Cardoso et al., 2006) and mapping search patterns in software artifact reviewing (Hungerford et al., 2004). Although extremely useful, such operationalisation falls short of providing an overview of the concepts comprised by the learning stage. One of the earliest (and only) studies in the IS domain that does provide an overview is the one by Mandviwalla and Hovav (1998) applying Business Process Redesign to learning theory. Tapping into learning theory, they identify the concepts of motivation, activity, understanding and feedback. This concurs with general learning theory which identifies a motivational, cognitive and volitional sub process to learning (Biggs, 1978; Convington, 2000; Valle et al., 2003). Learning can therefore be described as a process of I) motivation and II) activity whereby continuous reflections of III) beliefs about the goal-performance relation and IV) willingness to exert persistence and effort signify its progress.

The four concepts that constitute the process stage are elaborated on below.

- I) Motivation translates to the drive to engage in behaviour and has received theoretical attention in the form of behavioural intention (Venkatesh et al., 2003) and planning (Goodhue, 2006). A framework that integratively applies such concepts to a learning process is the Student Approaches to Learning (SAL) by Marton & Säljö (1976). Although slightly outdated (Pintrich, 2004), the theory holds when studying a single learning episode and is preferred for its simplicity. SAL dictates the learning approach can be broken down into learning motives and strategies.

Follow-up research has identified the learning approach to comprise a learning goal as well (e.g., Entwistle & Smith, 2002; Perugini & Bagozzi, 2001) and describes goal orientation to be included in Self-Regulated Learning (Pintrich, 2004). The approach to learning can therefore be described to include three factors decreasing in affect and increasing in feasibility, being motives, goals and strategies:

- Motive: a desire that energises and directs behaviour (Covington, 2000)
- Goal: thoughts about desired (or undesired) states or outcomes that one would like to achieve (or avoid) (Ford, 1992, p.43)
- Strategy: plan of action to adapt and change cognition (Pintrich, 2004)

II) Activity refers to the execution of the planned learning strategy and is strictly behavioural as such. Although acknowledged to be of relevance, strategy execution is exempted from inclusion in this research due to arguments of scope. Inclusion of this concept could have been conceptualised using, e.g., chunking (identifying coherent bits of information), tracing (scanning for information and identifying relevant bits) (Cardoso et al.'s, 2006; Santos & Badre, 1994), identifying problem-solving approaches (Chiew and Wang, 2004) or mapping search patterns (Hungerford et al., 2004).

III) Beliefs about the goal-performance relation refer to the consequences of pursuing a goal. These beliefs are therefore goal-specific and most important when goals are difficult (Locke & Latham, 2002, p.707). Two types of beliefs can be identified, being capability beliefs, i.e. beliefs about the self, and context beliefs, i.e. beliefs about the learning context (Ford, 1992, p.45). Due to isolation of the learning context, only capability beliefs are included in this debate. In existing modelling literature, the concept of capability beliefs has most often been referred to as (computer) self-efficacy.

IV) The volitional dimension is absent in process modelling literature, as continuation has only been researched in an inter-learning episodic context rather than intra-episodic. Although this theoretical gap is acknowledged, the volitional dimension is also exempted from inclusion in this conceptualisation. In accordance with Perugini and Conner (2000), this research is opinioned that attaining a learning goal implies volition through actualisation of a desired goal.

Learning thus comprises formation of a learning approach and self-efficacy beliefs. These two concepts are discussed in the next paragraph.

Summary §4.1

Due to existing process modelling literature having ignored the process stage of learning, general learning theory was consulted. The latter revealed that the process of learning can be broken down into motivation, activity, commitment and volition. Two concepts are included in this research being approach to learning (including motives, goals and strategy) and self-efficacy.

4.2 The process stage of process model learning

The process stage of process model learning thus comprises two activities, being setting an approach to learning and forming self-efficacy beliefs. Both concepts are reviewed in this paragraph.

4.2.1 Setting a learning approach

Choosing an approach to learning depends on the user's motivation to learn. This motivation can be either intrinsic (intra-personal) or extrinsic (inter-personal). The former relates to following a deep approach aimed at the creation of meaning. The latter fuels either a surface approach or an achieving approach which are respectively aimed at rote learning and outperforming others. The achieving approach is excluded from this debate due to its measurement-scales not being quite as apparent as the surface and deep ones (Biggs, 1978; Kember & Leung, 1998; Wong, Lin, & Watkins, 1996). Adding non-directed learning as absence of motivation, a three factor model is used illustrated in Table 4.

Table 4

Learning Strategies & Motives (Kember et al., 2004, p.268)

Categories	Motives	Goals	Strategies
Surface	extrinsic motivation	performance	memorisation
Deep	intrinsic interest	learning	understanding
Non-directed	absence	indifference	none

Table 4 illustrates the type of motives, goals and strategies which have been set based on extrinsic (surface), intrinsic (deep) or absence of (non-directed) motivation. These three concepts are briefly discussed below.

Motives

Motives express the user's desire as a drive towards action. They are affective in nature and can be used as a frame of reference for the user's perception of task requirements. Two types of motives can be distinguished, being surface and deep ones (Kember et al., 2004, p.268). Surface motives are tailored to the product of the learning process and are fuelled by extrinsic motivation; an example being desiring to meet a superior's expectations. In contrast, deep motives consider the intrinsic motivation to engage in knowledge creation in anticipation of the outcome; an example being learning for self-development.

Goals

Goals form the intentional component of the learning approach and reflect the user's interpretation of task requirements after assessing them for feasibility. As such, (goal) intention has received considerable attention in IS literature, be it mostly in utilisation focused research (e.g., Burton-Jones & Straub, 2003; Maes & Poels, 2007). In general, two types of goals can be identified being performance and learning goals. Performance goals are set based on extrinsic motivation and can be labelled as part of the surface approach. Learning goals "refer to increasing one's competency, understanding, and appreciation for what is being learned" (Covington, 2000, p.174) and are defined as part of a deep approach due to the intrinsic motivation.

Strategies

Strategy refers to making a plan about how to learn from a process model and therefore represents the behavioural intentional component. A deep learning strategy implies learning for understanding. Accordingly, the user engages in active interaction with the process model critically examining its soundness and attempting to link its information to existing mental models. In contrast, a surface learning strategy implies rote learning or learning for memorisation. The user tries to memorise the information in the process model without questioning it or trying to discover underlying patterns. Finally, a non-directed learning strategy implies non-systematic learning. When deploying this strategy the user has an aversion towards learning and shows indifference towards the outcome (Beattie et al., 1997).

4.2.2 Self-efficacy

Self-efficacy can be defined as “people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills one has, but with judgments of what one can do with whatever skills one possesses” (Bandura, 1986, p. 391). The concept of (computer) self-efficacy has often been used in information systems research (e.g. Compeau & Higgins, 1995; Marakas et al., 1998; Agarwal et al., 2000). Compeau and Higgins (1995) found self-efficacy to reduce anxiety and positively impact usage, while other studies found a negative impact on performance through overconfidence (Moores & Chang, 2009) or even no effect at all (Agarwal et al., 2000). This illustrates that self-efficacy is a contingent concept depending on the learning task at hand. Consistently, self-efficacy is defined as a concept belonging in the process stage of learning rather than in the presage one. Upon seeing the process model, the user forms expectations about whether her skills suffice to realise a desirable learning process and attain understanding.

Summary §4.2

Two concepts included in the stage of learning were reviewed in this paragraph. Setting a learning approach, comprising motives, goals and strategies, refers to the motivation that drives the user to learn from a process model. Self-efficacy refers to the user's beliefs about understanding the process model given the abilities s/he possesses.

Summary Ch.4

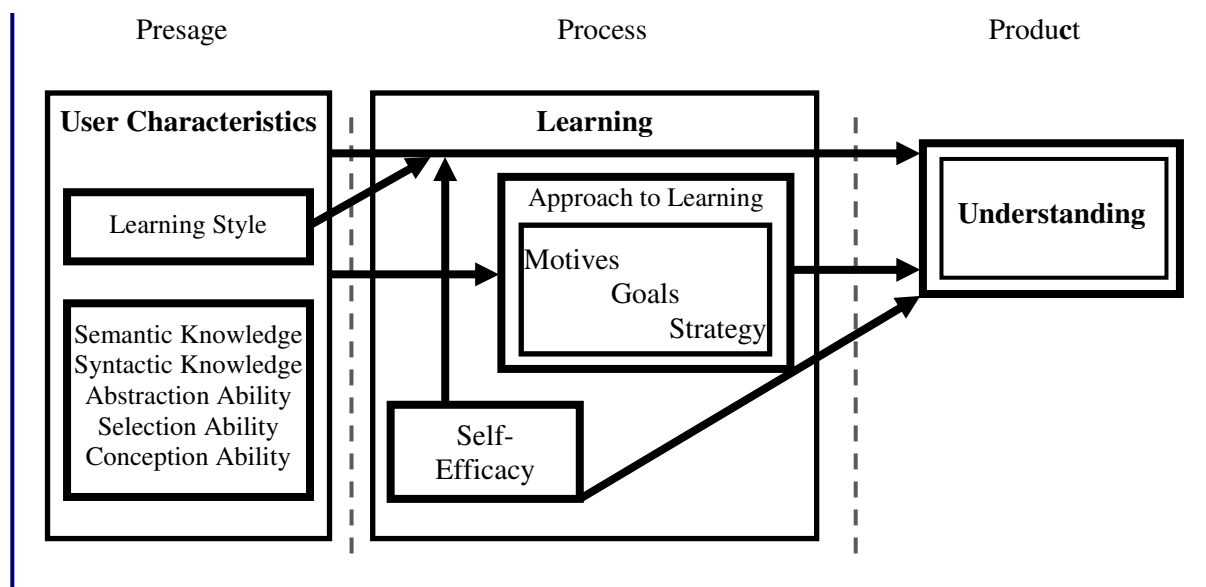


Figure 7 Theory of meaningful learning: the process stage (after: Mayer, 1989)

5. Learning from Business Process Models: understanding



When is a business process model understood?

This chapter discusses the product stage of the learning process and reviews understanding as a learning outcome. This chapter firstly reviews general learning theory and identifies three different levels of understanding based on the distinction between retention and transfer. Secondly, this theory is synthesised into a concept of product quality based on adequacy and purpose.

5.1 Understanding as a product of learning

The aim of this paragraph is to identify a way to distinguish between different types of learning outcomes, i.e. explain when a process model is understood. The Cognitive Theory of Multimedia Learning by Mayer (2001) explains how users construct understanding from multimedia messages such as process models. This theory was selected because it defines messages containing both visual and auditory components as the learning object. In addition, the cognitive theory of multimedia learning has been successfully implemented in existing empirical process modelling literature realising meaningful results (e.g., Masri et al., 2008; Recker & Dreiling, 2007)

Mayer (2001) distinguishes three different types of outcomes to a learning process, based on the distinction between retention and transfer. Retention relates to recognition and recall of the graphical elements captured in a process model. It therefore refers to the learning product of being able to remember and reproduce information. Transfer deals with the internalisation of the information in a process model. It therefore refers to the outcome of being able to solve problems not directly answerable from the information provided in the model (Gemino & Wand, 2005). Following this distinction, the three types of learning outcomes are illustrated in Table 5.

Table 5 *Different types of learning (after: Mayer, 2001)*

Learning Outcome	Cognitive Description	product	
		Retention	Transfer
No learning	No knowledge	Poor	Poor
Memorisation	Fragmented knowledge	Good	Poor
Understanding	Integrated knowledge	Good	Good

No learning occurs when the material is not understood nor remembered; fragmented learning refers to a high level of recognition and retention combined with a low level of transfer, which is also referred to as memorisation; understanding is attained when the material is both comprehended and can be acted upon, therefore requiring the user to construct an own coherent representation of the graphical elements depicted in the process model. An important assumption to this theory is that the taxonomy does not imply a hierarchy of learning outcome superiority. Normative judgements can only be made based on the compatibility between the learning outcome and the learning goal, rather than based on one of the two in isolation.

Summary §5.1

Three different learning outcomes can be identified depending on the levels of retention and transfer, being no learning, memorisation and understanding.

5.2 Understanding as a product of process model learning

Due to the assumption of none of the learning outcomes being superior, a reference point is needed against which the outcome can be compared for adequacy. Since the learning product is conceived to be theoretically equal to goal-attainment, a pre-specified goal can be regarded such a reference point.

The validity of this claim is illustrated by Mendling and Recker (2007) and Recker and Mendling (2007). Based on semiotic (Lindland et al., 1994) and ontological theory (Wand & Weber, 1995), Mendling and Recker (2007) propose a model quality equation including representational fidelity (including syntactic and semantic aspects), the clarity of the model purpose (including pragmatic aspects) and the competence of the modeller. Building on this equation, Recker and Mendling (2007) claim the user's need fulfilment should be used as a norm for model adequacy linking artifact evaluation to learning outcome. Extending this logic, the interdependence between user, model and task therefore dictates that the agreement between the user and the task specifications, i.e. the learning goal, dictates model adequacy and therefore performance adequacy.

The learning goal is set at memorisation, rating no learning as an insufficient result and memorisation and understanding as adequate results.

Summary §5.2

The concepts of purpose and adequacy illustrate that model quality depends on a fit between user abilities, technique capabilities and task requirements. Hence learning outcome should be assessed relative to the agreement between the user and task requirements, i.e. the learning goal.

Summary Ch.5

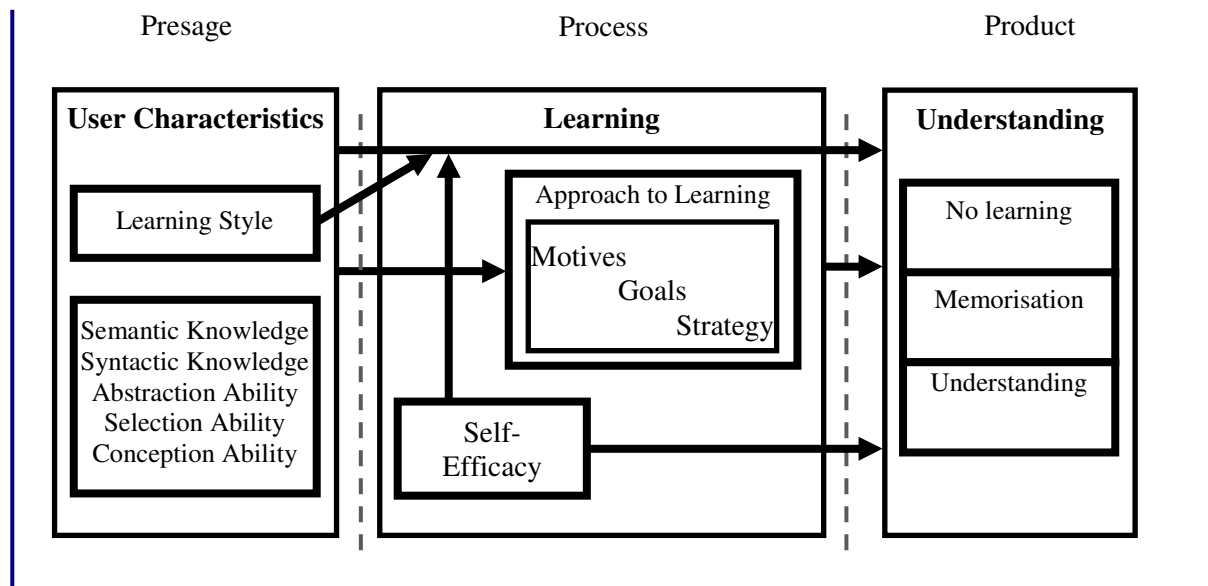


Figure 8 *Theory of meaningful learning: the product stage (after: Mayer, 1989)*

6. Hypotheses

In this chapter, the theoretical model proposed in chapter five is translated into a measurement model. Based existing process modelling and cognitive theory, relations between the different constructs are theorised putting the emphasis of this research on pragmatic abilities. In accordance with this theoretical proposition, the hypotheses are introduced resulting in the measurement model visualised in Appendix E.

Prediction effects

Knowledge

Existing process modelling literature has devoted extensive attention to the impact of syntactic and semantic knowledge in its discourse on expertise. Recker and Dreiling (2007) found notation knowledge does not increase understanding; Khatri et al. (2006) conclude that domain knowledge only aids specific types of problem-solving; and Mendling et al. (2009) found that understanding is independent from previous notation or previous domain knowledge. These results indicate that the differences in understanding found amongst process model users are most likely not attributable to differences in knowledge. In contrast, cognitive load theory (Chandler & Sweller, 1991) implies both semantic and syntactic knowledge should increase the understanding of process models.

The cognitive load exerted by the content mainly depends on the focus required to identify the (most) appropriate bits of information to create a mental image of a process (Chandler & Sweller, 1991, p.295). Having domain knowledge can be expected to aid in the identification of the most appropriate process elements, hence minimising intrinsic load and aiding understanding.

H1: Semantic knowledge positively affects understanding process models.

The cognitive load exerted by the content presentation mainly depends on the impression of dispersion and incoherency of the information. Therefore, having knowledge about the rules of how information in a process model is presented and how the objects in a process model cohere is expected to decrease extraneous load and aid understanding.

H2: Syntactic knowledge positively affects understanding process models.

Cognitive ability

Cognitive informatics theory dictates cognitive abilities play a fundamental facilitative role in learning, comprehension and problem solving (Wang et al., 2006). Concurring with this notion, existing modelling research has theorised these abilities to play a key role in understanding, for example abstraction ability (Bennedsen & Caspersen, 2006) and spatial visualisation ability (Huotari et al., 2004). Despite the abundance of theoretical attention, their effect on understanding process models has not yet been empirically validated. Therefore the hypotheses on the three cognitive abilities identified in chapter three are formulated using process modelling (related) theory.

Abstraction ability is used to simplify information by deducing common attributes (Wang et al., 2006, p.6). Complex process models are often high in size which depends on the amount of information and the flow in which the information is presented (Vanderfeesten et al., 2007). In order to aid the user in relating a large amount of information to the real world, the objects in complex models are typically organised in classes and attributed properties from a finite list (Recker & Mendling, 2007). Being able to mentally organise information in classes and properties can therefore be expected to generate similar benefits and aid the user in enacting a large amount of information to create process model understanding.

H3: Abstraction ability positively affects understanding process models.

Selection ability is used to cognitively simplify models which contain irrelevant information. According to Becker et al. (2000) relevant models contain no information that can be eliminated from the model without leading to loss of meaning for the user. Through exerting intrinsic cognitive load, as well as contributing to size and complexity, inclusion of irrelevant information would therefore impede understanding. Mentally improving the flow simplicity by undoing it from irrelevant parts of information is therefore expected to facilitate understanding by reducing the error-proneness of the learner. Although indirect, the reduction of error-proneness through selection ability is expected to be positively related to understanding.

H4: Selection ability positively affects understanding process models.

Conception ability is used “to construct a ‘to be’ relation between an object or its attributes and existing objects/attributes” (Wang et al., 2006, p.6). This facilitates the integration of new information which is essential to the creation of meaning. With nesting requiring the integration of control constructs with sequences of activities (Cardoso et al., 2006), the ability to construct ‘to be’ relations is heavily appealed to. Additionally, deep nesting not only requires users to construct such complex relations but also to store them in their short-term memory and have them available for future integration at a later point in time (Santos & Badre, 1994). Due to this process being essential in enacting complex process models, conception ability is therefore theorised to improve understanding in a direct way rather than through counteracting complexity.

H5: Conception ability positively affects understanding process models.

Learning style

Existing process modelling literature that reviews empirical quality mostly proposes theoretical frameworks, lacking convincing empirical evidence. Examples are Becker et al. (2000) on different layout conventions, Moody (1996) on graphical representation, Mendling and Recker (2008) on labels and icons, Nickerson et al. (2008) on spatial layout and Schrepfer et al. (2009) on secondary notation. Existing research thus provides indication about the effect of lay-out on understanding, yet provides neither certainty nor a set of conclusive guidelines. This is especially troublesome for complex models which are theoretically furthest away from feeling intuitive. Due to the lack of applicable guidelines and this research using complex process models, thorough inspection of the different elements in the model is expected to prevail over taking a more holistic approach to ‘get the picture’ (Felder & Soloman, 2010). As such, sensing learners are expected to outperform intuitive learners hence theorising a positive effect of sensing learning on understanding.

H6: Sensing learning positively affects understanding process models.

Moderation effects

Learning style

Sensing learners are theorised to be good at learning facts and memorising material. They are typically portrayed as careful and thorough whereby they learn best if a connecting to the real world can be established. Intuititors like discovering new concepts and grasping new ideas. They prefer discovering new relations and are known to be impatient and inferior with details (Felder & Soloman, 2010). These two learning styles therefore do not only differ in their way they enact information, but also in the way they approach a learning task. Consistently, besides the direct effect on understanding it can also be expected that learning style will affect the effectiveness with which other user characteristics are utilised.

H7: Learning style influences the effect of user characteristics on understanding process models

Self-efficacy

Due to the equivocal yet significant effects of self-efficacy found in previous research (e.g. Agarwal et al., 2000; Compeau & Higgins, 1995; Moores & Chang, 2009) it is theorised to be a significant predictor for understanding process models, be it positive or negative. Because self-efficacy also relates to the perception of control over the utilisation of skills, self-efficacy is theorised to have both a direct effect on understanding and a moderating effect on the user-understanding relationship (Fishbein et al., 2000).

H8: Self-efficacy affects understanding process models.

H9: Self-efficacy influences the effect of user characteristics on understanding process models.

Mediation effects

Learning Approach

As the learning goal is set at memorisation, users following a surface approach are expected to attain an adequate result based on goal-approach compatibility. In addition, due to memorisation being a pre-requisite to transfer, users following a deep approach are also expected to attain adequacy. Hence it is theorised that learners following both a surface and deep approach are expected to attain understanding.

H10: A deep learning approach positively mediates the user-understanding relation.

H11: A surface learning approach positively mediates the user-understanding relation.

Control variables

Four control variables have been selected based on user-process model interaction theory (Van de Wouw et al., 2010) and existing IS literature (Topi & Ramesh, 2002). Firstly, the user characteristics theorised to have an impact are expected to manifest themselves alongside more basic demographics of the participants. To test for the impact of such factors, age and education were controlled for due to their proven impact in previous IS research (e.g., Topi & Ramesh, 2002). Secondly, this research has delineated its scope to only one learning episode, thereby forgoing effects of experience. To compensate for this delineation and to seek consistency with existing process modelling literature (e.g., Mendling et al., 2009; Recker & Dreiling, 2007; Reijers & Mendling, 2008), domain and modelling experience were incorporated as control variables.

III. Methodology

7. Research Design

This chapter discusses the various elements of the research design. Five elements are discussed being the research goal, type, objects, variables and subjects.

7.1 Research goal

The goal of this research was to explore the relation between user characteristics and understanding in order to explore the accuracy of the conceptual model and provide leads for both user training and artifact improvement. The according research question was:

How do user characteristics explain differences in user understanding of business process models?

7.2 Research type

The research type was defined as empirical confirmatory quantitative research using a survey design. The research was classified empirical due to the collection of primary data, confirmatory due to the objective to estimate the user-understanding relation according to the hypotheses posed in chapter six and quantitative due to numeric scales being used for data collection. The survey type was electronic survey by arguments of reach. The survey invited the user to fill out the survey in a serious way and covered the whole screen in order to minimise the impact of secondary task attention. The data gathered was quantitative in nature. The survey included introductory texts, multiple questions and two process models.

The survey comprised questions about the constructs proposed in the theoretical chapter. The constructs in the theoretical framework were mostly measured using items derived from existing scales. Nevertheless, some of the item operationalisations required some adjustment to be tailored to this specific research. In order to do this in a rigorous way, the stages of scale development by Recker and Rosemann (2007) were used, validated by an ex-post stage as applied by Mendling et al. (2007). Accordingly, the research methodology was divided into four stages building on the output of the literature study.

Table 6 *Stages in the research design*

Stages	Activity	Purpose
Initium	Panel study	Validate the instrument and procedure qualitatively
Ex-ante	Pilot testing	Validate the instrument and procedure quantitatively
Survey	Empirical survey	Gather the actual data
Ex-post	Panel discussion	Discuss the research findings

Initium

By means of expert interviews the procedure and instrument design were validated. The unit of analysis was methodological experts with a sample of two, being dr. G. Rooks and dr. A. de Jong. At this stage, the concerns were mostly methodological requiring feedback on the structure of the research design and on the potential threat of procedural choices on the internal validity. The discussions centred around the type of items and variables in the research design, the proposed analyses and the consistency between the research questions, hypotheses and research design. The output was a procedure to data analysis.

Ex-ante

By means of empirical survey the procedure and instrument contents were validated. The unit of analysis was process modelling experts with a sample of three, being dr. T. De Bruin, dr.ir. H.A. Reijers and dr. J.C. Recker. At this stage, the focus was on the survey content requiring feedback on the items, their operationalisations and the internal validity threatened by

confounding and spurious relationships. The discussion centred around the type of questions that were asked, the way the questions were formulated and the discriminant validity of the questions. Besides looking at the actual survey, the interpretability of the results was also anticipated on. The output was a revised version of the questionnaire.

Survey

Four steps were identified in this stage of data acquisition. Firstly, the respondents were asked to provide some personal data. Secondly, the respondents were briefly confronted with the process model they had to learn and were asked to report on their self-efficacy and form an according learning motive and strategy as the learning goal was provided. Thirdly, respondents were asked to start learning from the process model. Finally, the process model was removed and the respondents had to answer 21 recall questions based on the product from the learning process (Khatri et al., 2006).

Ex-post

By means of panel discussion, the results of the survey and their implications were discussed. The unit of analysis was process modelling experts with a sample of four, being dr. S.J.B.A. Hoppenbrouwers, prof.dr. J. Mendling, dr. J.C. Recker and dr. B. Weber. At this stage, the concerns were mostly about the validity of the design, the implementability of the results and the creation of a research agenda. The discussion centred around the low amount of variance explained by the research model, the type of conclusions that could validly be drawn from it, the implications of these conclusions and the design of follow-up in this research programme. The output was a critical review incorporated in the discussion section of this research.

7.3 Variables

Four types of independent variables were used, being predictors, mediators, moderators and control variables. Next to these four categories, one dependent variable was used. Table 7 provides an overview of the variables under inspection including their measurement type.

Table 7 *Measurement variables and their typology*

Concept	Variable Type	Measurement Type
Knowledge	Independent Variable	Ordinal
Cognitive Ability	Independent Variable	Interval
Learning Style	Independent Variable / Moderator	Ordinal
Self-Efficacy	Independent Variable / Moderator	Ordinal
Learning Approach	Mediator	Ordinal
Understanding	Dependent Variable	Interval
Age	Control Variable	Ordinal
Education	Control Variable	Ordinal
Domain Experience	Control Variable	Interval
Modelling Experience	Control Variable	Interval

7.4 Objects

Only one business process was incorporated in this research represented in two complementary process models. The choice for only one process was made based on considerations of research validity, more specifically based on a trade-off between internal and external validity. Strictly formal, the utilisation of one model deterred the external validity of the research because the results would be attributable to characteristics of this model as well. In contrast, utilising multiple models would have made the results more generalisable yet also more prone to have been a result of model treatment decreasing the internal validity. Despite the existence of information equivalence theories, this research desired to avoid the results being attributable to model features like secondary notation or modularisation. Hence, although the external validity was somewhat decreased only one process was selected. Additionally, a minimum of external validity was assumed based on the choice for two complex models. The thesis was that users would have been able to learn from a simple model, i.e. display homogeneity, yet would face difficulties learning from complex models, i.e. display heterogeneity. The gains of extending testing the results against a relatively homogeneous group were therefore perceived to be outweighed by the methodological costs (expressed in additional sample size or run time).

Two complementary process models were used as objects in this research with a main purpose of communicating with stakeholders. The notation that they were modelled in was BPMN. The models originated from the Shared Service Agency (SSA) Queensland and described part of their recruitment process, being the fulfilment of vacancies (see Appendix F). Model A, The Priority Placement Process, gave a general overview of the procedure while model B, The Advertising Specific Vacancies Process, provided a more detailed description of part of the priority placement procedure. In the next paragraph a concise overview of the process described in these models is given.

First, an internal assessment was executed looking for suitable candidates. If so, an appointment would have been made and the data would have been forwarded to payroll. If not, the documentation was forwarded to the recruitment team. They processed the documents and checked if additional information would be required. If so, the documents went back to the Client Agency, if not the documents passed on to the advertisement type identification. A medium was chosen after which the advertisement was checked for changes and forwarded to be released. Consecutively, the Vacancy Processing event linked up with the object 'Receive and Process Applications' in the Priority Placement Process. The data was send back to the Client Agency who assessed the suitability of the candidate. If the candidate was found suitable, an appointment would have been made and the data would have been forwarded to payroll. If not, the process would have repeated itself.

These models were selected based on two requirements, being origin and complexity. Both of these requirements are elaborated on below:

- **Origin**
The models needed to originate from practice to guarantee purpose and avoid researcher-bias. As the models were created with a specific purpose in mind an according notation was selected based on ontological feasibility. The practical origins therefore guaranteed some compatibility between model features and model task (Goodhue, 2006). In addition, the purpose of the model avoided that the model had been specifically built for this research. This avoided potential biases based on synchronisation of the research purpose and model characteristics.
- **Complexity**
The models needed to be complex to guarantee that the task of understanding is of substantial difficulty. This is required to generate fluctuations in user understanding which allowed testing its relation with differences in user characteristics. This was realised by allowing the models to be slightly incorrect and by having them exert a substantial amount of cognitive load, expressed in size (Mendling et al., 2009) and cognitive load (Chandler & Sweller, 1991).

- Incorrectness:** Although complementary, the processes in the two models were not correctly coupled. Model A displayed an overview of the entire process containing objects that globally describe the recruitment procedure. Although model B gave a more detailed overview of part of this same procedure, it was unclear how the objects in model B were coupled to the objects in model A. Consequently, the incorrectness made it difficult to assess how the two models fit together and how decisions in model B affect model A and vice versa.
- Size:** The combined size of the models needed to be substantial in order to generate differences in user learning and understanding. This required the models to exceed the maximally theorised chunk size ability in order to necessitate abstraction. Consequently a large process was selected exceeding 50 objects (Cardoso, 2006; Mendling et al., 2009).
- Cognitive Load:** The model structure needed to exert high cognitive load on the user (Gruhn & Laue, 2006). This meant branching and modularisation were required, preferably replenished with iteration or recursion and parallel flow. Modularisation was only indicated by the existence of a sub process (visible as the icon in object Check ad appeared) yet was absent in the rest of the model. 3 instances of branching were present, being: if additional information is needed then send a request for information to the client agency; if change in the electronic file is required then create another file; if an application is received, then send it of to panel. Iteration was present in one instance, being: repeat advertising vacancies until a suitable candidate is found. Finally, one instance of parallel flow - viz. identify priority placement phase - was present in the process depicted in both models.

7.5 Subjects

In this paragraph, the research subjects are discussed looking at group compilation, general demographics of the population and reservations due to the sampling method.

Groups by knowledge

Three groups of respondents were identified to participate in this research which were selected based on knowledge. Defining knowledge as a group property prevented having to include knowledge related questions to approximate knowledge, making the results less susceptible to bias and therefore more reliable. Two types of knowledge were relevant in this research, being semantic/domain knowledge and syntactic/modelling notation knowledge. Consequently, three groups were identified being one group with high semantic knowledge, one group with high syntactic knowledge and a control group with both low semantic and low syntactic knowledge listed in Table 8.

Table 8 *Respondent groups by syntactic and semantic knowledge*

Three Respondent Groups			
Group	Members	Score on Semantic Knowledge	Score on Syntactic Knowledge
SSA business practitioners	35	<u>80.0%</u>	4.25%
BPMN experts	22	33.0%	<u>67.5%</u>
control group	35	34.0%	30.0%

The group of business practitioners comprised 35 members that were selected from SSA Queensland. This group had superior semantic knowledge ($\mu = 80\%$) compared to the other two groups, explained by the process model originating from SSA and all members having been/being involved with the process.

The group of Business Process Modelling Notion (BPMN) experts comprised 22 people including students enrolled in the course Business Process Management at the Eindhoven University of Technology, academic staff at the University of Innsbruck (Austria) and corporate partners in the Netherlands. This group had superior syntactic knowledge ($\mu = 67.5\%$) compared to the other two groups.

The control group consisted of 35 people and mainly comprised graduate students selected from the Radboud University Nijmegen and Maastricht University complemented with SSA employees with inferior semantic knowledge. Members of this group scored low on both semantic knowledge ($\mu = 34\%$) and syntactic knowledge ($\mu = 30\%$).

Demographics

The demographics of the participants showed that 70 percent was between age 20 and 29, 92 percent of the participants originated from either the Netherlands or Australia, the male/female ratio was 1.46 and almost 60 percent attended Tertiary education (for a more extensive overview of the Demographics see Appendix H).

Reservations

Two reservations were acknowledged when analysing the data, being (I) the sample containing an overrepresentation of students (and fresh graduates) and (II) the possibility of decreased outcome validity due to context heterogeneity.

- (I) Having the BPMN expert group mainly comprise students (and fresh graduates) can be questioned due to a lack of practical validity and a limited ability for generalisation (Veres & Mansson, 2005, p.99). The latter especially holds when assessing specific business impact (Goodhue et al., 2000) or learning curves associated with training in new technologies (Basili et al., 1999, p.722). Based on the argument that this research mainly aimed to provide insight into the user-understanding relation rather than assess business impact, the disadvantage of using students is argued to be forgone. Nevertheless, it does potentially affect the actionability of the recommendations in the conclusion section.
- (II) Any learning process is inherently highly contextual, making context isolation one of the critical factors in the determination of outcome validity. However, the demographics showed a level of pluriformity in personal contexts. To counter these differences, age, education and domain & modelling experience were included as control variables to test for their impact. Based on these considerations, this research has attempted to guarantee an acceptable level of internal and outcome validity.

Acknowledging these reservations, data from all respondents was used when the statistical analysis was initiated.

8. Operationalisation

This chapter discusses the operationalisation of the research design by reviewing the instrumentation and data analysis of the research. §8.1 elaborates on the scales used in the survey per stage of learning while §8.2 looks out for the statistical test that are to be conducted.

8.1 Instrumentation

Instrumentation was considered in accordance with the stages of learning by Biggs (1987). The presage stage considered the stage prior to learning and inquired into user characteristics present prior to showing the respondents the process models. The process stage considered what happened during learning hence gathering the relevant data after having briefly shown the participants the process models. The product stage considered the post learning stage and inquired into the level of understanding attained by the participants after having been shown the process models. The operationalisations of the concepts are discussed per stage.

8.1.1 Presage stage

Introduction

The general introduction to the survey explains the intention of the survey, setup in three stages (presage, process and product) and type of questions per stage.

Demographics

Some demographics were collected which were typified as basic demographics and experience demographics. The basic demographics under consideration were age, sex, nationality and level of education. The domain experience demographics were work experience at SSA, work experience at Queensland Government, work experience in recruitment and work experience in advertising vacancies. The modelling experience demographics were general process modelling experience, BPMN process modelling experience, number of BPMN models created, number of BPMN models read and training received in BPMN (after: Mendling et al., 2009; Schrepfer et al., 2009).

Syntactic and Semantic Knowledge

The level of knowledge assumed by the participant selection procedure was verified using some questions on syntax and semantics. The syntactic questions were derived from Mendling and Strembeck (2008) and Schrepfer et al. (2009), whereas the semantic questions were derived from Burton-Jones and Meso (2008). The syntactic questions quizzed the respondents by asking some theoretical questions about the BPMN notation whereas the semantic questions required the respondents to rate their own level of domain knowledge on a 7-point Likert scale.

Cognitive Ability

Cognitive ability was tested for using the Kit Reference Tests for Cognitive Factors by Ekstrom et al. (1963) and the Differential Aptitude Test by Wit and Compaan (2005).

I. Abstraction ability

Although abstraction ability has been identified as an important indicator of programming aptitude and success (e.g., Bennedsen & Caspersen, 2006), existing IS research is yet to propose an instrument suitable for its measurement. Therefore, the concept of size reduction was taken as an initial concept. Size could be cognitively reduced by identifying common properties for operators and operands to cluster them accordingly. Abstraction ability regards the first part of this process. Hence the *Abstract Reasoning: Thinking in Figures* test was selected from the Differential Aptitude Test (Wit & Compaan, 2005) to measure abstraction ability which required the respondents to finalise visual series by deducing their underlying rule.

II. Selection ability

Due to the lack of theory on selection ability in the area of modelling in general, the concepts of object-relevance (and nesting) were taken as initial concepts. These concepts were operationalised as a test that required the user to scan large collections of graphical elements for relevant one(s) requiring choice along the way. Hence the *Choosing a Path Test* was selected from the visual battery of the Kit of Reference Tests for Cognitive Factors (Ekstrom et al., 1963) to measure selection ability which required visual scanning from respondents in order to choose one path out of five which adhered to a pre-specified condition.

III. Conception ability

Due to the lack of theory on conception ability in the area of modelling in general, the quality metrics of nesting, modularisation and uniqueness were taken as initial concepts. These concepts were operationalised as a test that required the user to memorise smaller pieces of information and mentally integrate them to form a conception of the model. Hence the *Form Board Test* was selected from the visual battery of the Kit of Reference Tests for Cognitive Factors (Ekstrom et al., 1963) to measure conception ability which required the user to decide how many out of five (rotated) pieces should be used to form a larger figure.

Learning style

According to the aim of testing the intuitiveness of the learning style, the sensing versus intuitive learning scale by Felder and Soloman (2010) was used. They defined 11 questions mapping a learner's score on the sensing-intuitive learning continuum. These questions were selected based on their succinctness, proven robustness and validity and due to its frequent application in learning in technological contexts.

8.1.2 Process stage

Introduction

The introduction to the process stage specified the task requirements in a general manner inviting the respondents to set their own approach to learning. In addition, this introductory piece provided information about what to expect in the next sections.

Self-efficacy

Self-efficacy has been operationalised in a multitude of ways, both as an isolated predictor and embedded in behavioural theory. Within the IS discipline, the operationalisation by Compeau and Higgins (1995) is a well-established standard. Consistently, the more recent operationalisation by Moores & Chang (2009) has a similar mark-up explicitly inquiring about the ability to organise. As this research aimed to measure the confidence of deploying one's abilities in an upcoming task, a more action-oriented operationalisation of self-efficacy was favoured. Examples of such operationalisations were the ones by Wood and Locke (1987) and Phillips and Gully (1997). In accordance with Bandura (1991), the latter operationalisation was used as a basis for adaptation due to the level of task-specificity. Consistent to Breland et al. (2001) such an adaptation was made and incorporated in this research.

Learning approach: Motives & Strategies

As a revision of Biggs' (1987) Learning Process Questionnaire, Kember et al. (2004) released the Revised Learning Process Questionnaire (R-LPQ-2F). Although the questions mainly pertained to study behaviour in the long term, they were revised to fit one-episodic short term learning. This way, motives more closely resembled desire and strategies more closely related to behaviour. This increased the compatibility with the theory of goal-directed behaviour by Perugini and Bagozzi (2001). In addition, by replacing study specific terms with broader learning concepts the survey was adapted to fit a larger audience.

8.1.3 *Product stage*

Understanding

Aranda et al. (2007) proposed operationalising understandability according to four metrics, being correctness of understanding, time, confidence and perceived difficulty. Correctness was the only metric followed up on because time was considered a metric of performance rather than strictly understanding and confidence and perceived difficulty were only operationalisable as self-attributed metrics. Objections to the latter options were their accuracy and validity. Operationalising correctness was executed through questions of recall. In this research, recall considered asking semantic questions by means of multiple choice (e.g. Khatri et al., 2006; Mendling et al., 2007; Recker & Dreiling, 2007). Recall questions were decided upon based on arguments of time and validity. Not incorporating transfer questions kept the run time of the survey as concise as possible and prevented researcher interpretation of the answers, thereby reducing the chance of a biased outcome. The questions were composed building on the notion of distance by Reijers and Mendling (2008) and the aspects of understandability by Melcher et al. (2009). This resulted in the incorporation of 21 questions, 4 general questions based on small distance, 4 general questions based on long distance, 3 questions on concurrency, 4 questions on exclusiveness, 4 questions on order and 3 questions on repetition. The latter four categories were balanced on distance.

8.2 **Data analysis**

The data derived from the survey was analysed using six types of statistical analyses which are briefly introduced in this paragraph. Firstly, the data was prepared conducting missing value analysis and calculating Mahalanobis' distance (Field, 2009). Consecutively, an all items exploratory factor analysis and a reliability analysis were conducted to create scales for the variables. Only understanding did not meet the requirements approaching it as a formative construct rather than a reflective one (Coltman et al., 2008). The rest of the variables were labelled reflective and summated accordingly. Having created the variables, correlation analysis was conducted to provide an overview of the relations between the variables. Fifthly, multiple linear regression analysis was executed to test the hypotheses due to this research aiming to assess the relation between one dependent and multiple independent variables (Hair et al., 2006, pp188-191). Besides providing insight into the predictive power of the single independent variables and their predictive power as a variate, linear regression analysis also provided insight into the relative importance of, and relationship between the independent variables. Finally, logistic regression was executed to nuance the results derived from linear regression analysis by assessing the impact of the different user characteristics on each of the five dimensions of understanding (Field, 2009).

IV. Results

9. Initium

In the initium phase of the experiment two senior statisticians were consulted to give their opinion on the research design. These discussions yielded both remarks pertaining to the general setup as well as related to specific variables. Both are discussed in this chapter in that respective order.

9.1 General remarks

The small population used in this research suffices, yet usage of moderators should be approached with hesitation. The experiment may lack the statistical power to find such effects. Given the statistical setup, LISREL can be used for measurement. Three approaches can be chosen: a) Use PLS (Partial Least Squares), b) compare the effects and models per group, interpreting the differences between them, c) include group differences as a dummy variable in regular LS analysis. The procedure, largely consistent to the procedure proposed in Hair et al. (2006) would be as follows:

- Mention your alpha's per scale and erase unnecessary questions.
- Execute Exploratory Factor Analysis.
- Explore the (causal) relations in SPSS.

Before starting this procedure, it is advisable to closely look at the way respondents answered the questions due to the quantity of questions in the survey. Mahalanobis' Distance, measuring outliers, can be used to verify the respondents' composure to the test, i.e. check whether the questions were answered seriously.

In order to generate an acceptable response rate multiple incentives should be offered to aspired participants. Providing feedback, offering a benchmark with respect to the mean-score and material rewards would be examples of such incentive schemes. Applying the first two would require the participants to fill out their email address; this requires guaranteeing the participants discretion with the results rather than full anonymity. Before setting out the survey, qualitative piloting suffices, due to the incorporation of almost only existing scales, with a minimum number of two respondents.

9.2 Specific variables

Four variables were singled out by the statisticians and explicitly commented on.

- Learning style
Utilisation of item-response theory is advisable for the learning style variable. To test the level of agreement between the scores of the respondents a Mokken-scale could be used (e.g., Van Schuur, 2003). This variable can be captured in the final model ranging from -11 to 11.
- Self-efficacy
Inclusion of the self-efficacy variable should be taken under consideration given the limited anticipated statistical power of the investigation due to the amount of respondents. Moderating effects usually show when using a high N, hence decreasing the chances of self-efficacy having a significant effect. Besides, the nature of self-efficacy is substantially different from the rest of the variables included in this research not pertaining to modelling/domain expertise nor learning.
- Approach to learning
To test the factors in the approach to learning, an exploratory factor analysis suffices backed up by existing evidence. This variable should be incorporated in the model as a dummy variable, i.e. taking either a surface or deep approach to learning.
- Understanding
An experimental element could be added to this research by varying the dependent variable, i.e. understanding. A modus operandi to contemplate is utilisation of multiple models to test for understanding. An example is usage of two models differing in the level of complexity. The contrast between the two allows for conclusions to be drawn about the type of user characteristics utilised to cope with additional complexity. Such an experimental setup is advisable for follow-up research and is referred to in the discussion section. In addition, the theoretical framework should elaborate on the choice for complexity as the main model feature under inspection.

10. Pilot

Consistent to research design, two basic types of pilots exist being qualitative and quantitative. The advantage of a quantitative pilot lies in testing the internal validity of the scales, whereas a qualitative pilot mainly focuses on the appropriateness of the scales. By arguments of expected internal validity, qualitative piloting was decided upon. The expectation stemmed from usage of existing scales and the level of joint development, including the model creators, in developing the understanding scale. Three senior researchers formed the pilot panel, providing feedback on the research design and contents of the questionnaire.

10.1 General Questionnaire Contents

General comments were given on the lay-out of the instrument and usage of English. In addition, it was pointed out that the connecting sections needed to give a more accurate description of what the participants could expect in the next part. All these comments were incorporated into the final version of the survey.

10.2 Specific questions

Four variables were singled out by the pilot members and explicitly commented on.

- Level of education
Level of education distinguished seven categories of education, amongst them identifying TAFE education and trade education. This caused the answer categories to be specifically catered towards the Australian educational system. While the survey aspired to attract a larger cultural base than just Australians, these two answer possibilities were integrated into college education to apply to a broader group of respondents.
- Models created/read
The questions inquiring into the amount of models created and read required the participants to give an estimated number of models. Adding the word 'roughly' emphasised estimation is required, thereby stimulating participants to do so.
- Strategy
Question 9 of the Strategy battery as part of Approach to Learning asked the participants whether they aspired to learn the model: by 'rote'. This was perceived as potentially confusing and therefore altered to: by 'heart'.
- Understanding
Discussion arose to whether the questions on understanding should be answered while having the process models available to the participants or having them taken away. The advantage of having the model present while answering the questions was assumed to be exclusion of the effect of short-term memory. A disadvantage was that the questions would inquire into information searching skills rather than understanding. To stay conceptually close to the theoretical model, the latter option was decided upon having the respondents answer the questions without the model available to them.
Related to the questions on understanding themselves, discussion arose on how to make sure the level of understanding by the business practitioners is indeed a product of learning. Alternatively, semantic experts could be tapping into their existing knowledge when answering these questions. To control for this effect, to some extent, experience was adopted as a control variable.

11. Survey

Six types of analyses were conducted using the data obtained from the survey which is reported on in this chapter. These types of analysis were missing data & outlier analysis, factor analysis, reliability analysis, correlation analysis, regression analysis and logistic regression analysis. The results from all six types of analyses were reported on in this chapter.

11.1 Missing data, outlier analysis & data preparation

88 cases were included after missing data and outlier analysis. The results of three respondents were erased due to a substantially incomplete set of answers (>50%), ranging from having answered a third of the questions to none at all (Hair et al., 2006). The rest of the cases were scanned for missing values.

Missing data

- Cases

The threshold for cases was a missing value rate of 10%. Cases displaying a missing value rate above this value were deleted while missing values from cases scoring below or equalling 10% were replaced by the average of the case score on that particular latent variable (Hair et al., 2006, p.64). This method resulted in two deletions from the group of business practitioners.

- Variables

Next, the variables were assessed for missing values using a threshold of 15% for independent variables and 6% for dependent variables to qualify them for deletion. Although dependent items ideally do not contain missing values at all, a threshold percentage was used due to missing values being present in nearly all dependent items (Hair et al., 2006, p.56). The dependent item U13 violated the threshold having a missing value percentage of 6.7%. After inspection this item had already been discussed with the model creators and project manager during instrument creation as being ambiguous. Hence U13 was deleted from the final data set making it comprise 20 dependent items.

Outliers

Outlier analysis was performed using Mahalanobis distance at a significance level of $p < .001$. Although the sample size could be labelled small, the large number of predictors caused usage of a threshold value of 25 for the independent variables (Field, 2009, p.218). This led to one case being removed from the control group violating both the distance on self-efficacy (34.68) and learning strategy (32.15).

Data preparation

The last step in the initial stage of data analysis was data preparation and entailed a) recoding syntactic knowledge, cognitive ability, selection ability, conception ability and understanding into a dichotomous score of correctness plus b) reversing the answer categories of the negating questions of self-efficacy.

11.2 Factor analysis

Initially, all items were assessed on meeting the assumptions to factor analysis (for a complete description of this procedure see Appendix I). Based on the data type criterion, only semantic knowledge, self-efficacy, motive to learning and strategy to learning were incorporated in the factor analysis. Although Hair et al. (2006, p.113) state a small number of dummy variables can be included in factor analysis, the amount of dichotomous items, viz. syntactic knowledge, the three cognitive abilities and understanding, was regarded too high to incorporate all of them. Consecutively, factor analysis was executed. Visual overviews of the two final solutions reported on below can be found in Appendix J.

All items

All eligible items were included in one integrative factor analysis to assess the amount and uniqueness of factors present in the data. Principal factor analysis was used because the main objective was to discover latent structures in the data. Consistent with Ford et al. (1986) multiple methods were used for factor identification. The Kaiser criterion based on an eigenvalue > 1 suggested 10 factors were present, the variance criterion (> 60% of variance explained) suggested 7 factors were present and scree testing suggested 5 or 6 factors were present. Most notably, the results indicated that two self-efficacy factors were present, that the learning factors were rather diffused and that no convincing motive factor, i.e. containing multiple items with substantial factor loadings, could be distinguished. Finally, a considerable amount of correlations >.30 were found suggesting interrelationships between the factors. This illustrated closeness explained by the fact that all items were self-attributed scores related to motivation.

Building on these results, follow-up factor analysis was conducted to generate a more conclusive solution. The aim of this analysis was to distinguish a definite amount of meaningful factors that displayed high discriminant validity. First of all, the amount of factors was set. The previous all item-analysis illustrated presence of six or seven factors. In line with Conway & Huffcut (2000, p.152) both scenarios were explored to assess the interpretability of their outcomes. The scenario with 6 factors appeared to be most parsimonious and is reported on in this paragraph (The result of this analysis is listed in Appendix J as the Final Solution.) The analysis was run excluding the non-loading variables one-by-one based on their contribution to the six factors that were distinguished. Erasing SL3, ML7, ML1, ML8, SL5, ML6, SL7 and ML5 caused all the factors still present in the solution to display factor-loadings exceeding .4 on at least one of the six factors. Although only containing loading items with high communalities, the discriminant validity of the solution was still low due to the presence of crossloading items. To increase the purity of the factors all crossloaders were excluded from the solution one-by-one. This led to the exclusion of ML4, SL2, ML2 and SE3 respectively. Six factors remained in the final solution being:

- Performance self-efficacy comprising SE1, SE2, SE6
- Semantic Knowledge comprising SEK1, SEK2
- Surface Strategy to Learning; Memorisation comprising SL9, SL10, SL11
- Deep Approach to Learning comprising ML3, ML9, ML10, ML11, SL1
- Surface Strategy to Learning; Minimising Scope comprising SL4, SL6, SL8
- Achievement self-efficacy comprising SE4, SE5, SE7, SE8

These factors were accepted as input for reliability analysis.

SeK: Semantic Knowledge, SyK: Syntactic Knowledge, AA: Abstraction Ability, CA: Conception Ability, SA: Selection Ability, LS: Learning Style, PSE: Performance Self-Efficacy, ASE: Achievement Self-Efficacy, DAL: Deep Approach to Learning, SLms: Strategy to Learning by minimising scope, SLms: Strategy to Learning by memorisation U: Understanding

11.3 Reliability analysis

Following the factor analysis, the scales were assessed on their internal consistency. In Table 9 each variable is shown followed by the computation and according Cronbach's alpha. Scales ideally had to score above .7, whereby an alpha lower than .6 was unacceptable (Hair et al., 2006, p.139). Single items were removed from the scale if $\Delta\alpha > +.05$ and removed if $\Delta\alpha < +.001$.

Table 9 Reliability analysis; variables, computation and alphas

Reliability analysis		
Variables	Computation	Cronbach's α
Semantic Knowledge (SeK)	SUM(scores) / n	.958
Syntactic Knowledge (SyK)	ADD(n correct)	.975
Abstraction Ability (AA)	ADD(n correct) – (n incorrect / n correct)	.807
Selection Ability (SA)	ADD(n correct) – (n incorrect / n correct)	.879
Conception Ability (CA)	ADD(n correct) – (n incorrect / n correct)	.781
Learning Style (LS)	ADD(scores)	.835
Performance Self-Efficacy (PSE)	SUM(SE1,SE2,SE6) / 3	.785
Achievement Self-Efficacy (ESE)	SUM(SE4,SE5,SE7, SE8) / 4	.786
Deep Approach to Learning (DAL)	SUM(ML3, ML9, ML10, ML11, SL1) / 5	.710
Surface Strategy to Learning; MS (SLms)	SUM(SL4, SL6, SL8) / 3	.725
Surface Strategy to Learning; ME (SLme)	SUM(SL9,SL10,SL11) / 3	.664
Understanding (U)	SUM(scores) / n	.413

The table illustrates that the internal consistency of the memorisation surface strategy to learning scales did not meet the threshold of .7, yet met the cut-off value of .6. The results generated using this factor were therefore interpreted with caution.

Furthermore, Table 9 shows that the level of internal consistency for the understanding variable violated the lower threshold of .6. The score implied that no latent dimension underlay the understanding items. Two alternative remedies were assessed to improve the internal consistency.

- All variables were included in a reliability analysis following the pre-specified rules for incorporation and removal. This had no result as none of the items generated a minimum .05 increase upon deletion. This indicated that the items could not be regarded interchangeable for none could be excluded from the factor without changing its conceptual domain.
- Sub-scales were composed based on the theoretical underpinning themes of the questions. This generated alpha-scores ranging from .02-.27 which were insufficient. This indicates that no multiple latent dimensions are underlying the understanding items.

The results of these two attempts indicated that a reflective approach to data analysis would be futile for no dimensions underlay the items, i.e. the questions showed too little overlap, nor were the items interchangeable, i.e. the questions were too specific. Based on these findings, a formative approach to data analysis was considered.

A formative approach assumes the variance in the predictor items are not explained by an underlying dimension, but rather that the items are all unique aspects that give rise to an umbrella variable (Coltman et al., 2008). It can thus be argued that understanding a specific part of a process model made a unique contribution to the umbrella of process model understanding. Subsequently, differences in process model understanding were not equally perceived in each of the indicator items alike, e.g. low process model understanding coincided with high understanding of concurrency and vice versa. To reduce the data set to a workable set of items, the six steps in Coltman et al. (2008) and Diamantopoulos & Winklhofer (2001) were used for item selection. Before starting the analysis, the output was identified as five items displaying low communality, signifying they represent separate dimensions, but displaying high correlation with the non-included items, signifying they represent the full scope of the theoretical concept of understanding.

SeK: Semantic Knowledge, SyK: Syntactic Knowledge, AA: Abstraction Ability, CA: Conception Ability, SA: Selection Ability, LS: Learning Style, PSE: Performance Self-Efficacy, ASE: Achievement Self-Efficacy, DAL: Deep Approach to Learning, SLms: Strategy to Learning by minimising scope, SLms: Strategy to Learning by memorisation U: Understanding

- 1) Multicollinearity analysis was conducted to assess whether some variables did indicate a latent underlying dimension. Analysis showed that none of the items had a VIF > 10, hence excluding none.
- 2) Correlation analysis with one item as global indicator, being question U7, was executed to test which items showed theoretical closeness and directionality with this global indicator. No significant correlations were found for the items, hence excluding none.
- 3) General correlation analysis was consulted to look for unidirectional variables with strong (>.25) significant correlations. As a result, items U1, U10, U15 and U20 were accepted as formative indicators.
- 4) As understanding exclusiveness was not represented amongst these variables, the items inquiring into exclusiveness were screened on communality. Item U6 was selected because it showed the highest communality, i.e. gave indication to represent the full concept.
- 5) A final formative solutions was accepted comprising five items, being U1: Understanding of general features (Uge), U6: Understanding of exclusiveness (Uex), U10: Understanding of concurrency (Uco), U15: Understanding of order (Uor) and U20: Understanding of repetition (Ure). Based on this selection, one case was deleted because it answered missing on all 5 items.
- 6) Based on these five items an aggregated variable for understanding was computed that was used in linear regression analysis.

The result is a formative understanding variable (U) comprising five indicator items (Uge, Uex, Uco, Uor & Ure). A potential disadvantage of aggregation is loss of conceptual richness, due to the unique variation of the five items not being fully represented in the summated scale (Coltman et al., 2008). Acknowledging this disadvantage, five item-specific logistic regression analyses were executed next to the linear regression analysis with the aggregated variable.

11.4 Correlation Analysis

To assess correlation for non-normally distributed variables, amongst others the dummy variables for semantic and syntactic knowledge, spearman's rho was used.

Table 10 Correlation analysis by stage of learning

Correlation Analysis												
ρ	User Characteristics						Learning Process					Understanding U
	SEK	SYK	AA	SA	CA	LS	PSE	ASE	DAL	SLms	SLme	
SEK	1											
SYK	-.417**	1										
AA	-.362**	.250*	1									
SA	-.420**	.323**	.688**	1								
CA	-.184†	.162	.577**	.640**	1							
LS	.444**	-.265*	-.188†	-.337**	-.213*	1						
PSE	.272*	.027	-.025	-.060	-.004	-.004	1					
ASE	-.063	.212*	.255*	.241*	.324**	-.319**	.461**	1				
DAL	-.109	.234*	.002	.005	.138	-.128	.153	.187†	1			
SLms	.180†	-.002	-.117	-.215*	-.170	.197†	-.165	.045	-.202†	1		
SLme	-.271*	-.027	.228*	.335**	.175	-.303**	.009	-.152	-.081	.206	1	
U	-.178†	.200†	.255*	.225*	.217*	-.158	-.150	.140	-.014	.120	-.002	1

** : Significant @ p< .01

* : Significant @ p< .05

† : Significant @ p< .1

Correlation analysis illustrated relations between user characteristics and learning process variables and understanding, be it modest in magnitude. Correlations between learning process variables and understanding were fully absent indicating little chance of prediction effects between them.

SeK: Semantic Knowledge, SyK: Syntactic Knowledge, AA: Abstraction Ability, CA: Conception Ability,
 SA: Selection Ability, LS: Learning Style, PSE: Performance Self-Efficacy, ASE: Achievement Self-Efficacy,
 DAL: Deep Approach to Learning, SLms: Strategy to Learning by minimising scope, SLms: Strategy to Learning by memorisation
 U: Understanding

11.5 Linear regression analysis

Firstly, the variables were checked for meeting the assumptions to linear regression analysis (for a complete description of this procedure see Appendix K). This led to the transformation of abstraction ability, selection ability, conception ability and performance self-efficacy. Secondly, multiple linear regression analysis was executed, testing for main effects, mediation and moderation. The results of these tests are discussed in that respective order and can be found in Table 11.

Table 11 *Multiple linear regression analysis testing for main prediction, moderation and mediation*

Independent Variables		Dependent Variable: Understanding						Hypotheses	
		Prediction Accuracy			Mediation Models		Moderation Models		
		1a Presage	1b Deep Learning	1c Surface Learning	2a Deep Learning	2b Surface Learning	3a Learning Style	3b Self- Efficacy	
		β	β	β	β	β	β	β	
User Characteristics									
Semantic Knowledge		.199			.174	.190	.236	.088	H1
Syntactic Knowledge		.015			.063	.049	.105	2.276	H2
Abstraction Ability		.069			.044	.046	.097	-.693	H3
Selection Ability		.074			.071	.068	-.111	-.1674	H4
Conception Ability		.157			.189	.183	.149	2.014	H5
Learning Style		-.050			-.075	-.066	-.022	-.033	H6
Learning Process									
Performance Self-Efficacy			-.291*	-.263*	-.172	-.170			H8
Achievement Self-Efficacy			.217†	.182	.042	.025			
Deep Approach to Learning			-.062		-.102				H10
Memorisation Strategy				-.038		.031			H11
Minimising Scope Strategy				.122		.061			
Control Variables									
Domain Experience		-.256			-.174	-.163	-.320	-.229	
Modelling Experience		.076			.077	.081	.068	.059	
Age		.175			.147	.139	.167	.142	
Education		.188			.136	.154	.187	.142	
Interaction Terms									
LS*SeK							-.089		
LS*SyK							.126		
LS*AA							-.020		H7
LS*SA							-.293		
LS*CA							.032		
PSE*SeK								-.075	
PSE*SyK								2.198	
PSE*AA								-.777	
PSE*SA								-.1697	
PSE*CA								1.803	
ESE*SeK								-.031	H9
ESE*SyK								-.223	
ESE*AA								.118	
ESE*SA								.163	
ESE*CA								-.072	
Model Statistics									
Model Fit		F(10, 76)=	F(3, 83)=	F(4, 82)=	F(13, 73)=	F(14, 72)=	F(14, 71)=	F(20, 66)=	
		1.520	2.121	1.809	1.379	1.236	1.340	.915	
Adjusted R ²		.057	.038	.036	.054	.037	.056	-.020	

** : Significant @ p < .01

* : Significant @ p < .05

† : Significant @ p < .1

Model 1: Prediction Accuracy

Model 2: Mediation

Model 3: Moderation

SeK: Semantic Knowledge, SyK: Syntactic Knowledge, AA: Abstraction Ability, CA: Conception Ability,
 SA: Selection Ability, LS: Learning Style, PSE: Performance Self-Efficacy, ASE: Achievement Self-Efficacy,
 DAL: Deep Approach to Learning, SLms: Strategy to Learning by minimising scope, SLms: Strategy to Learning by memorisation
 U: Understanding

Model 1: Multiple linear regression analysis testing for prediction accuracy

To test hypotheses 1 to 6, multiple linear regression analysis was used testing for main prediction effects. Consistently, all user characteristics and control variables were included in one model assessing their accuracy as predictors for process model understanding. The result is depicted as Model 1a in Table 11.

Table 11 illustrates that none of the independent variables qualified as a significant predictor for understanding process models. Consistently, the model proved to be insignificant as well. This led to the acceptance of H_0 assuming no relation exists between the predictors and understanding.

To verify the absence of predictors amongst both the hypothesised set of user characteristics and control variables, stepwise regression analysis was conducted. The results showed that understanding could most accurately be predicted using a model that included conception ability ($\beta = .232^*$) and education ($\beta = .211^*$). Although significant ($R^2: .099$; $F[2,84]=5.710^{**}$), the model was not accepted as an accurate prediction model because it failed to meet the minimally required R^2 of 10% (Hair et al., 2006, p.195).

Model 2: Multiple linear regression analysis testing for mediation

To test hypotheses 8, 10 and 11, eight regression analyses were conducted testing for presence of a mediation effect. Mediation was approached using a recursive model, viz. including three prediction effects, due to the theorised absence of feedback loops (Hair et al., 2006, p.852). The assumption to mediation is 1) significance of the user characteristics on understanding, significance of the learning process on understanding, 2) significance of the user characteristics on the learning process and 3) a carry over effect of the significance of the user characteristics to the significant learning process variables in the mediation model (Hair et al., 2006, pp866-869). Three steps were therefore executed. Firstly, the predictive power of the user characteristics and learning process variables on understanding were tested in model 1a and 1b & 1c respectively. Secondly, the predictive power of the user characteristics on the learning process variables was tested which are listed in Table 12. Thirdly, all user characteristics and learning process variables were incorporated in model 2 assessing their impact on understanding.

Table 12 *Multiple linear regression analysis testing the user-learning process relationship*

Multiple linear regression analysis			
Independent Variables	Dependent Variable		
	DAL Model 3a	LSms Model 3b	LSme Model 3c
	β	β	β
User Characteristics			
Semantic Knowledge	-.202	-.010	.054
Syntactic Knowledge	.232	-.287*	.292†
Abstraction Ability	-.065	.087	.029
Selection Ability	.023	.044	-.065
Conception Ability	.169	-.059	-.079
Learning Style	-.013	.254*	.144
Control Variables			
Domain Experience	.018	-.087	.021
Modelling Experience	-.006	.073	-.236
Age	.144	-.109	-.044
Education	-.201	.142	-.127
Model Statistics			
Model Fit	F(10, 76)= 1.176	F(10, 76)= 1.903†	F(10, 76)= .953
Adjusted R ²	.020	.095	-.005

** : Significant @ p < .01 DAL: Deep Approach to Learning
 * : Significant @ p < .05 LSms: Learning Strategy by minimising scope
 † : Significant @ p < .1 LSme: Learning Strategy by memorisation

Table 11 illustrates insignificance of the predictors in model 1a, thereby violating the assumptions to mediation analysis. In contrast, model 1b shows a positive significant effect for achievement self-efficacy beliefs and a negative effect of performance self-efficacy beliefs on understanding process models. Table 12 shows absence of significant effects predicting a deep approach to learning, whereas syntactic knowledge and a sensing learning style proved negative significant predictors for a learning strategy by minimising scope whereas syntactic knowledge was a positive predictor for using a memorising learning strategy. Due to the scarcity of significant prediction effects and their diffusion over the different models, both mediation models proved insignificant finding no evidence of mediation.

Due to the inability to compute a significant prediction model that incorporated user characteristics, control variables and learning process variables, all variables comprised by these three categories were included in a stepwise analysis. The solution with the highest proportion of variance explained in understanding ($R^2: .104$; $F[2,84]=5.997^{**}$) is a model containing conception ability ($\beta= .298^{**}$) and performance self-efficacy ($\beta= -.219^*$), with syntactic knowledge and modelling experience as runners up. Although failing to meet the threshold in management science ($>.25$) the model exceeded the minimum of 10% to qualify as a significant prediction model (Hair et al., 2006, p.195).

Model 3: Multiple linear regression analysis testing for moderation

To test hypotheses 7 and 9, moderation analysis was executed. Table 11 shows the three types of interaction terms incorporated in the moderation models, being user characteristics minus learning style with learning style, performance self-efficacy and achievement self-efficacy. These interaction terms were created by mean-centring and multiplying the relevant variables. Two analyses were conducted, being one incorporating the learning style interaction terms and one incorporating the self-efficacy interaction terms. Both analyses included two steps. Firstly, a model incorporating the five relevant user characteristics, control variables and moderator variable was assessed on significant prediction effects and its level of explained variance in understanding. Secondly, the relevant interaction terms were added to assess whether some interaction terms proved significant and whether the moderation model was a significant improvement to the original measured in increase of R^2 (Hair et al., 2006, p.202).

Model 3a and 3b in Table 11 illustrate that none of the interaction effects were significant. In addition, the explanatory power of both models proved to have diminished compared to the originals with $\Delta R^2: .001$ and $\Delta R^2: .077$ respectively. Individual assessment of the interaction terms only showed the moderation effect between learning style and selection ability to be significant ($\beta= -.227^\dagger$) where respondents with high selection ability understood significantly more using a sensing rather than an intuitive learning style.

11.6 Logistic regression analysis

Finally, the effects of the user characteristics and learning process variables on each of the five dimensions of understanding were assessed. These analyses were executed to nuance the results derived from the multiple linear regression analyses. Aggregating the five dimensions to one understanding variable could have potentially evened out more subtle effect worth identifying. Although not directly relevant to answer any hypotheses, single dimension analysis was employed to add more depth to the results found on understanding. Due to each of the dependent variables being dichotomous (true or false), logistic regression was conducted.

For all five dimensions of understanding, all variables comprised by user characteristics, control variables and learning process variables were added to the analyses. This method was selected to be able to compare these results to the results derived from linear regression analyses. Besides single prediction effects, the likelihood ratio, Nagelkerke's R^2 and predictive accuracy were reported on. The Nagelkerke's R^2 was chosen for because of its range [0,1] (Field, 2009, p.223) and the likelihood ratio and predictive accuracy was inspected to assess model fit. Additionally, the predictor b's were analysed to estimate the relative contribution of each variable using Wald's analysis.

SeK: Semantic Knowledge, SyK: Syntactic Knowledge, AA: Abstraction Ability, CA: Conception Ability,
 SA: Selection Ability, LS: Learning Style, PSE: Performance Self-Efficacy, ASE: Achievement Self-Efficacy,
 DAL: Deep Approach to Learning, SLms: Strategy to Learning by minimising scope, SLms: Strategy to Learning by memorisation
 U: Understanding

A potential disadvantage to using the Wald's statistic is the possibility of an inflated b and according error on the insignificance of a variable (Field, 2009, p.224). The logistic regression analyses showed no high Wald values were found, therefore requiring no validation. Table 13 illustrates the results of each of the five analyses.

Table 13 *Logistic regression analysis testing the user-process-understanding relationship*

Logistic regression analysis					
Independent Variables	Dependent Variable; 5 dimensions of Understanding				
	General	Concurrency	Exclusiveness	Order	Repetition
	Exp(b)	Exp(b)	Exp(b)	Exp(b)	Exp(b)
User Characteristics					
Semantic Knowledge	1.373	.420	1.101	.158	.488
Syntactic Knowledge	.531	.380	3.253	.481	.639
Abstraction Ability	1.002	1.003	.998	1.004	1.000
Selection Ability	1.024*	1.015†	1.002	.978†	.982*
Conception Ability	.988	1.006	1.005	1.028*	1.009
Learning Style	.985	1.035	.986	1.045	.958
Learning Process					
Performance Self-Efficacy	.868†	.984	1.004	.877	.988
Achievement Self-Efficacy	2.026	.324*	.836	1.855	1.738
Deep Approach to Learning	.924	.999	.624	1.543	.786
Memorisation Strategy	1.397	1.073	1.124	2.449	.614
Minimising Scope Strategy	.927	1.006	1.167	.554	1.511
Control Variables					
Domain Experience	1.221	1.429	.845	.459	.378†
Modelling Experience	.975	.436	3.032*	.924	.898
Age	1.079	1.319	1.050	3.657*	1.080
Education	.878	1.354	1.250	1.948†	.942
Model Statistics					
Log-Likelihood	82.487	94.592	101.2488	68.466	103.646
	F(15)=21.873	F(15)=20.896	F(15)=16.017	F(15)=20.242	F(15)=16.029
Nagelkerke R ²	.318	.291	.227	.325	.225
Prediction Accuracy	82.8%	72.4%	71.3%	85.1%	64.4%

** : Significant @ p < .01

* : Significant @ p < .05

† : Significant @ p < .1

Table 13 illustrates that the estimated model was most accurate for understanding order, followed by general understanding, concurrency, and finally exclusiveness & repetition. The results of the logistic regression analyses in Table 13 indicated presence of some significant prediction effects besides the effect of performance and achievement self-efficacy found in Table 11.

Most notable were the effects of selection ability. Having high selection ability proved beneficial when attaining general understanding and understanding of concurrency whereas it proved unbeneficial when attempting to understand order and repetition. Remarkably, these effects almost perfectly balanced each other out leaving selection ability an insignificant predictor to overall understanding. In contrast to its impact on overall understanding, achievement self-efficacy beliefs proved unbeneficial when trying to understand concurrency. Modelling experience proved a positive predictor for understanding exclusiveness, as were conception ability, age and education for understanding order. Finally, domain experience proved to be a negative predictor for understanding repetition.

Based on these analyses especially the role of selection ability was nuanced. Although H₀ was accepted for its effect on overall understanding, it is very closely related to it exemplified by rejecting H₀ for 4 of the 5 understanding dimensions.

12. Ex-Post

This chapter reports on the separate panel discussions held with four senior researchers in a one-on-one format. The topics that were discussed included sufficiency of the hypotheses, adequacy of methodology, validity and strength of results and an outlook on the conclusion and discussion sections. It should be noted that each expert was informed of the research setup, design and results by a summarising four-pager (comprising information on the theory, hypotheses, correlation, regression and interaction analyses plus some preliminary conclusions) thereby limiting the depth of the feedback.

Hypotheses

The theory on process model quality was deemed too large in quantity and too complex to point out essentially complementary metrics that were lacking in the hypotheses. Potential additions could have been visualisation of model elements or level of agreement, yet these are not vital to the setup as was.

Methodology

Both general methods as well as specific variables were commented on.

Methods

In addition to the methods indicated in paragraph 8.2, cluster analysis and variance-covariance analysis were suggested. Cluster analysis can be used to assess whether there were groups of respondents having an equal pattern in understanding scores. Based on these patterns predictors for cluster placement could be identified as alternatives to predictors for understandability. It is vital to keep in mind that these clusters should not be ranked hierarchically, but merely contrasting with appropriate labels. Variance-covariance analysis can be used to even out the wide ranges of some of the variables in the design (e.g. selection ability). By transforming these wide ranging ratio variables to an ordinal scale, these variables can be included in co-variation analysis as supplement/alternative to moderation analysis with regression models like applied in multivariate analysis. After comparing the output of these analyses to the results reported on in chapter 11, no more meaningful results were found discarding the alternatives and sticking with regression analysis.

Variables

Since no existing literature exists on how to translate quality into user characteristics, the translation in this research could have been subject to bias. This could especially apply to empirical and pragmatic quality due to their theoretical ambiguity which causes alternative operationalisations to be widely conceivable. A potential consequence could thus be that by choosing a specific operationalisation, other aspects of understandability were overlooked, e.g., chunking ability may have been overlooked when relating size to abstraction ability only. Consequently, it was pointed out that the non-significance of the regression models and low predictive power of the cognitive abilities and learning style may have been a result of the operationalisation rather than them playing a neglectable role in the real world.

The dependent variable of understanding only measured retention which generated usable results but was insufficient for drawing conclusions about transfer. The theoretical compatibility would thus have been optimised when open problem solving questions were used in addition to the dichotomous ones measuring retention. In addition, due to the strongly comprised time frame some of the user characteristics may have become irrelevant. It can be expected that understanding therefore was much more likely to have been a result of experience and routine rather than of user characteristics.

Results

The overall impression of the results was that they looked interesting and usable. Although the limitations to these results should explicitly be acknowledged, the findings were deemed useful to complement conceptual literature on model understandability. Especially the results on knowledge appeared counter intuitive for they were expected to be the other way around, i.e. semantic experts were expected to have a clearer understanding of general features than syntactic experts. Besides counter intuitive, this is also very surprising due to the level of complexity of the model. A possible explanation was brought up being that semantic experts might have become overconfident due to their familiarity with the process to study the general overview of the model.

Outlook

Conclusion

Structure-wise, it was suggested to report on the findings per test due to the sheer magnitude of results retrieved. Organising the data this way would keep it understandable.

Report-wise, the conclusions should make explicit reference of the delineations and limitations of the piece. The formative approach did allow explorative conclusions to be drawn feeding in to future research, yet needed to express caution when generalising.

The most sensitive issue in the conclusions was the low proportion of variance explained by the regression models. Possible explanations were identified as threefold, being statistical invalidity, low sample size and delineations in the model. In other words, one or more of the variables could have been flawed, the sample size could have been too low or the insignificance could be a result of most variance being explained by factors other than included in the scope of this research. To deal with this partial significance, it was advised to also report on the effect that proved insignificant. Some of the non-findings were counter-intuitive, hence the report had to incorporate lack of significance equally to significant relations found.

Discussion

Three alternative explanations for the results were brought forward, feeding into the discussion section of the report.

1. Understandability is but one aspect of quality causing the other dimensions to be potential spurious factors to the results in this paper.
2. The effects of short-term memory and chunking capacity (plus their interactions with other variables) were neglected. These concepts were theoretically regarded as important sources to explaining variation in understanding and could have been expected to play a role here as well.
3. The expectations towards the participants were unclear. Too little guidance was provided concerning the type of understanding questions that would be asked about the model. Due to ambiguous expectations, it was difficult deciding what to focus on hence having to make a selection. This causes the results to be biased, i.e. a syntactic expert would have been able to answer the questions about concurrency yet did not have time to take in all information and did not receive sufficient guidance to know concurrency would be one of the features that would be inquired into.

V. Conclusion and Discussion

13. Conclusion

In this chapter the conclusions of this research are drawn taking two steps. Firstly, the hypotheses were falsified using the survey results. Consecutively, the general conclusions were drawn building on the hypotheses and main ideas in the theoretical framework. The conclusions are divided into three parts, discussing the legitimacy of the main question, methods for model improvement and possibilities for user training.

13.1 Hypotheses

In chapter one the main research question was introduced along with some sub questions. These sub questions inquired into the identification of pertinent user characteristics in the presage stage, conceptualisation of the process stage and qualification of the learning product. These sub questions were theoretically answered and led to eleven hypotheses being posited in chapter six. Each of these hypotheses is falsified and discussed in this paragraph. Table 14 provides an overview of the research outcomes.

Table 14 *11 hypotheses and their results*

Hypotheses			
Hypothesis	Variable	Effect on understanding	Supported?
H1	Semantic Knowledge	+	no
H2	Syntactic Knowledge	+	no
H3	Abstraction Ability	+	no
H4	Selection Ability	+	no
H5	Conception Ability	+	yes
H6	Learning Style	-	no
H7	Learning Style Interaction	=	no
H8	Self-Efficacy	=	yes
H9	Self-Efficacy Interaction	=	no
H10	Deep Approach to Learning	+	no
H11	Surface Approach to Learning	+	no

+ positive effect
 - negative effect
 = effect

H1 Semantic knowledge positively affects understanding process models. False

Although semantic knowledge had a significant negative relation with understanding ($\rho = -.178^\dagger$), it proved to have no effect on understanding accepting H_0 in all regression models and rejecting hypothesis 1. The only significant result generated for the semantic knowledge group was a negative prediction effect of a deep approach to learning on understanding ($\beta = -.609^*$). A possible explanation for this result is domain experts experiencing high cognitive load when taking a deep approach to learning. Due to the semantic experts being able to relate the information to pre-existing knowledge, the cognitive load exerted by the information is increased requiring more heavy processing. Less information may have been adopted as a result of this.

H2 *Syntactic knowledge positively affects understanding process models.* **False**

Although syntactic knowledge had a significant positive relation with understanding ($\rho = .200^\dagger$), it proved to have no effect on understanding accepting H_0 in all regression models and rejecting hypothesis 2. Syntactic knowledge did have a significant effect on choosing a surface approach to learning whereby it was a positive predictor for choosing a memorisation strategy ($\beta = .292^\dagger$) yet a negative predictor for minimising scope ($\beta = -.287^*$). These results suggest that knowledge of the notation facilitated learning the information by heart yet did not motivate the modelling experts to minimise their efforts. The insignificant result on understanding makes this research extend the results found by Recker and Dreiling (2007) proposing the impact of syntactic knowledge might not only transcend notation specificity, but may be neglectable in general.

H3 *Abstraction ability positively affects understanding process models.* **False**

Although abstraction ability had a significant positive relation with understanding ($\rho = .255^*$), it proved to have no effect on understanding accepting H_0 in all regression models and rejecting hypothesis 3. This research thereby concurred with Bennedson and Caspersen (2006) in theorising abstraction ability to play a role, but finding no such empirical evidence. A possible explanation might be that the concept of abstraction ability is too integrative to capture in one assessment and should rather be operationalised using a multiple test battery.

H4 *Selection ability positively affects understanding process models.* **False**

Although selection ability had a significant positive relation with understanding ($\rho = .225^*$), it proved to have no effect on understanding accepting H_0 in all linear regression models and rejecting hypothesis 4. In contrast, logistic regression analysis showed selection ability to be a significant predictor for general understanding ($\exp[b] = 1.024^*$), understanding concurrency ($\exp[b] = 1.015^\dagger$), understanding order ($\exp[b] = .978^\dagger$) and understanding repetition ($\exp[b] = .982^*$). The discrepancy in effects, the first two being positive predictors while the latter two are negative ones, suggests that thinking about processes in a sequential way substantially differs from thinking about processes as flow with loops. A possible explanation is that they differ in cognitive load with the former mainly appealing to the cognitively lower order process of search while the latter also appeals to the higher order process of reasoning (Wang et al., 2006). The positive effect of search on understanding has also been described in existing literature that proved novices understood a process model significantly better when same-level gateways were given the same colour, i.e. usage of lollipops. This research therefore contends that despite absence of an effect on understanding, selection ability does play a significant role in understanding process models.

H5 *Conception ability positively affects understanding process models.* **True**

Although conception ability had a significant positive relation with understanding ($\rho = .217^*$), it proved to have no effect on understanding accepting H_0 in all formal regression models. In contrast, regression analysis based on optimising the proportion of variance explained, i.e. stepwise regression analysis, indicated conception ability to be the most accurate predictor of understanding ($\beta = .298^{**}$) explaining approximately 7% of its variation which caused hypothesis 5 to be accepted. This result indicated understanding process models is a process of mentally integrating parts of the model to create more integrative chunks. In their discourse on modularisation Reijers and Mendling (2008) showed that models featuring chunk indications had a positive impact on user understanding. In line with their argument, it could be posited that conception ability helps users to mentally decrease cognitive load by excluding irrelevant information through making meaningful chunks.

H6 *Sensing learning positively affects understanding process models.* **False**

Learning style proved to have no effect on understanding accepting H_0 in all regression models and rejecting hypothesis 6. In contrast, having an intuitive learning style was proven to be a significant predictor for choosing a learning strategy by minimising scope. This indicates that intuitors, preferring innovative ideas and using a more holistic approach to learning, do not perceive a process model as something that necessitates extensive inspection. Altogether, these results suggest that the call for more intuitive models (e.g. Moody, 1996) may empirically be regarded a less prevalent programme in the area of process model understandability.

H7 Learning style influences the effect of user characteristics on understanding process models. False

Learning style proved to have no interaction effect with any of the user characteristics on understanding accepting H_0 in the regression analysis and rejecting hypothesis 7. Separately adding the interaction effects to the basic regression model revealed learning style did have interaction with selection ability ($\beta = -.219^\dagger$), where sensing learners having high selection ability significantly outperformed their intuitive selection able peers. Although small in magnitude, this effect can be considered noteworthy due to it manifesting itself while using a small sample and a rather large set of independent variables. However, because this effect was absent in the full moderation model learning style is accepted to have no influence on the user-understanding relation. It can therefore be concluded that other factors than secondary notation may determine the understandability of complex process models.

H8 Self-efficacy affects understanding process models. True

Self-efficacy proved to have a significant effect on understanding accepting H_a in the basic linear regression models and accepting hypothesis 8. The effect of performance self-efficacy on understanding proved to be negative both when taking a surface ($\beta = -.263^*$) and deep ($\beta = -.291^*$) approach to learning. In contrast, the effect of achievement self-efficacy on understanding proved to be positive ($\beta = .217^\dagger$), yet only manifested itself when taking a deep approach to learning. Theoretically, the discrepancy can be explained by coupling performance self-efficacy beliefs to overestimation (Chiew & Wang, 2004) and achievement self-efficacy beliefs to outcome expectations (Compeau et al., 1999). Consistently, feeling confident about one's performance is therefore harmful to user understanding whereas feeling confident about being able to master the assignment and outperform others is beneficial to it. Potentially, the former brings about a decrease in intrinsic motivation whereas the latter increases extrinsic motivation. Self-efficacy can be concluded to play a significant role in attaining process model understanding, yet persists to be an elusive construct in the learning process.

H9 Self-efficacy influences the effect of user characteristics on understanding process models. False

Self-efficacy proved to have no interaction effect with any of the user characteristics on understanding accepting H_0 in the regression analysis and rejecting hypothesis 9. Additionally, none of the individual effects proved significant rendering the effect of self-efficacy as a moderator neglectable.

H10 A deep learning approach positively mediates the user-understanding relation. False

H11 A surface learning approach positively mediates the user-understanding relation. False

Learning approach proved to be no mediator of the effect of any of the user characteristics on understanding accepting H_0 in the mediation analysis and rejecting hypotheses 10 and 11. The absence of a mediation effect can mainly be attributed to the absence of prediction effects between user characteristics and process model understanding and approach to learning and process model understanding. In addition, syntactic knowledge and learning style manifested themselves as significant predictors to taking a surface approach to learning while none of the user characteristics determined taking a deep approach to learning. These results are surprising due to motivation being a facilitating process to higher order cognitive processes (Wang et al., 2006) and approach to learning being theorised to fulfil a similar role. A possible explanation could be that the learning process in the questionnaire was mainly extrinsically motivated, thereby distorting the relation between setting a learning approach and attaining a learning goal.

Control variables

Although domain experience ($\rho = -.265^*$) and education ($\rho = .269^*$) had a significant relation with understanding, all four control variables proved to have no effect on understanding accepting H_0 in all regression models. In contrast, regression analysis based on optimising the proportion of variance explained, i.e. stepwise regression analysis, indicated education to be the third most accurate predictor of understanding ($\beta = .211^*$) explaining approximately 6% of its variation. Intelligence can therefore be expected to play a role in understanding complex process models as it is theorised to underlie all cognitive processes in the brain (Wang et al., 2006). In addition, modelling experience and domain experience were found to be significant predictors of dimensions of understanding where modelling experience proved a positive predictor whereas domain experience proved a negative predictor. Especially the negative effect of domain experience is counterintuitive, yet could potentially be explained by its relation with performance self-efficacy ($\rho = .283^{**}$). An alternative explanation is more research specific, having the participants with relevant domain experience scoring significantly lower on education ($F[1,50]=17.860^{**}$).

In conclusion, conception ability and self-efficacy were accepted to affect understanding which is visualised in Figure 9.

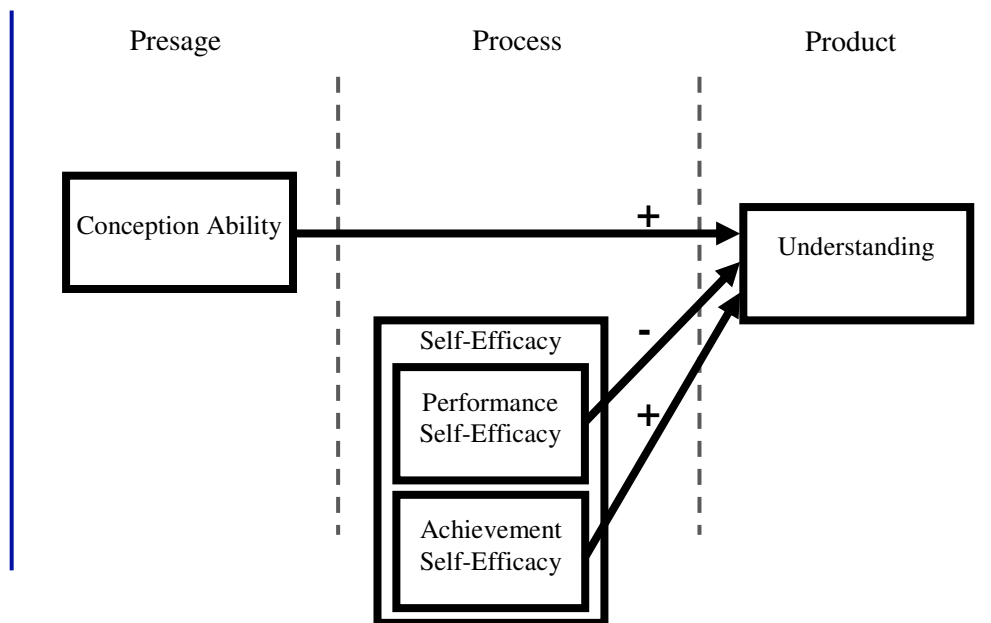


Figure 9

Conclusions visualised in measurement model

13.2 General conclusions

In chapter six, eleven hypotheses were posited based on the sub-questions to answer the main research question. Having answered the sub questions and hypotheses both theoretically and empirically, the main research question can now be answered using these insights. The research question is:

How can user characteristics contribute to a better understanding of business process models?

Firstly, the validity of answering this question using this data and the legitimacy of this question are discussed. Consecutively, the main question is answered focusing on model improvement and user training.

Legitimacy

Before answering the research question, the general impression obtained from this research was that the process models were quite complex and difficult to understand. This translated itself into about half of the respondents reaching a lower level of understanding than they would have gambling (20 two-choice questions were asked hence gambling would have resulted in a score of 10). Another reason for these low scores was the low interrelationship between the different understanding items. The items inquired into multiple unrelated and detailed aspects of the model, presumably decreasing the likelihood of attaining a high score on understanding. In addition, the results confirmed that understandability was but one aspect of quality and the variables included were but some aspects of understandability. Especially the predictive power of the models ($R^2 \approx [6\%, 15\%]$) indicated the existence of a substantial error term external to the model. It can therefore be concluded that user characteristics only account for a small proportion of the variance in understandability and that optimising process model understanding could still substantially benefit from improving the modelling artifact, be it based on user-model interaction or more conventional process model quality literature.

Given the delineations of this research, the findings suggest that some user characteristics indeed matter and can therefore be utilised to contribute to a better understanding of business process models. Using the taxonomy by Van Bommel et al. (2007) especially pragmatic quality was illustrated to impact process model understandability with strong prediction effects for conception ability and selection ability.

Looking at the interaction between user and process model illustrated that the situatedness of learning significantly impacts understandability through variables like performance self-efficacy and achievement self-efficacy. These concepts were proven to play a predictive role in the formation of understanding thereby illustrating the importance of the process stage of learning when examining the impact of user characteristics on understandability. The latter indicates situatedness, which further confirms the notion of process model understandability being an emergent property.

Building on this explorative data with caution, this research emphasises the usefulness of a fit perspective on improving process model understandability (e.g., Goodhue, 2006; Topi & Ramesh, 2002) rather than conceptualising the user separate from the model through taking a model-centric perspective. By doing so, user-centred design could be deployed to identify essential user-model interaction effects and improve the emergent understandability of process models accordingly. Rather than serving as a replacement, such research should be utilised to complement the existing body of mainly artifact-centred process model quality literature (e.g., Becker et al., 2000; Cardoso et al., 2006; Vanderfeesten et al., 2007). The legitimacy of such conduct can be increased by future research not only focusing on identifying essential user characteristics but also on opening *the black box* of the process stage of learning and exploring how interaction shapes understanding. Conducting research into essential user characteristics should ideally be converging and rigorous, for example using the forthcoming framework by this author and colleagues (Van de Wouw et al., 2010). Conducting research into the process stage could be executed extending on the approach taken in this research or taking new perspectives, e.g. using chunking, tracing or pattern registration (e.g., Hungerford et al., 2004; Santos & Badre, 1994).

Yet regardless of methodology, both the impact of user characteristics and the impact of the learning process should be understood in order to make user-centred design contribute to more understandable process models. After all, understandability is a perception, not a benchmark.

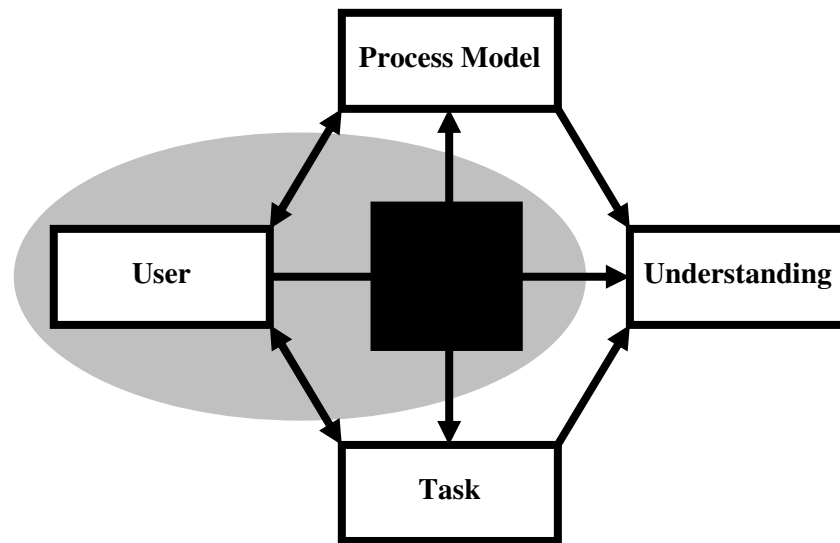


Figure 10 *Black box in User-Process Model interaction*

Acknowledging the interaction between user and process model, both sides are discussed when reviewing the contribution towards a better understanding of process models. Due to the rigorous design of this research, mainly general conclusions are drawn. These conclusions are accompanied with explorative design suggestions for their application in process model improvement.

Model understandability

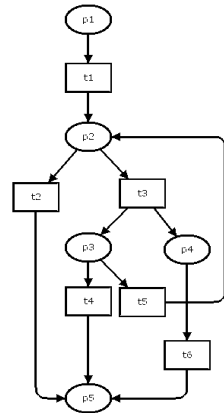
Conception ability proved to be the most accurate predictor for process model understanding serving as the operationalisation of nesting and referring to the ability to create meaningful chunks out of smaller pieces of information. Additionally, selection ability was found to affect understanding revealing object-relevance is of importance when learning from a process model in a sequential way while all information is required to enact loops and gateways. Finally, semantic and syntactic knowledge only displayed a weak relation with understanding while learning style displayed none at all. Synthesising these conclusions, complex process model understandability mainly relates to nesting depth and the ease with which users can chunk information in the model. From an analyst's perspective modularisation and a lower nesting depth makes a model easier to enact (Gruhn & Laue, 2006; Reijers & Mendling, 2008) while these model features, through reduced size, are associated with less error-proneness from a modeller's perspective (Vanderfeesten et al., 2007). Due to the insignificance of syntactic quality, size and pragmatic quality, future research should aim to optimise understandability using the other quality dimensions (Siau & Tan, 2005) as means to realise low perceived nesting depth and high chunkability. The focus should therefore be placed on using secondary notation and creating meaningful clusters.

Design: Clarifying the process flow by using secondary notation to decrease perceived nesting depth and improve chunkability should thus enjoy priority in optimising pragmatic process model quality. Ideas to improve the understandability of complex models should therefore look like:

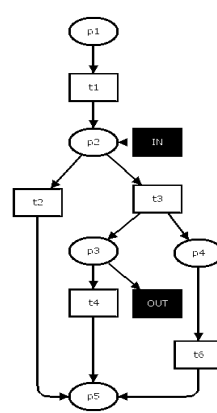
Perceived nesting depth

- Extending the research on secondary notation aimed at using colours to decrease perceived nesting depth (Dijkman, 2010), e.g. decreasing the amount of line crossing and edge bends by replacing the arcs connecting non-local objects with similarly coloured *in* and *out* transitions.

Including lone crossing

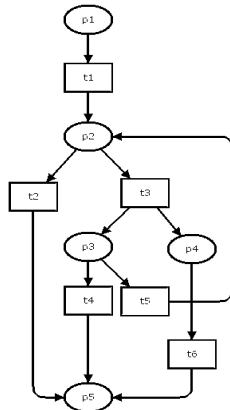


Excluding line crossing

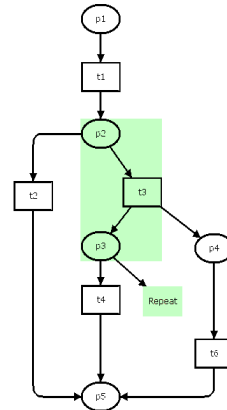


- Extending the research on secondary notation aimed at using colours to increase the (perceived) locality of transitions, e.g. by indicating repetition through a similarly coloured object as the part of the process to be repeated, rather than a non-local arc.

Featuring non-locality



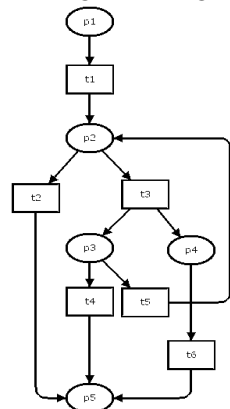
Featuring perceived locality



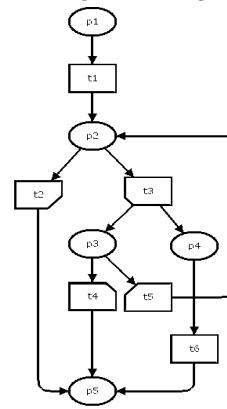
Chunkability

- Extending the research on model simplification by means of aggregation, e.g. by improving the chunkability of a model by providing chunking cues.

Excluding chunking cues



Including chunking cues



User training

Firstly, performance self-efficacy was found to be the strongest negative predictor for process model understandability. In line with Moores and Chang (2009) overconfidence was thus related to negative learning performance. This assumption was rivalled by arguments of cognitive load due to significant correlations between performance self-efficacy and domain knowledge and experience, and between achievement self-efficacy and syntactic knowledge and experience. These relations may suggest that the strong performance beliefs are justifiable because they coincide with domain expertise, but that the domain expertise deteriorated performance by increased cognitive load due to content familiarity. In contrast, achievement confidence beliefs are more procedural in nature which coincided with syntactic expertise and catered for an improved learning process. Inconsistent to these assumptions is the absence of an effect of knowledge in the results. However, the consequence of not having knowledge was compelling. Control group respondents that understood the model strongly relied on conception ability and some little modelling experience in their learning process, i.e. on creating chunks and being familiar with reasoning about the relation between an artifact and the real world. These findings emphasise the importance of inference - like in process model ontology - when creating understanding (Wand & Weber, 1995; Wang et al., 2006).

Secondly, conception ability was found to be a significant positive predictor for understanding while abstraction ability was not. Mental integration can therefore be labelled a more important skill for process model analysts than mentally labelling the information based on common denominators. In addition, selection ability proved a positive predictor for end-to-end understanding, even more so combined with a sensing learning style, while a negative predictor to enacting loops and repetition. Moreover, it can therefore be concluded that if the learning goal is understanding end-to-end flow then object-by-object browsing while scanning for object-relevance is the most effective learning strategy. If the goal is attaining more integrative understanding then chunking is more essential to attaining understanding.

Therefore, this research would like to propose user training to focus on making inferences between process models and the real world as well as making an assessment about which strategy being most relevant to use, end-to-end scanning, i.e. mentally following one path in the state space, or conceiving process-wide overview, i.e. mental conception. Additionally, Figure 11 proposes a conceptualisation of the process model user explaining approximately 12% of variation in user understanding. By seeing this model as an initial concept, future research can contribute to the optimisation of user training through its refinement.

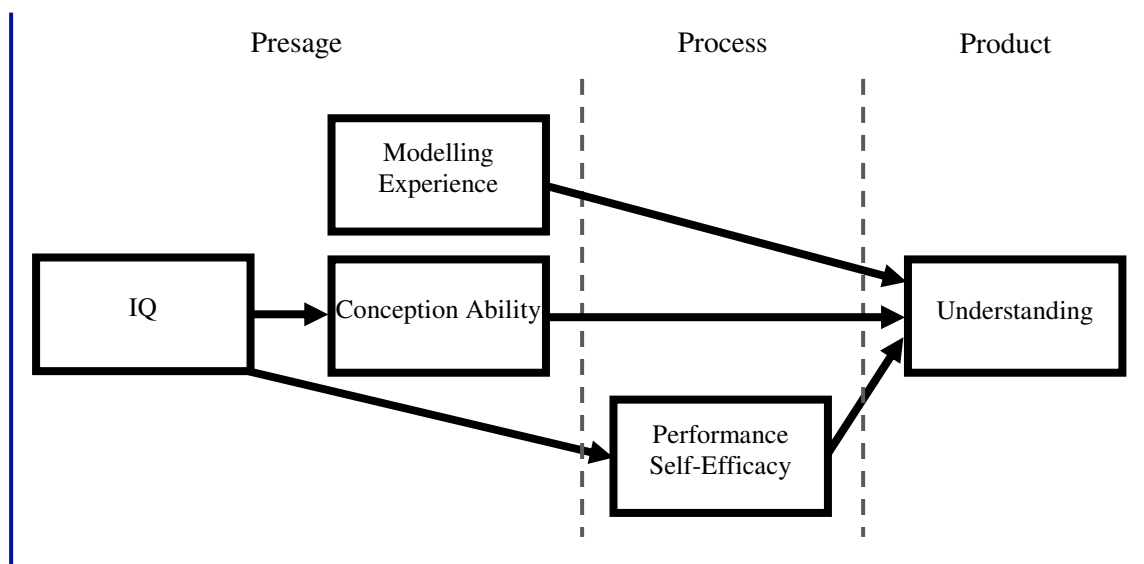
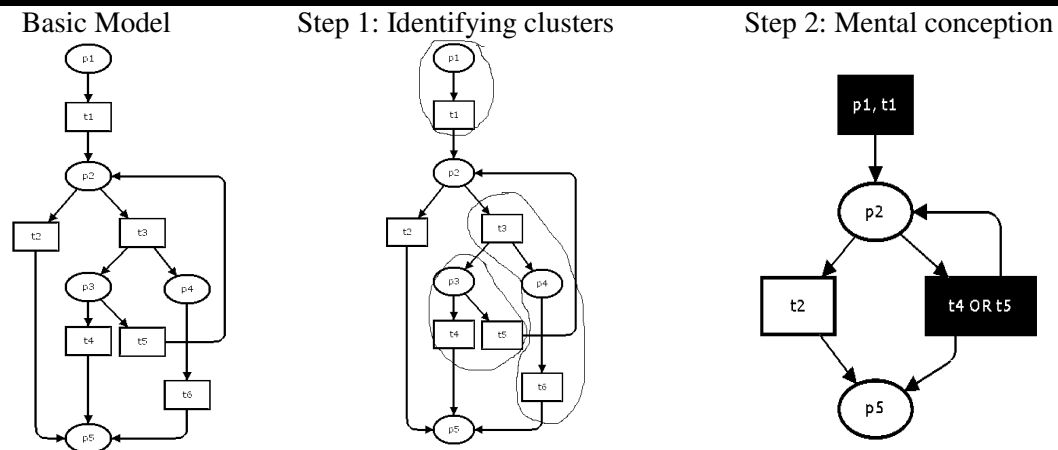


Figure 11

The process model user conceptualised

Design: Training should thus focus on inference reasoning, assessing learning goal-strategy compatibility and improving conception ability. Due to the latter being a form of intelligence, the trainability of such skills can be questioned. However, according to Chandler and Sweller (1991, p.294) even the higher cognitive process of problem-solving (Wang et al., 2006) can be improved on by using worked examples. This research therefore proposes to use worked examples to train users in attaining the goal of process model understanding. In these examples, extensive attention should be given to drawing inference and using existing knowledge and experience.

- Example of a worked example illustrating learning for integrative understanding



Step 3: Assess whether the centrality of the decision t4 or t5 fits existing knowledge

Step 4: Conceive how existing knowledge can be used to aid decision making in t4 and t5

Step 5: Inference questions

What happens if the choice *t4 OR t5* would have to be made in the first step of the process?

Process step t7 is added to the process. Where would you include it?

...

13.3 Fin

In conclusion, the legitimacy of this modus operandus has been proven by 1) identifying and testing some essential user characteristics, 2) generating significant and meaningful results and 3) being able to rank causes and come up with advice to improve model understandability as well as user training based on these findings. This research therefore illustrated the possibilities for user-centred design on a single process model level. Although these research results harboured too little statistical power to make recommendations that work towards more universal guidelines, indication has been given on how to improve complex models in general. More endeavours on single model improvement can thus be accumulated into the creation of a set of user-validated guidelines to ultimately make complex process models more understandable.

14. Discussion

This chapter discusses the limitations of this research, evaluates its outcomes and looks out for follow-up research. Due to the inherent subjectivity of user-oriented research, necessitating interpretivism, a large variety of topics were identified for inclusion in this chapter. Only the most notable ones were included giving an indication rather than an exhaustive overview of the implications of this research.

Limitations

Four major topics were identified as limitations to this research, being I) research subject selection, II) choosing the research objects, III) formative item-selection and IV) isolating the chance of spurious relations.

I. The sample used in this survey displayed heterogeneity in their user characteristics. Although the potential impact of this sampling heterogeneity was already discussed in §7.5, it needs to be emphasised that it is very plausible that the results were subjected to noise. Despite using four control variables to diminish the likelihood of noise, the differences found in understanding may have equally been attributable to other user characteristics (e.g. educational methods, verbal versus visual learning style, philosophical experience) as they were to the characteristics included. Lacking the methodological design to verify this suspicion can be perceived a limitation.

II. Only two complementary business process models were used as objects in this research selected based on complexity criteria. These models were shown to all the respondents thereby excluding the possibility to test for the impact of separate complexity metrics through treatment. An additional source of complexity was the syntactical incorrectness of the models. SSA, from where the process models originated, found itself in a low state of maturity at the time of measurement therefore facing issues typical for that stage, e.g., syntactic model incorrectness. Utilisation of these models was decided upon theorising the slight syntactical incorrectness would make enactment even more difficult optimising the variance between groups. Absence of such differences therefore indicated that the model complexity was a potential contributing factor to the low understandability scores and low internal cohesion of the understanding dimension. Lacking the methodological design to verify this suspicion can be perceived a limitation.

III. Selecting five items to construct a formative variable might have been a source of bias. One of the assumptions to formative analysis is that the items are non-interexchangeable. In contrast to reflective testing, formative items therefore mainly comprise unique variance which allows capturing complex constructs in a fewer amount of items. The risk of the non-interexchangeability is the lack of formal validation techniques other than based on trial and error. This research attempted to decrease the amount of bias in the formative item selection procedure by pre-specifying both the selection procedure, looking at a mix of theory and correlation & communality scores, and the procedural outcome, five unrelated variables. Nevertheless, it should be pointed out that usage of a formative approach to understanding while setting out to use a reflective one can be perceived a potential limitation to this research.

IV. Guaranteeing the internal validity of the results inherently is an important issue in user-oriented research. This research has attempted to exclude or capture most of the potential sources of covariance in order to realise an acceptable level of internal validity. Nevertheless, four important potential spurious effects were identified as uncontrolled for and are discussed below.

1. Although acknowledged to play a role and attempted to have been isolated, the effect of learning context was extremely difficult to exclude or fully capture and therefore most likely deteriorated the internal validity of the results. At least one respondent indicated that s/he was distracted by a colleague when filling out the questionnaire. Sources of noise were conceivable in a wide array and most likely influenced the learning process in all cases some way or another.

2. The learning process investigated in this research can be typified as a process mainly appealing to short-term memory. The effect of differences in short-term memory was not controlled for neither excluded in this research. The significant relations found in this research may therefore have been attributable to variation in short-term memory as much as to the causes identified.
3. The objects were presented to some respondents on paper and to others electronically based on arguments of operational feasibility (available amount of computers at one time) and reach (of the electronic survey). This effect was controlled for during regression analysis proving to be non-significant. Nevertheless, it should be acknowledged as a potential source of noise and therefore limitation to this research.
4. The understanding questions were created based on a discourse on process model syntax (Melcher et al., 2009) which discussed model structure and was therefore closely related to visual cognitive ability, specifically selection ability. Due to the nature of process models, comprising graphical elements expressing auditory and visual information, users were inherently necessitated to engage in visual cognitive enactment reducing the potential bias stemming from syntactic emphasis while composing the understanding questions. Nevertheless, this procedure may have had a contribution which favoured syntactical experts and contributed to the significance of selection and conception ability.

Evaluation

When the research design and results were evaluated, the results on abstraction ability and learning approach were interpreted as surprising. In addition, the dependent variable was regarded the most controversial element hence making it a topic to discussion.

Independent variable insignificance

Although abstraction ability has yet received little empirical attention, it was expected to have had a significant impact due to enacting process models being assumed to require heavy visual cognitive processing. In addition, the significance of selection and conception ability and the high level of communality between the three visual cognitive abilities further sparked the unexpectedness of these results. Due to the limitations of this research design, abstraction ability was still advised to be considered for inclusion in follow-up research.

The marginal impact of learning approach was interpreted as surprising due to motivation being attributed a central position in the most acknowledged conceptualisations of the learning process. Like indicated in §13.1, learning in this research being mainly extrinsically motivated could have led to a bias in the results of learning approach. When future research focuses on opening the black box of the process stage it is advised that learning approach should not be excluded from the variables under consideration.

Dependent variable insufficiency

When evaluating the dependent variable, the most important conclusion was that measuring understandability this way did not suffice. Dichotomous questions only approximate the concept of memorisation and provide no insight into user rationale or knowledge internalisation, hence disabling it to measure understanding. This insufficiency was captured by recognising two important issues. Primo, merely using dichotomous scales to measure understanding raised questions on the certainty of the understandability score being an actual result of learning. Complementary questions should have inquired into argumentation, i.e. having to provide a rationale for choosing an answer, or an 'I don't know'-category should have been included to prevent respondents from gambling behaviour. Secundo, strictly no problem-solving questions were asked to test for transfer making understandability more prone to bias and limiting the options to distinguish different levels of understanding. Aranda et al. (2007) advice operationalising understandability using multiple indicators where using merely one indicator could potentially generate biased results. The inclusion of transfer questions would have reduced this bias as well as given more depth to the conclusions consistent to Mayer (2001) and Recker and Dreiling (2007). These issues indicated that possibilities were overlooked to increase the statistical power and validity of the dependent variable.

Consequently, future research should:

- a) Look into these contemplations to realise an acceptable level of construct validity
- b) Explore options for creating a more valid scale for understandability/understanding that prevents these issues from arising in the first place. A fundamental idea might be the layered reference model of the brain (Wang et al., 2006) that describes which different processes are appealed to when engaging in learning and problem-solving. Inquiring into the outcomes of these separate processes could provide an indication of the level of understanding attained by process model users.

Outlook

In this paragraph, some tangible suggestions are made for future research.

In the *presage stage*, the set of user-characteristics could be altered towards a(n even) more actionable set. By drawing, for example, on software analyst component skills rather than process model quality literature the actionability of the results could potentially be increased. Examples would be the inclusion of memory (Cardoso et al., 2006) or formal discourse skills (Le et al., 2005).

Additionally, future research defining user characteristics as a moderator for model quality should consider using more pragmatic user characteristics as control variables rather than experience and expertise to optimise the validity of their outcomes.

In the *process stage*, alternative methods could be explored to map the learning process. Equal to the presage stage, more actionable operationalisations are conceivable using chunking theory, e.g. by utilising Santos and Badre's theory of automated chunking (1994), or pattern tracking, e.g. by using Hungerford et al.'s protocol method (2004).

In the *product stage*, usage of multiple models should allow for drawing more dynamic conclusions about the user characteristics utilised to cope with additional complexity. Such a setup would increase both the internal and external validity of the research outcomes.



References

- Aalst, W., van der. (1998). The Application of Petri Nets to Workflow Management. *The Journal of Circuits, Systems and Computers*, 8, 21–66.
- Agarwal, R., Sambamurthy, V., and Stair, R.M. (2000). Research Report: The Evolving Relationship Between General and Specific Computer Self-Efficacy--An Empirical Assessment. *Information Systems Research*, 11(4), 418-430.
- Aranda, J., Ernst, N., Horkoff, J., & Easterbrook, S. (2007). A Framework for Empirical Evaluation of Model Comprehensibility. *Proceedings of the International Workshop on Modeling in Software Engineering*, 7-13.
- Bandara, W., Tan, H.M., Recker, J., Indulska, M., & Rosemann, M. (2007). *Bibliography of process modeling: An Emerging research field*, retrieved June 20, 2009 from <http://eprints.qut.edu.au>.
- Bandura, A. (1991). Social-cognitive theory of self-regulation. *Organisational Behaviour and Human Decision Processes*, 50, 248-287.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.
- Basili, V.R., Shull, F., & Lanubile, F. (1999). Building Knowledge through Families of Experiments. *IEEE Transactions on Software Engineering*, 25(4), 456-473.
- Batra, D., & Kirs, P.J. (1993). The quality of data representations developed by nonexpert designers: An experimental study. *Journal of Database Management*, 4(4), 17-29.
- Ford, M.E. (1992). *Human Motivation: Goals, Emotions, and Personal Agency Beliefs*. Newbury Park, CA: Sage.
- Beattie, V., Collins, B., & McInnes, B. (1997). Deep and surface learning: a simple or simplistic dichotomy?. *Accounting Education*, 6(1), 1-12.
- Becker, J., Rosemann, M., & Uthamann, Von, C. (2000). Guidelines of Business Process Modeling. In: W. van der Aalst et al. (Eds.). *Business Process Management*, LNCS 1806, 30-49.
- Bennedsen, J., & Caspersen, M.E. (2006). Abstraction Ability as an Indicator of Success for Learning Object-Oriented Programming? *ACM SIGCSE Bulletin*, 2-5.
- Biggs, J.B. (1987). *The Learning Process Questionnaire (LPQ): Manual*. Hawthorn, Vic.: Australian Council for Educational Research.
- Biggs, J.B. (1987). *Student approaches to learning and studying*. Camberwell, Vic.: Australian Council for Educational Research.
- Biggs, J.B., Kember, D., & Leung, D.Y.P. (2001). The revised two-factor Study Process Questionnaire: R-SPQ-2F. *British Journal of Educational Psychology*, 71, 133–149.
- Breland, B.T., Donovan, J.J., Mullins, M.E., & Harvey, R.J. (2001). *Learning and Performance Goal Orientations' Influence on the Goal Setting Process: Is there an Interaction Effect?* Retrieved April 26, 2010 from <http://scholar.lib.vt.edu/theses/available/etd-05032001-162016/unrestricted/Breland.pdf>.

- Burton-Jones, A., & Grange, C. (2008). *Using Information Systems Effectively: A Representational Perspective*. Working Paper, Sauder School of Business, UBC, Handout for presentation at UQ Business School, October 30, 2008.
- Burton-Jones, A., & Meso, P.N. (2008). The Effects of Decomposition Quality and Multiple Forms of Information on Novices' Understanding of a Domain from a Conceptual Model. *Journal of the Association for Information Systems*, 9(12), 748-802.
- Burton-Jones A., & Straub, D.W. (2003). *Individual System Usage: A review of theories and methods*, Department of Computer Information Systems, Georgia State University.
- Cardoso, J. (2006). Process control-flow complexity metric: An empirical validation. In: *IEEE SCC 06*, Proceedings, 167-173.
- Cardoso, J., Mendling, J., Neumann, G., & Reijers, H.A. (2006). A Discourse on Complexity of Process Models. In: J. Eder, S. Dustdar et al. (Eds.): *BPM 2006 Workshops*, LNCS 4103, 115–126.
- Chandler, P., & Sweller, J. (1991). Cognitive Load Theory and the Format of Instruction. *Cognition and Instruction*, 8(4), 293-332.
- Chiew, V., & Wang, Y. (2004). Formal Description of the Cognitive Process of Problem Solving. *Proceedings of the Third IEEE International Conference on Cognitive Informatics*, 74-83.
- Conway, J.M., & Huffcutt, A.I. (2003). A Review and Evaluation of Exploratory Factor Analysis Practices in Organizational Research. *Organizational Research Methods*, 6(2), 147-168.
- Coltman, T., Devinney, T.M., Midgley, D.F., & Venai, S. (2008). Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business Research*, 61, 1250-1262.
- Compeau, D.R., & Higgins, C.A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *Management of Information Systems Quarterly*, 19(2), 189-211.
- Convington, M.V. (2000). Goal Theory, Motivation, and School Achievement: An Integrative Review. *Annual Review of Psychology*, 51, 171–200.
- Curtis, B., Kellner, M.I., & Over, J. (1992). Process Modelling. *Communication of the ACM*, 35(9), 75-90.
- Davis, F.D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Management of Information Systems Quarterly*, 13(3), 319-340.
- Diamantopoulos, A., & Winklhofer, H.M. (2001). Index Construction with Formative Indicators: An Alternative to Scale Development. *Journal of Marketing Research*, 38(2), 269-277.
- Dijkman, R. (2010). *Veel Procesmodellen? Weggooien, of ... serieus beheren!*, retrieved April 26, 2010, from <http://www.bpmroundtable.nl/>.
- Ekstrom, R., French, J., & Harman, H. (1976). *Manual for Kit of Factor-referenced Cognitive Tests*. Princeton, New Jersey: Educational Testing Service.
- Entwistle, N., & Smith, C. (2002). Personal understanding and target understanding: Mapping influences on the outcomes of learning. *British Journal of Educational Psychology*, 72, 321–342.

- Felder, R.M., & Soloman, B.A. (2010). *Index of Learning Styles*, retrieved April 26, 2010 from <http://www.ncsu.edu/felder-public/ILSPage.html>.
- Field, A. (2009). *Discovering Statistics Using SPSS (Introducing Statistical Methods series)*, 3rd ed. London: Sage Pub.
- Ford, M.E. (1992). *Human Motivation: Goals, Emotions, and Personal Agency Beliefs*. Newbury Park, CA: Sage.
- Ford, J.K., MacCallum, R.C., & Tait, M. (1986). The application of exploration factor analysis in applied psychology: A critical review and analysis. *Personell Psychology*, 39, 291-314.
- Gemino, A., & Wand, Y. (2003). Evaluating Modeling Techniques based on Models of Learning. *Communications of the ACM*, 46, 79-84.
- Gemino, A., & Wand, Y. (2005). Complexity and clarity in conceptual modelling: Comparison of mandatory and optional properties. *Data & Knowledge Engineering*, 55, 301-326.
- Gioia, D.A., & Pitre, I. (1990). Multiparadigm Perspectives on Theory Building. *The Academy of Management Review*, 15(4), 584-602.
- Goodhue, D.L., Klein, B.D., & March, S.T. (2000). User evaluations of IS as surrogates for objective performance. *Information & Management*, 38, 87-101.
- Goodhue, D.L. (2006). *Task-Technology Fit: A Critical (But Often Missing!) Construct in Models of Information Systems and Performance*. In: Zhang, P., & Galetta, D. (eds.) *Human-Computer Interaction and Management Information Systems: Foundations, Advances in Management Information Systems*, 184,-204, M.E. Sharpe: Armonk, New York.
- Goodhue, D.L., & Thompson, R.L. (1995). Task-Technology Fit and Individual Performance. *Management of Information Systems Quarterly*, 19(2), 213-236.
- Gruhn, V., & Laue, R. (2006). *Complexity Metrics for Business Process Models*. 9th international conference on business information systems, 1-12.
- Hair, J.F.jr., Black, W.C., Babin, B.J., Anderson, R.E., & Tatham, R.L. (2006). *Multivariate Data Analysis*, 6th edition. New Jersey: Pearson Prentice-Hall.
- Hovorka, D.S., Germonprez, M., & Larsen, K.R. (2008). Explanation in Information Systems. *Information Systems Journal*, 18, 23-43.
- Huang, W., Eades, P., & Hong, S. (2009). Measuring effectiveness of graph visualizations: A cognitive load perspective. *Information Visualization*, 8(3), 139-152.
- Hungerford, B.C., Hevner, A.R., & Collins, R.W. (2004). Reviewing Software Diagrams: A Cognitive Study. *IEEE transactions on software engineering*, 30(2), 82-96.
- Huotari, J., Lyytinen, K., & Niemelä, M. (2004). Improving Graphical Information System Model Use With Elision and Connecting Lines. *ACM Transactions on Computer-Human Interaction*, 11(1), 26-58.

- Jackson-Kokkonen, A., Bandara W., & Rosemann, M. (2009). Elements of BPM Expertise: A Greater Understanding of BPM Talent and Human Capital. *Handbook on Business Process Management*. Ed: M. Rosemann and J. vom Brocke. Springer-Verlag Berlin (in press).
- Kember, D., Biggs, J., & Leung, D.Y.P. (2004). Examining the multidimensionality of approaches to learning through the development of a revised version of the Learning Process Questionnaire. *British Journal of Educational Psychology*, 74, 261-280.
- Kember, D., & Leung, D.Y.P. (1998). The dimensionality of approaches to learning: An investigation with confirmatory factor analysis on the structure of the SPQ and LPQ. *British Journal of Educational Psychology*, 68, 395-407.
- Khatri, V., Vessey, I., V., Ramesh, P.C., & Sung-Jin, P. (2006). Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge. *Information Systems Research*, 17, 81-99.
- Krogstie, J. (2003). Evaluating UML Using a Generic Quality Framework. In: Favre, L. (ed) *UML and the Unified Process*. IRM Press: London.
- Krogstie, J., Sindre, G., & Jørgensen, H. (2006). Process models representing knowledge for action: a revised quality framework. *European Journal of Information Systems*, 15, 91-102.
- Le, H., Cassilas, A., Robbins, S.B., & Langley, R. (2005). Motivational and Skills, Social, and Self-Management Predictors of College Outcomes: Constructing the Student Readiness Inventory. *Educational and Psychological Measurement*, 65, 482-508.
- Lindland, O.I., Sindre, G., & Sølvsberg, A. (1994). Understanding quality in conceptual modelling. *IEEE Software*, 11(2), 42-49.
- Locke, E.A., & Latham, G.P. (2002). Building a Practically Useful Theory of Goal Setting and Task Motivation. *American Psychologist*, 57(9), 705-717.
- Maes, A., & Poels, G. (2007). Evaluating quality of conceptual modelling scripts based on user perceptions. *Data & Knowledge Engineering*, 63, 701-724.
- Mandviwalla, M., & Hovav, A. (1995). Adapting business process redesign concepts to learning processes. *Business Process Management Journal*, 4(3), 186-203.
- Marakas, G.M., Yi, M.Y., & Johnson, R.D. (1998). The Multilevel and Multifaceted Character of Computer Self-Efficacy: Toward Clarification of the Construct and an Integrative Framework for Research. *Information Systems Research*, 9(2), 126-163.
- Marton, F. & Säljö, R. (1976). On qualitative differences in learning: I – outcome and process. *British Journal of Educational Psychology*, 46, 4-11.
- Masri, K., Parker, D., & Gemino, A. (2008). Using Iconic Graphics in Entity-Relationship Diagrams: The Impact on Understanding. *Journal of Database Management*, 19(3), 22-41.
- Mayer, R.E. (1989). Models for Understanding. *Review of Educational Research*, 59, 43-64.
- Mayer, R.E. (2001). *Multimedia learning*. New York: Cambridge University Press.
- Mayer, R.E., & Moreno, R. (2003). Nine Ways to Reduce Cognitive Load in Multimedia Learning. *Educational Psychologist*, 38(1), 43-52.

Melcher, J., Mendling, J., Reijers, H.A., & Seese, D. (2009). *On Measuring the Understandability of Process Models*, retrieved April 26, 2010, from <http://en.scientificcommons.org/47864140>.

Mendling, J., & Recker, J. (2007). Extending the Discussion of Model Quality: Why Clarity and Completeness May not Always be Enough, In: Pernici, Barbara and Gulla, Jon Atle, Eds. *Proceedings The 19th International Conference on Advanced Information Systems Engineering, CAiSE'07*, 109-121, Trondheim, Norway.

Mendling, J., & Recker, J. (2008) Towards Systematic Usage of Labels and Icons in Business Process Models.

Mendling, J., Recker, J.C., & Reijers, H.A. (2009). *Process Modeling Quality: A Framework and Research Agenda*, retrieved April 26, 2010 from <http://is.tm.tue.nl/staff/hreijers/H.A.%20Reijers%20Bestanden/TechnicalReport.pdf>.

Mendling, J., Reijers, H.A., & Cardoso, J. (2007). What Makes Process Models Understandable? In: Alonso, G., Dadam, P., & Rosemann, M. (eds.): *Proc. of the the 5th International Conference on Business Process Management (BPM 2007)*, 24-28. September 2007, Brisbane, Australia. Lecture Notes in Computer Science Volume 4714, 48-63.

Mendling, J., & Strembeck, M. (2008). Influence factors of Understanding Business Process Models, Proceedings of the 11th International Conference, Innsbruck, Austria, May 5-7, 142-153.

Moody, D.L. (1996). Graphical Entity Relationship Models: Towards a More User Understandable Representation of Data. In: Thalheim, B. (ed.): *Proceedings of the 15th International Conference on Conceptual Modeling (Conceptual Modeling – ER '96)*. October 1996, Cottbus, Germany. Lecture Notes in Computer Science Volume 1157, 227-244.

Moody, D.L. (1998). Metrics for Evaluating the Quality of Entity Relationship Models. In: T.W. Ling, S. Ram, and M.L. Lee (Eds.): *ER'98, LNCS 1507*, 211–225.

Moores, T.T., & Chang, J.C. (2009). Self-efficacy, overconfidence, and the negative effect on subsequent performance: A field study. *Information & Management*, 46, 69–76.

Nickerson, J.V., Corter, J.E., Tversky, B., Zahner, D., & Rho, Y.R. (2008). The Spatial Nature of Thought: Understanding Systems Design Through Diagrams. In: *Twenty Ninth International Conference on Information Systems (ICIS)*, Paris 2008

Nysetvold, A.G. & J. Krogstie (2005). Assessing Business Process Modeling Languages Using a Generic Quality Framework. In: *Proceedings of the CAiSE'05 Workshops*. Volume 1 (Castro, J. and E. Teniente, Eds.), pp. 545-556, FEUP, Porto.

Pask, G. (1988). Learning strategies, teaching strategies and conceptual or learning style. In: R. R. Schmeck (Ed.) *Learning Styles and Strategies*. New York: Plenum Press, 83-100.

Perugini, M., & Bagozzi, R.P. (2001). The role of desires and anticipated emotions in goal-directed behaviours: Broadening and deepening the theory of planned behaviour. *British Journal of Social Psychology*, 40, 79-98.

Perugini, M., & Conner, M. (2000). Predicting and understanding behavioural volitions: the interplay between goals and behaviours. *European Journal of Social Psychology*, 30, 705-731.

- Phillips, J.M., & Gully, S.M. (1997). Role of goal orientation, ability, need for achievement, and locus of control in the self-efficacy and goal-setting process. *Journal of applied psychology*, 82(5) 792-802.
- Pintrich, P.R. (2004). A Conceptual Framework for Assessing Motivation and Self-Regulated Learning in College Students. *Educational Psychology Review*, 16(4), 385-407.
- Pohl, K. (1994). Three Dimensions of Requirements Engineering. *ESPRIT Basic Research Action 6353 (NATURE)*, Nordrhein-Westfalen, Germany.
- Recker, J.C. (2006). Towards an understanding of process model quality. Methodological considerations. Queensland University of Technology: Brisbane.
- Recker, J.C. (2008). *Understanding Continuance of Process Modelling Grammars*. Brisbane, Australia: Queensland University of Technology.
- Recker, J., & Dreiling, A. (2007). Does It Matter Which Process Modelling Language We Teach or Use? An Experimental Study on Understanding Process Modelling Languages without Formal Education, *Proceedings of the 18th Australasian Conference on Information Systems*, 5-7 Dec 2007, Toowoomba.
- Recker, J., & Mendling, J. (2007). *Adequacy in Process Modeling: A review of Measures and a Proposed Research Agenda*, Proposition Paper, retrieved April 26, 2010, from <http://www.mendling.com/publications/07-BPMDS.pdf>.
- Recker, J.C., & Rosemann, M. (2007). Understanding the Process of Constructing Scales Inventories in the Process Modelling Domain. *15th European Conference on Information Systems*, 2014-2025.
- Reijers, H.A., & Mendling, J. (2008). Modularity in Process Models: Review and Effects. In: M. Dumas, M. Reichert, and M.-C. Shan (Eds.), *BPM 2008*, LNCS 5240, 20–35.
- Rogers, E. (1995). *Diffusion of Innovations* (4th ed). New York: Free Press.
- Santos, P.J., & Badre, A.N. (1994). Automatic Chunk Detection in Human-Computer Interaction. *Graphics, Visualisation & Usability Center*. Georgia Institute of Technology, Atlanta.
- Schrepfer, M., Wolf, J., Mendling, J., & Reijers, H.A. (forthcoming). *The Impact of Secondary Notation on Process Model Understanding*.
- Schuur, W.H., van. (2003). Mokken Scale Analysis: Between the Guttman Scale and Parametric Item Response Theory. *Political Analysis*, 11, 139–163
- Shanks, G., & Darke, P. (1995). Quality in Conceptual Modelling: Linking Theory and Practice. *PACIS 1997 Proceedings*. Paper 76, retrieved April 26, 2010 from <http://aisel.aisnet.org/pacis1997/76>.
- Siau, K., & Tan, X. (2004). Improving the quality of conceptual modeling using cognitive mapping techniques. *Data & Knowledge Engineering*, 55, 343–365.
- Topi, H., & Ramesh, V. (2002). Human Factors Research on Data Modeling: A Review of Prior Research, An Extended Framework and Future Research Directions. *Journal of Database Management*, 13(2), 3-19.

- Valle, A., Cabanach, R.G., Núñez, J.C., González-Peinda, J., Rodríguez, S., and Piñeiro, I. (2003). Cognitive, Motivational, and Volitional Dimensions of Learning: An Empirical Test of a Hypothetical Model. *Research in Higher Education*, 44(5), 557-580.
- Van Bommel, P., Hoppenbrouwers, S.J.B.A., Proper, H.A., & Van der Weide, P. (2007). *QoMo: A Modelling Process Quality Framework based on SEQUAL*. Institute for Computing and Information Sciences, Radboud University Nijmegen.
- Vanderfeesten, I., Reijers, H.A., Mendling, J., Aalst, Van der, W.M.P., & Cardoso, J. (2007). On a Quest for Good Process Models: The Cross-Connectivity Metric. *Lecture Notes in Computer Science*, 480-494.
- Van de Wouw, S.G., Recker, J.C., & Reijers, H. (forthcoming). Understandability of Process Models: A user's perspective on learning.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management of Information Systems Quarterly*, 27, 425-478.
- Veres, C., & Mansson, G. (2005). Cognition and modelling: foundations for research and practice. *Journal of Information Technology Theory and Application*, 7(1), 93-104.
- Vessey, I., & Galletta, D. (1991). Cognitive Fit: An Empirical Study of Information Acquisition. *Information Systems Research*, 2(1), 63-84.
- Wand, Y., & Weber, R. (1995). On the deep structure of information systems. *Journal of Information Systems*, 5, 203-223.
- Wang, Y., Wang, Y., Patel, S., & Patel, D. (2006). A Layered Reference Model of the Brain (LRMB). *IEEE Transactions on Systems, Management, and Cybernetics (Part C)*, 36(2), 1-12.
- Wit., J., & Compaan, E. (2005). *DAT NL A | Differentiële Aanleg Test voor Onderwijs Versie A: Havo/Vwo*. Amsterdam: Pearson Assessment and Information B.V.
- Wong, N. Y., Lin, W. Y., & Watkins, D. (1996). Cross-cultural validation of models of approaches to learning: An application of confirmatory factor analysis. *Educational Psychology*, 16, 317-327.
- Wood, R.E., & Locke, E.A. (1987). The Relation of Self-Efficacy and Grade Goals to Academic Performance. *Educational and Psychological Measurement*, 47(4), 1013-1024.
- Zmud, R.W., & Boynton, A.C. (1991). Survey Measures and Instruments in MIS: Inventory and Appraisal. In: K. Kraemer, J.I. Cash, and J.F. Nunamaker (Eds.), *The Information Systems Research Challenge: Survey Research Methods*, Volume 3, Harvard Business School, Boston, MA, 149-180.

Appendices

APPENDIX A

Philosophical approach

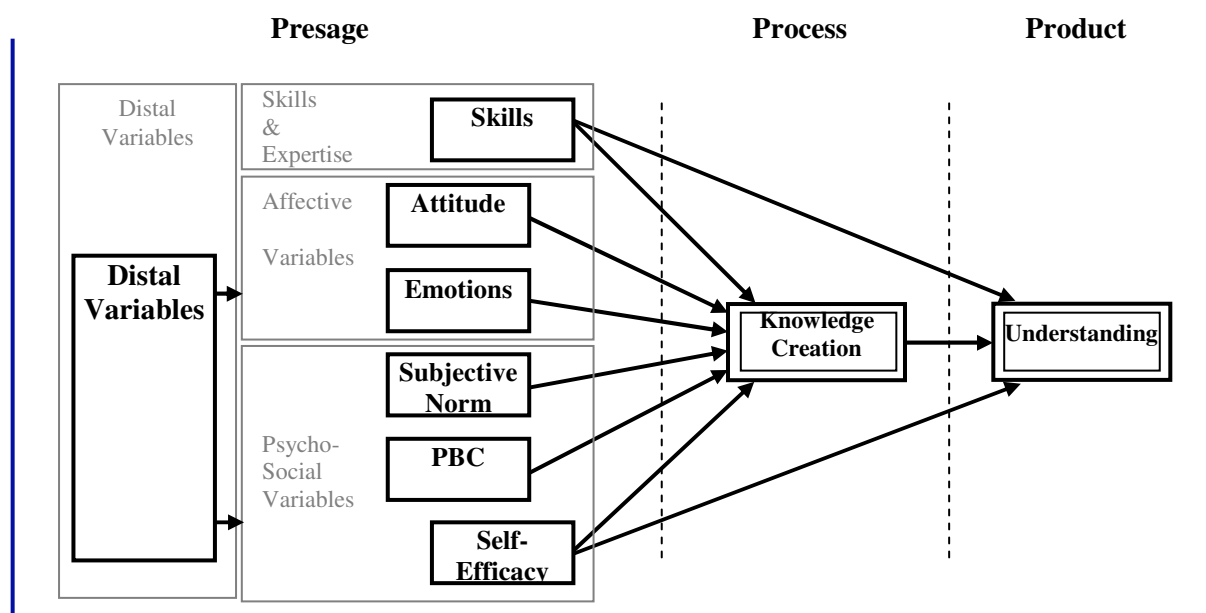
This research positions itself in the interpretivist-functionalist transition zone (Gioia & Pitre, 1990). This multiparadigm perspective bridges interpretivism and functionalism using structure (Gioia & Pitre, 1990, p.592). In short, the latter is based on the conception that humans perceive and structure in order to organise (interpretivism). Yet this structuring process is constrained by existing structures (functionalism). Hence humans structure and organise the world in a domain constrained by existing structures (interpretivist-functionalist transition zone). Applied to understanding process models:

- Humans try to understand process models by choosing an individual learning approach,
- Yet the seemingly infinite approaches to learning are constrained by interpersonal similarities and common notions about desirable goals of learning.
- Consequently, the process of human learning is executed given the constraint of a finite number of approaches to learning.

This research thus assumes subjective reality of human enactment to generate a learning outcome (response), while aiming at deductive theory building. By studying the way an organism enacts stimuli into a response, attention is given to the mediating effect of the organism (Stimulus-Organism-Response). By doing so, this research can contribute to the dominant S-R approach in process modelling literature (Hovorka et al., 2008).

APPENDIX B

User Characteristics in the learning process (Van de Wouw et al., forthcoming)



APPENDIX C

A Layered Reference Model of the Brain (Wang et al., 2006)

Subconscious Processes		Conscious Processes	
Layer 1 Sensational cognitive processes	Layers 2-4 Subconscious cognitive processes	Layer 5 Meta cognitive processes	Layer 6 Higher cognitive processes
1.1 Vision	2. Memory	5.1 Attention	6.1 Recognition
1.2 Audition		5.2 Concept establishment	6.2 Imagery
1.3 Smell	3. Perception	5.3 Abstraction	6.3 Comprehension
1.4 Tactility	3.1 Self- consciousness	5.4 Search	6.4 Learning
- Heat	3.2 Motivation	5.5 Categorization	6.5 Reasoning
- Pressure	3.3 Willingness	5.6 Memorization	6.6 Deduction
- Weight	3.4 Goal setting	5.7 Knowledge representation	6.7 Induction
- Pain	3.5 Emotions		6.8 Decision making
- Texture	3.6 Sense of spatiality		6.9 Problem solving
1.5 Taste	3.7 Sense of motion		6.10 Explanation
- Salt			6.11 Analysis
- Sweet	4. Actions		6.12 Synthesis
- Bitter			6.13 Creation
- Sour			6.14 Analogy
- Pungency			6.15 Planning
			6.16 Quantification

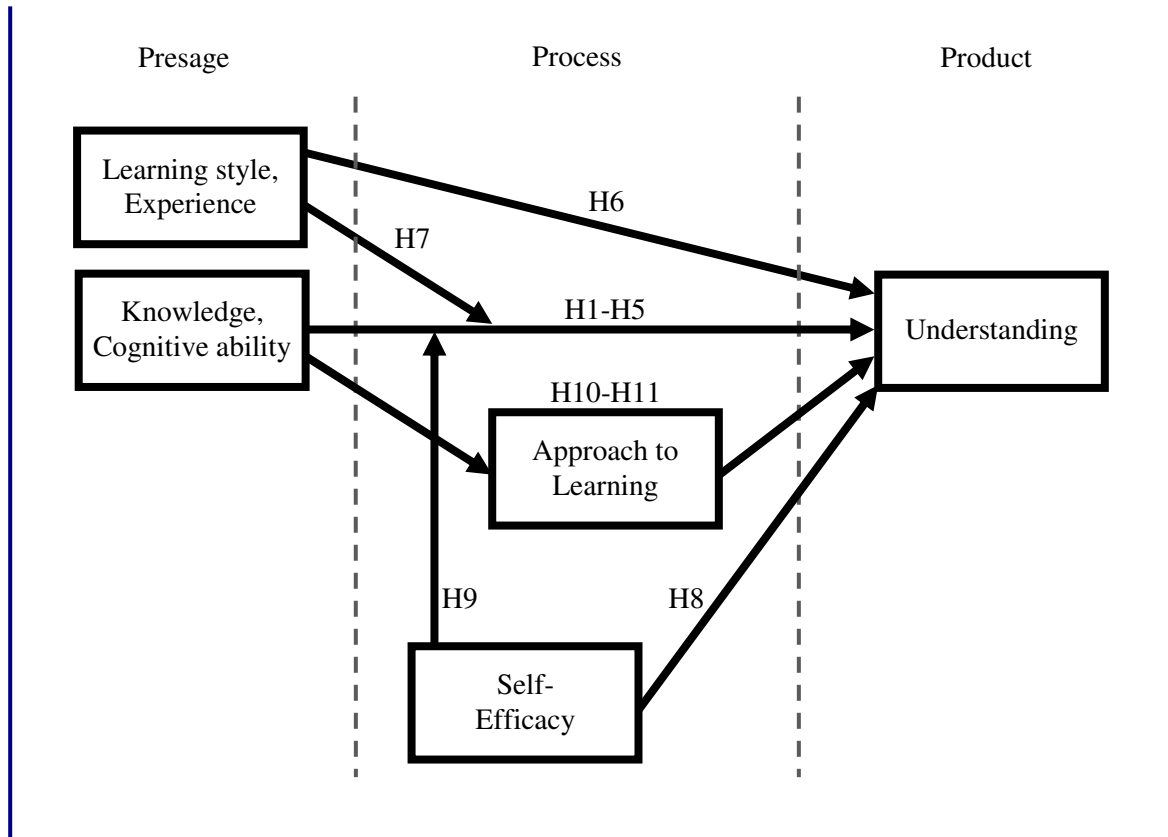
APPENDIX D

Language-Domain Appropriateness (Nysetvold & Krogstie, 2005, p.6)

Criteria to establish the Language-Domain Appropriateness	
Number	Requirement
1	The language should support the following concepts (a) processes, that must be possible to decompose (b) activities (c) actors/roles (d) decision points (e) flow between activities, tasks and decision points
2	The language should support (a) system resources (b) states
3	The language should support basic control patterns
4	The language should support advanced branching and synchronization patterns
5	The language should support structural patterns
6	The language should support patterns involving multiple instances
7	The language must support state based flow patterns
8	The language must support cancellation patterns
9	The language must include extension mechanisms to fit the domain
10	Elements in the process model must be possible to link to a data/information model
11	It must be possible to make hierarchical models

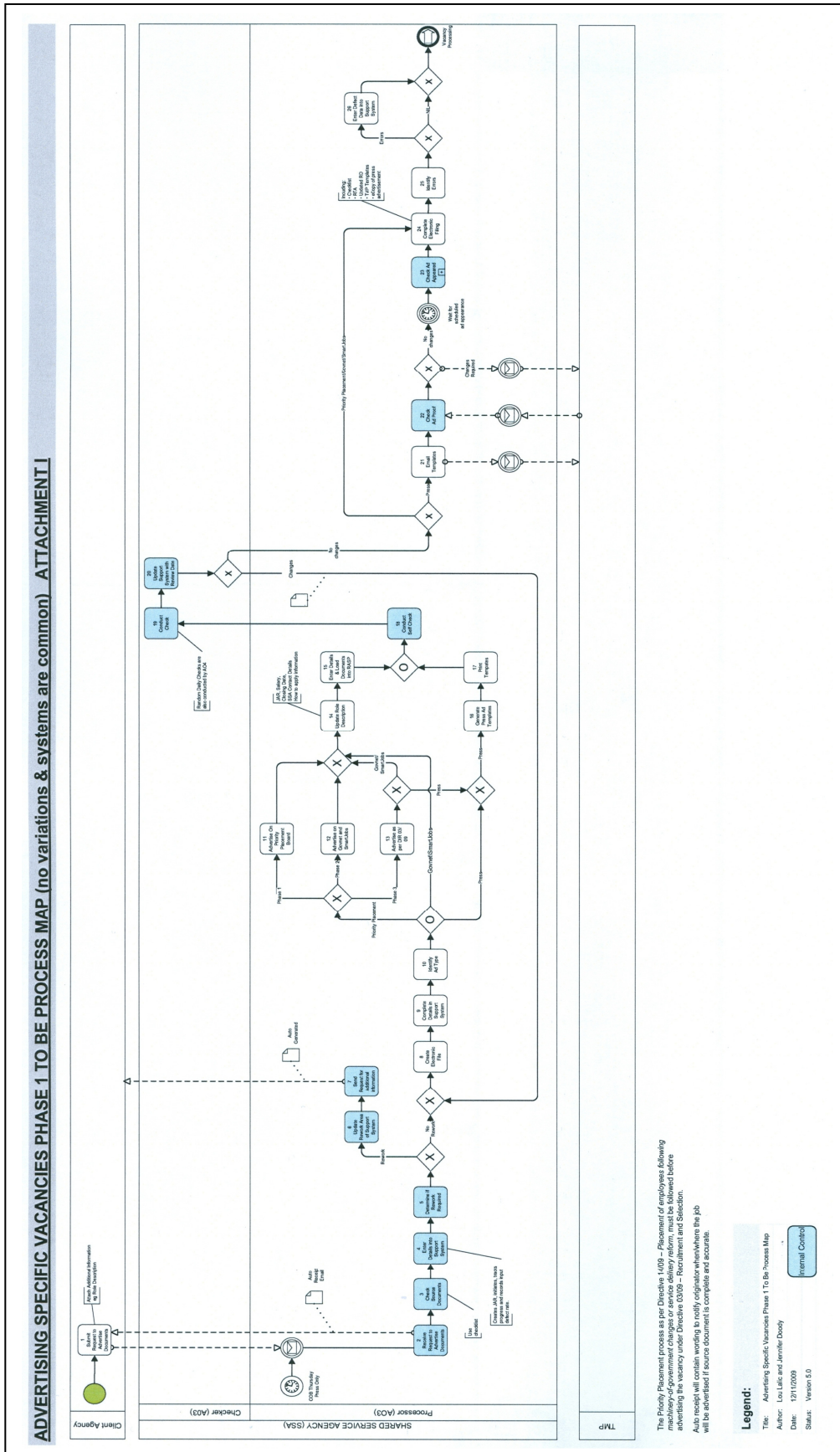
APPENDIX E

Measurement Model

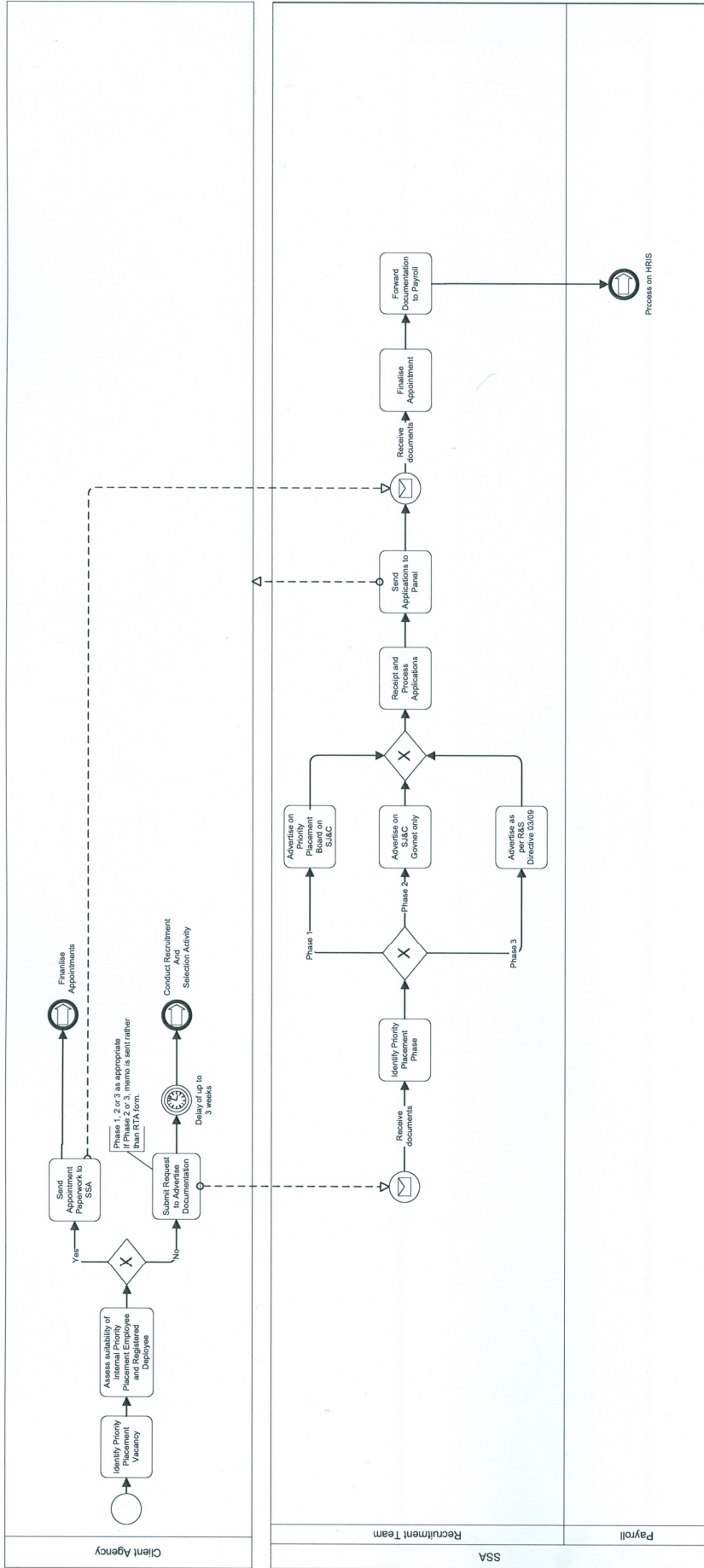


APPENDIX F

SSA Process Models



PRIORITY PLACEMENT PROCESS



Legend:

Title: Priority Placement Process
 Author: Lou Lalic / Jennifer Doody
 Date: 12/11/2009
 Status: Version 2.0

X Exclusive split eg Yes / No

APPENDIX G

Survey

Dear participant,

First of all, we would like to thank you for your cooperation in this research program. This research is part of a project by the Eindhoven University of Technology and aims to increase the understandability of business process models.

What we ask of you is to give us 50 minutes of your time to answer some questions. Some of these questions will be based on your existing knowledge and others will be based on the process model you will be shown during this survey. The questions can be subdivided into three parts, which can be characterised as:

-) general knowledge and skills
-) learning approach
-) contents of the business process model

Your answers will be treated with strict confidentiality and will not be used for other purposes than this research. Should you have some questions about this or other issues, please do not hesitate to contact our team at s.g.v.d.wouw@student.tue.nl.

The option exists to receive feedback on your performance on this assessment. Should you desire to do so, please fill out your email address below. A reminder is in place that even when you do fill out your address your results will still be handled strictly confidential.

Email address: (optional) _____

Note:

Please answer all questions, unless indicated otherwise.

Please answer all questions honestly and based on your own perceptions and beliefs.

Thanks again for your participation and good luck!
On behalf of the research team, Sander

Demographics

Age: <20
 Between 20 and 29
 Between 30 and 39
 Between 40 and 49
 Between 50 and 59
 60+

Gender: Male Female

Nationality: _____

Level of Education: Below Year 12 (or equivalent)
 Year 12 (or equivalent)
 Professional Qualification
 College-level Qualification
 University-level Qualification
 Other

SSA Knowledge and Experience

How long have you worked at SSA (or a preceding SSP)? _____yrs _____mths

How long have you worked for Queensland Government? _____yrs _____mths

Recruitment Knowledge and Experience

How long have you worked in recruitment? _____yrs _____mths

How long have you worked in advertising vacancies? _____yrs _____mths

Please answer the next two questions using this scale:

Very Low	Low	Average	High	Very High
1	2	3	4	5

	1	2	3	4	5
1. Compared to other staff working in the area of processing vacancies, I would rate my level of knowledge in this area as:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2. If I were asked a question about processing vacancies, I would rate the likelihood of my being able to answer this question correctly as:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Process Modelling Knowledge and Experience

Do you have any experience with process modelling? Yes No

If no, please go to the next page.

How long have you been modelling processes? _____yrs _____mths

How many months have you been modelling in BPMN? _____yrs _____mths

Roughly, how many BPMN models have you created in the last 12 months? _____

Roughly, how many BPMN models have you read in the last 12 months? _____

What BPMN training have you received:

- None
- University subjects
- On-the-job
- Employer provided
- Other

Please answer the next block of questions about process modelling using this scale:

True	False
1	2

	True	False
1. For exclusive choices, exactly one of the alternative branches is activated.	<input type="checkbox"/>	<input type="checkbox"/>
2. Exclusive choices can be used to model a repetition.	<input type="checkbox"/>	<input type="checkbox"/>
3. If two activities are concurrent, then they are executed at the same time.	<input type="checkbox"/>	<input type="checkbox"/>
4. If an activity is modelled to be part of a loop, then it has to be executed at least once.	<input type="checkbox"/>	<input type="checkbox"/>
5. For joining multiple paths out of an OR split, you can use either XOR or AND gateways.	<input type="checkbox"/>	<input type="checkbox"/>
6. An OR gateway activates either one or all outgoing paths.	<input type="checkbox"/>	<input type="checkbox"/>
7. Every task in a process model has to be executed at least once.	<input type="checkbox"/>	<input type="checkbox"/>
8. A process model can have multiple starts and ends.	<input type="checkbox"/>	<input type="checkbox"/>

IMPORTANT!


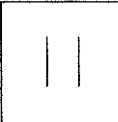

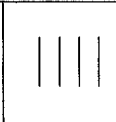

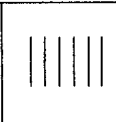

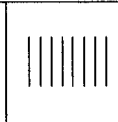

The next three sections will measure three aspects of cognitive ability including abstraction, selection and conception.

Your score in each of these sections will be the number of questions marked correctly reduced by a fraction of those marked incorrectly. It is therefore not to your advantage to guess unless you are able to eliminate one or more of the answer choices as wrong. Work as quickly as you can without sacrificing accuracy.

Abstraction Ability

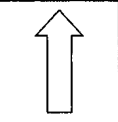
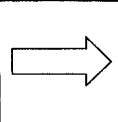
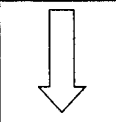
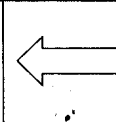
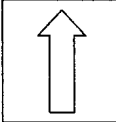
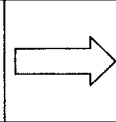
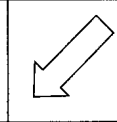
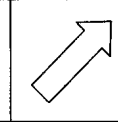
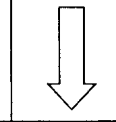
This section comprises four figures on the left and five possible alternatives on the right. You need to choose a fifth figure from the alternatives on the right to follow the sequence of figures on the left.

Example I

Sequence of figures				Possible answers				
								
				A	B	C	D	E

In Example 1, one stripe was added in each figure in the sequence shown on the left. In this example E would be the correct answer because it includes five stripes.

Example II

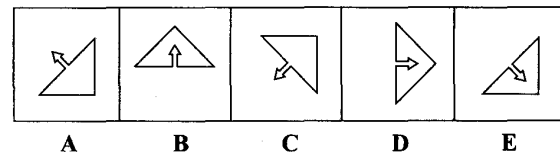
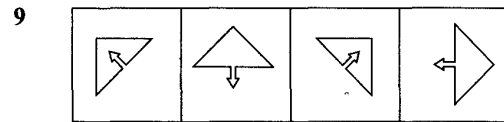
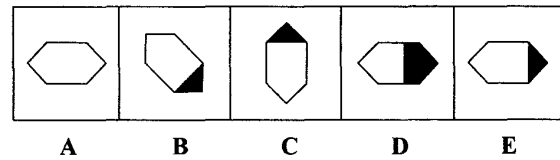
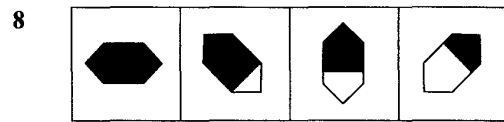
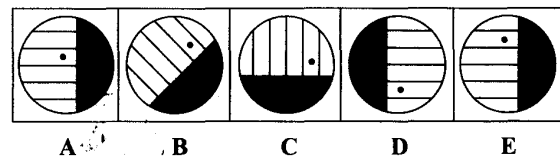
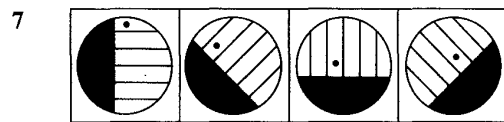
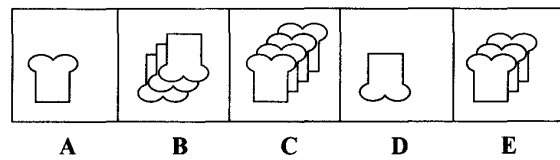
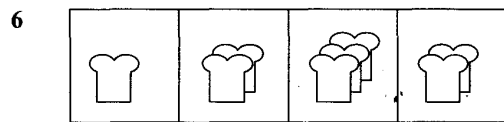
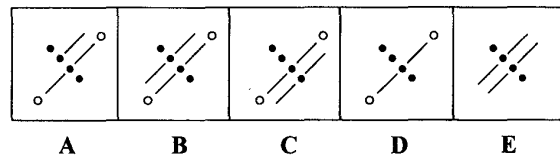
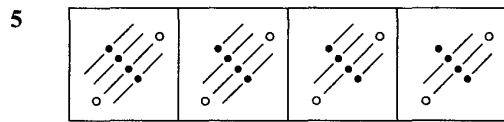
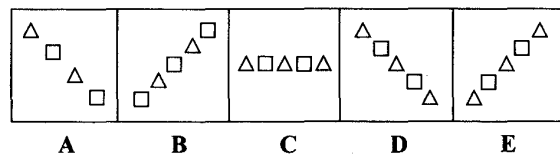
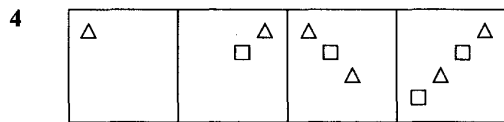
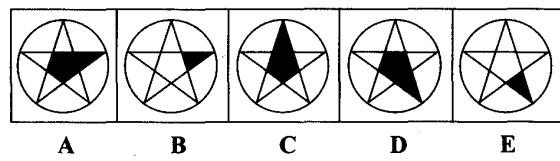
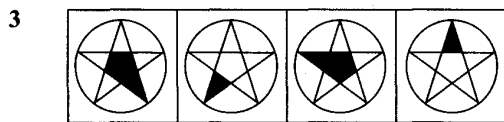
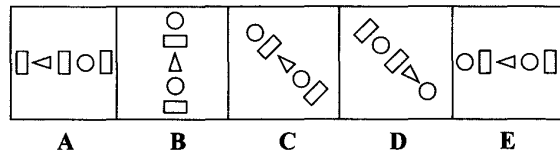
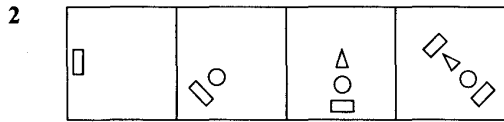
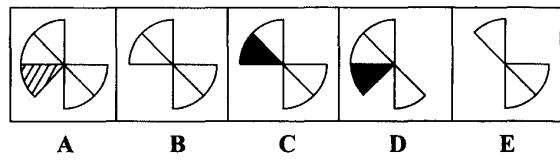
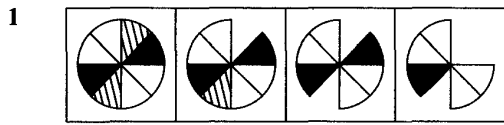
Sequence of figures				Possible answers				
								
				A	B	C	D	E

In Example II, the arrow makes a quarter turn to the right in the sequence shown on the left. In this example A would be the right answer because the arrow points upward.

You have 5 minutes to complete as many questions in this section as you can.

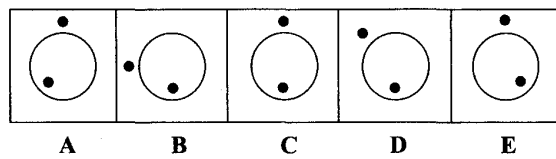
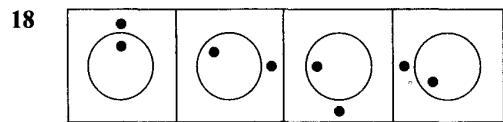
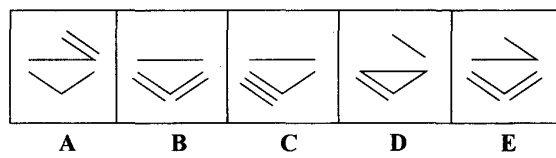
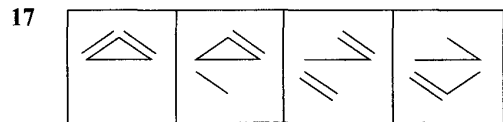
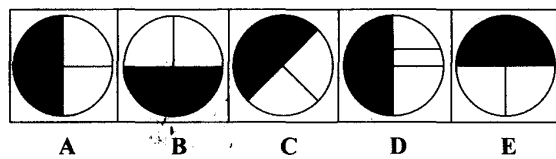
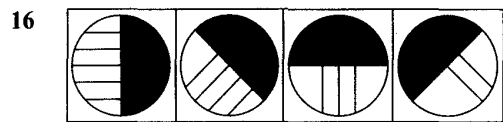
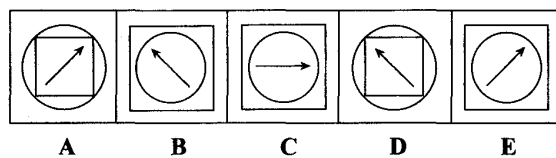
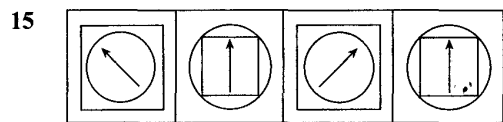
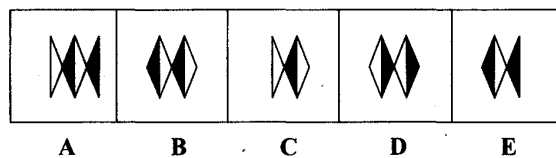
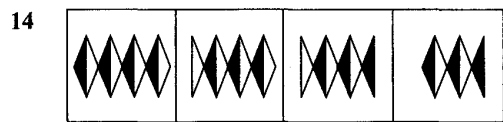
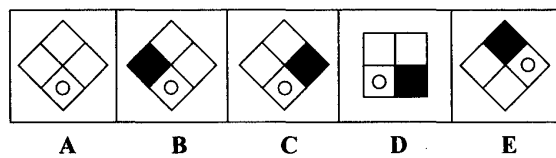
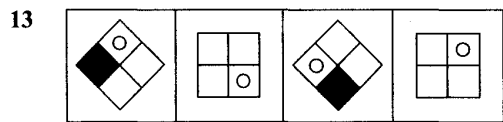
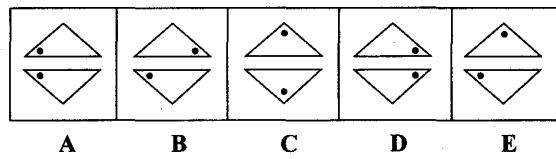
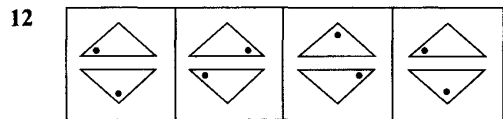
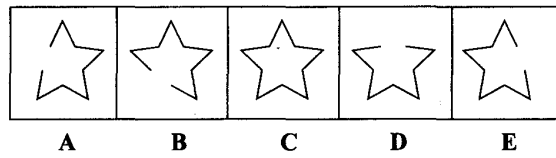
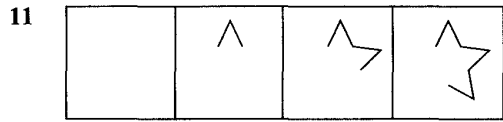
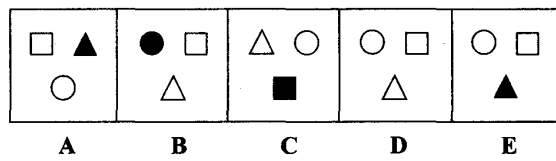
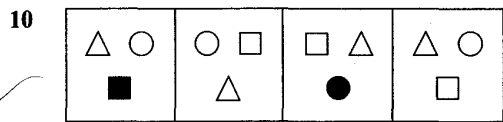
Sequence of figures

Possible answers



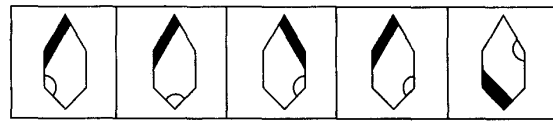
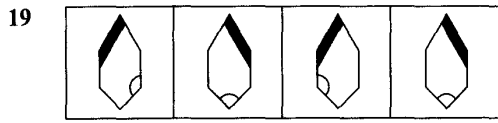
Sequence of figures

Possible answers

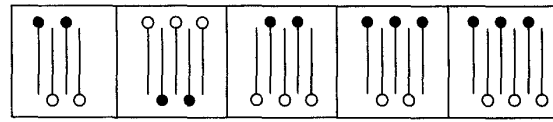
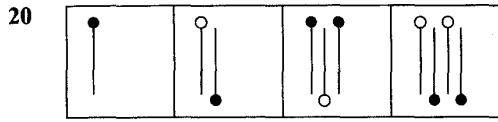


Sequence of figures

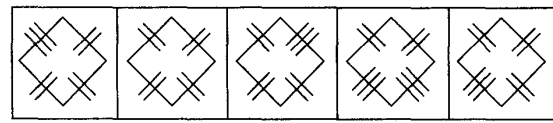
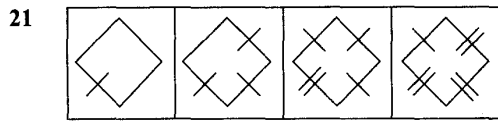
Possible answers



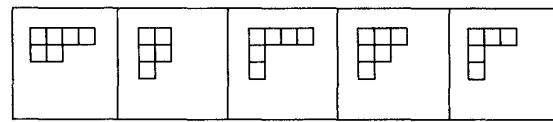
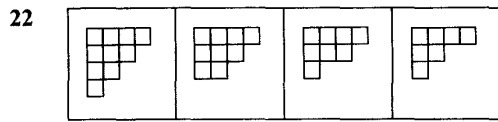
A B C D E



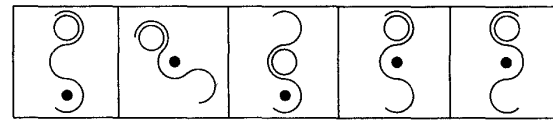
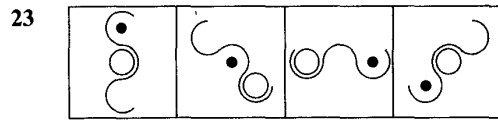
A B C D E



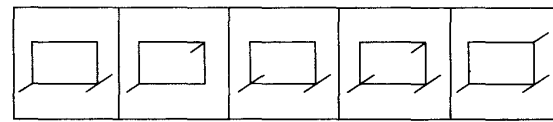
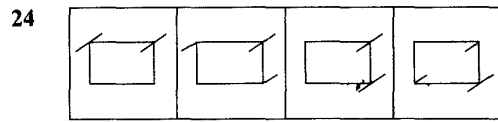
A B C D E



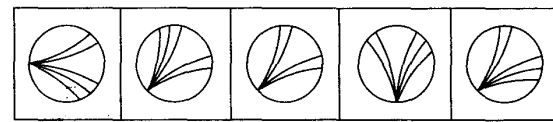
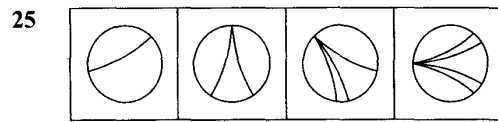
A B C D E



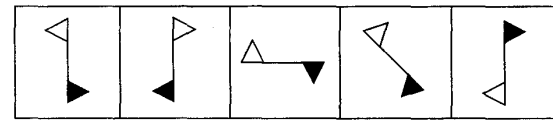
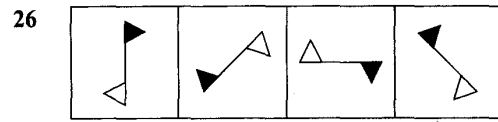
A B C D E



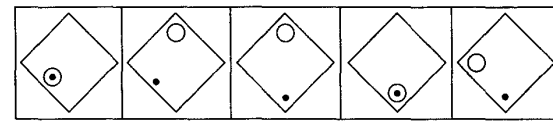
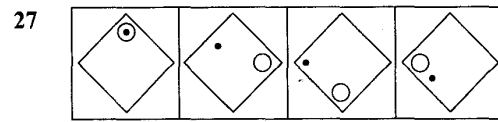
A B C D E



A B C D E



A B C D E

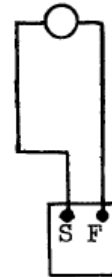


A B C D E

Selection Ability

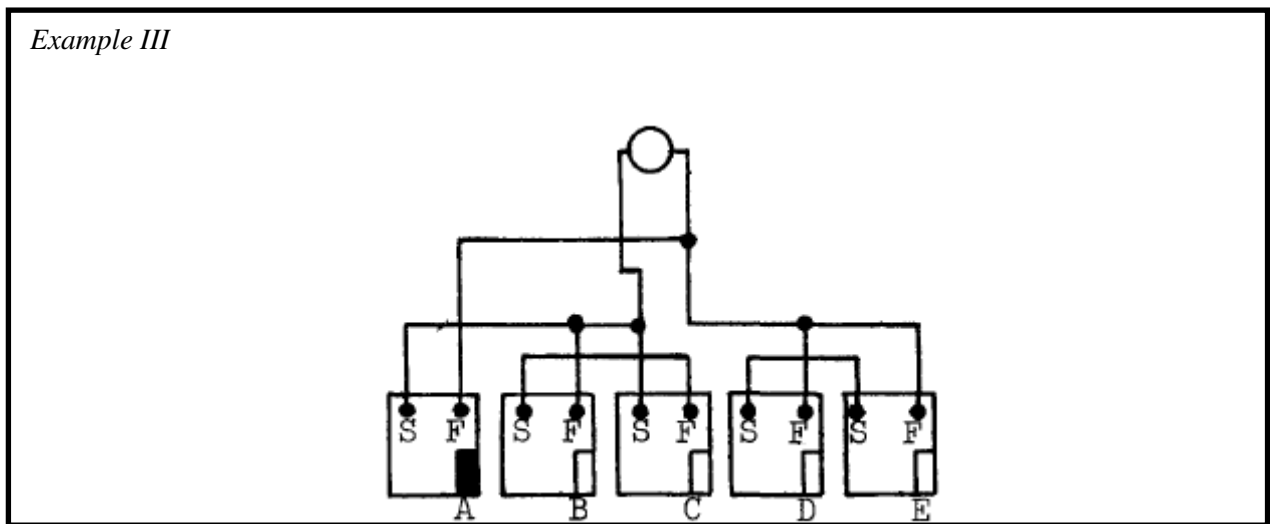
This section measures your ability to choose a correct path from among several choices.

In the following diagram is a box with dots marked S and F. S is the starting point and F is the finish. You are to follow the line from S, through the circle at the top of the picture and back to F.



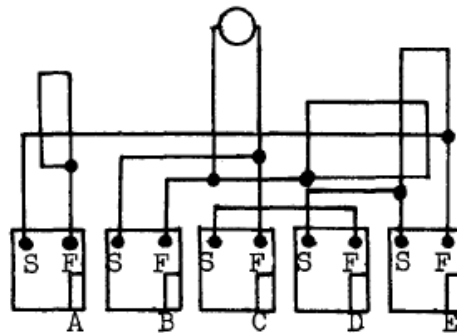
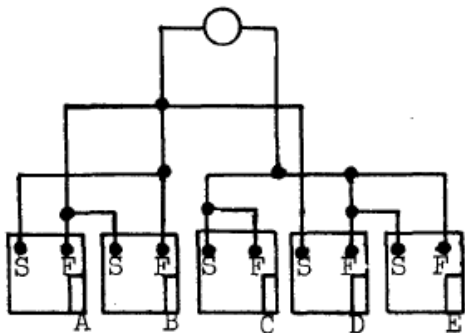
In each question in this section there will be five such boxes. Only one box will have a line from the S, through the circle and back to F in the same box. If lines meet or cross, you can only change direction if there is a black dot. If lines meet or cross but there is no dot you cannot change direction. You need to show which box has the line through the circle by colouring the space provided at the lower right of that box.

Example III



In Example III, the first box is the one which has the line from S, through the circle, and back to F. The space lettered A, has therefore been blackened.

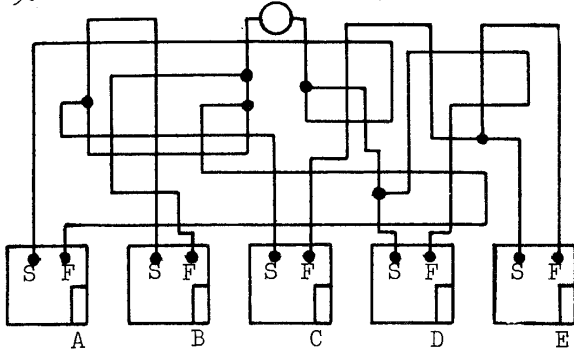
Each diagram in this section has only one box which has a line through the circle and back to the F. Some lines are wrong because they lead to a dead end. Some lines are wrong because they come back to the box without going through the circle. Some lines are wrong because they lead to other boxes that do not have lines going through the circle. Now try the next two practice examples.



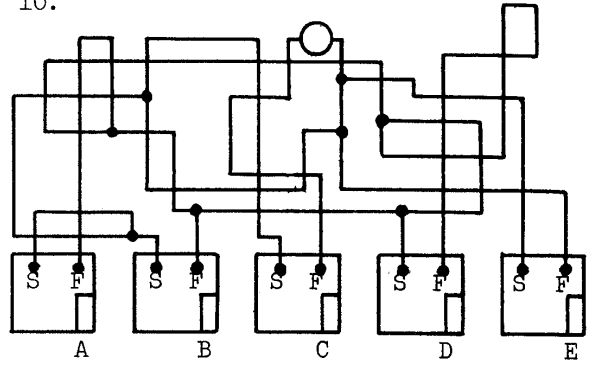
For the first example you should have marked the space lettered D. For the second example the answer is B.

You have 5 minutes to complete as many questions in this section as you can.

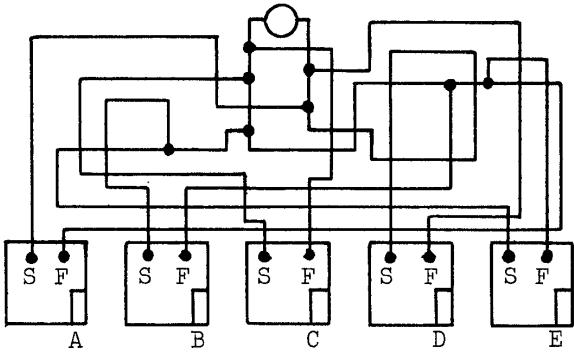
9.



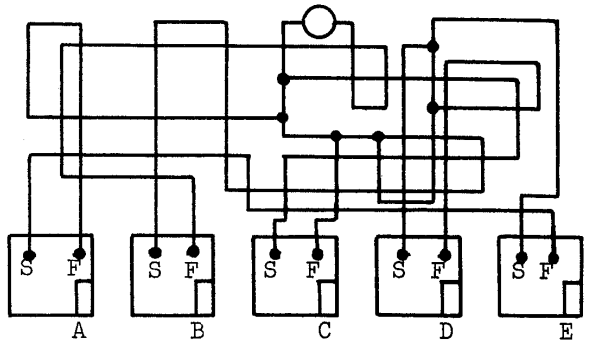
10.



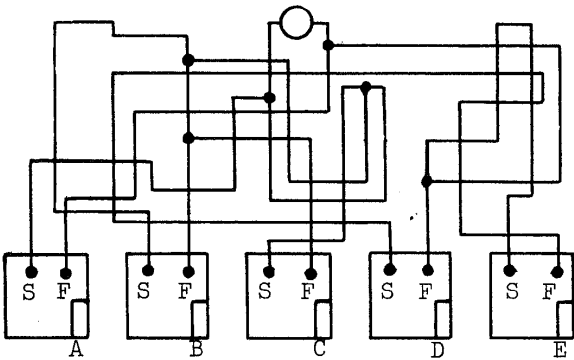
11.



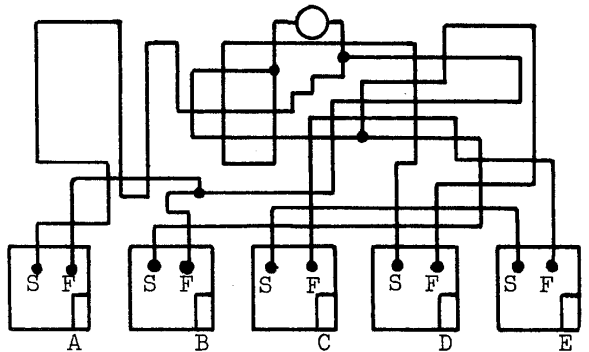
12.



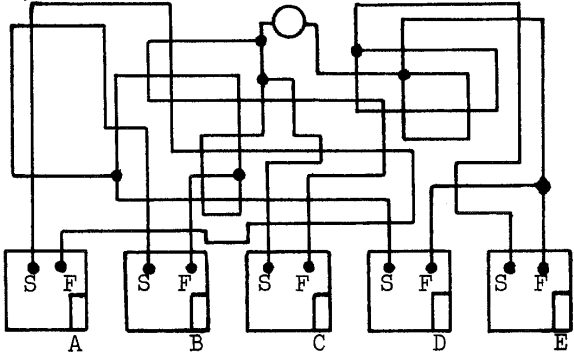
13.



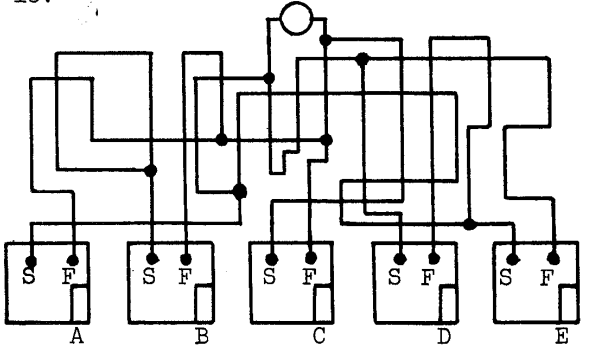
14.



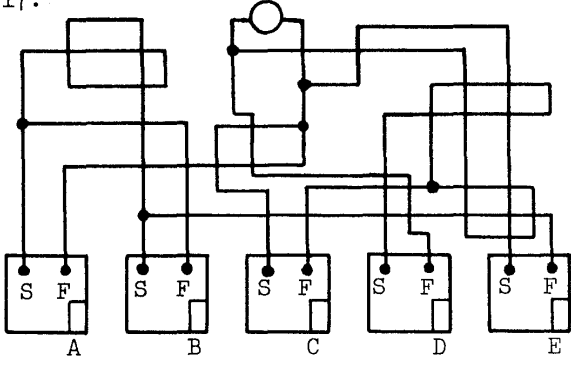
15.



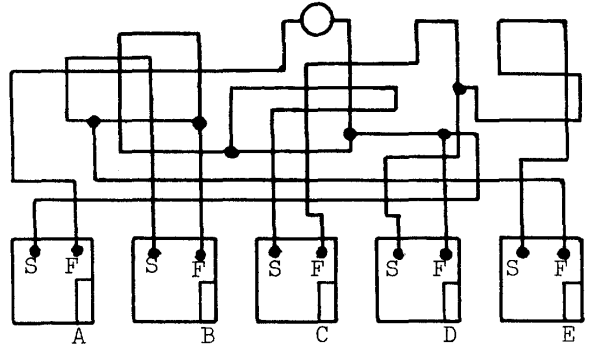
16.



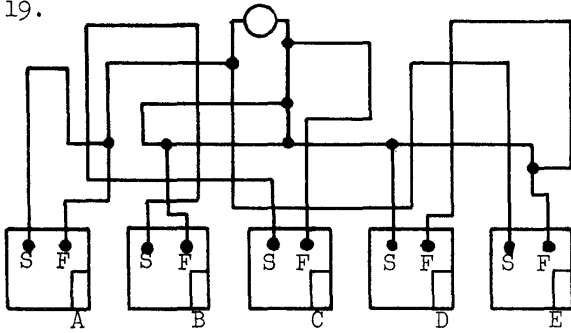
17.



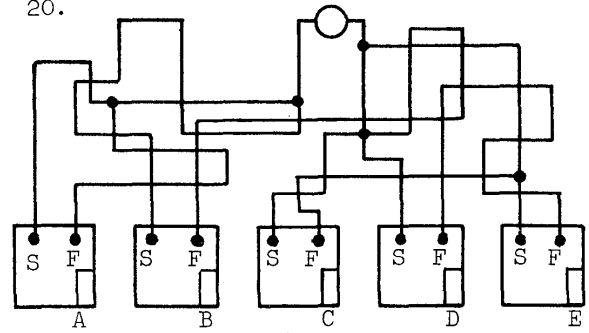
18.



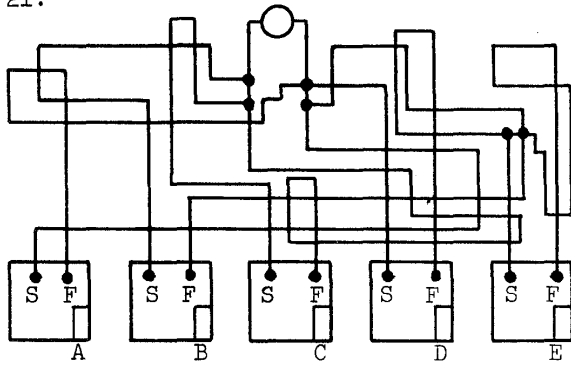
19.



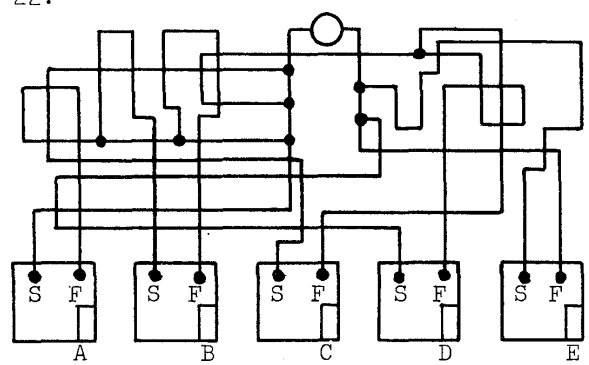
20.



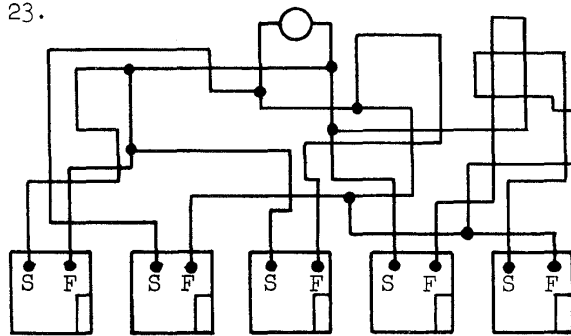
21.



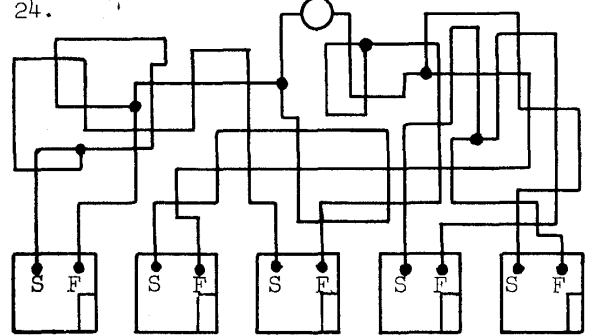
22.



23.



24.

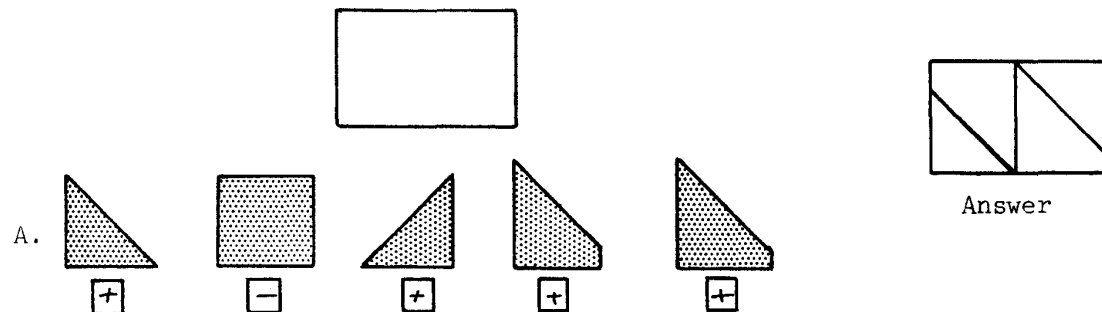


Conception Ability

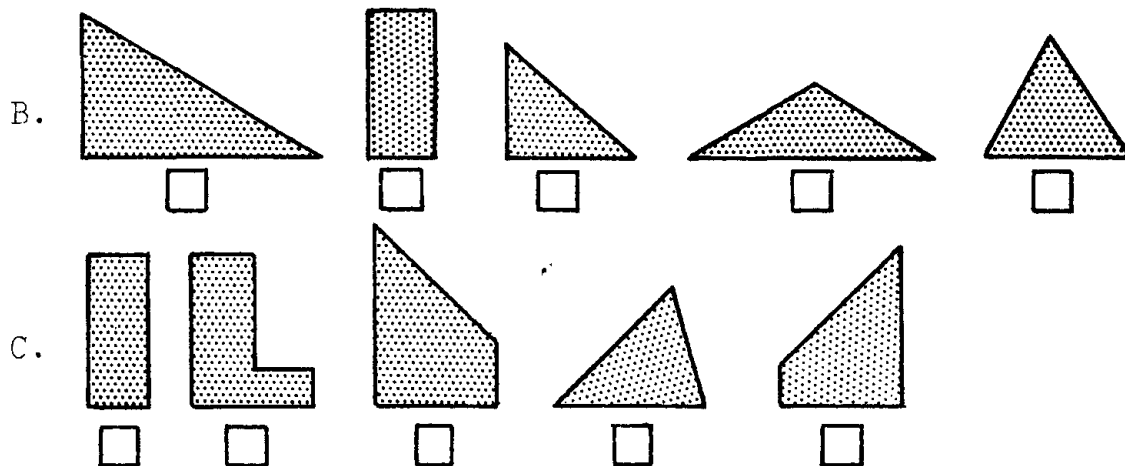
This section measures your ability to tell what pieces can be put together to make a certain figure.

Each page of this section is divided into two columns. At the top of each column is a geometrical figure. Beneath each figure are several problems. Each problem consists of a row of five shaded pieces. Your task is to decide which of the five shaded pieces will make the complete figure when put together. Any number of shaded pieces, from two to five, may be used to make the complete figure. Each piece may be turned around to any position but it cannot be turned over. It may help you to sketch the way the pieces fit together. You may use any blank space for doing this. When you know which pieces make the complete figure, mark a plus (+) in the box under ones that are used and a minus (-) in the box under ones that are not used.

In example A, below, the rectangle can be made from the first, third, fourth and fifth pieces. A plus has been marked in the box under these places. The second piece is not needed to make the rectangle. A minus has been marked in the box under it. The rectangle drawn to the right of the problem shows one way in which the four pieces could be put together.

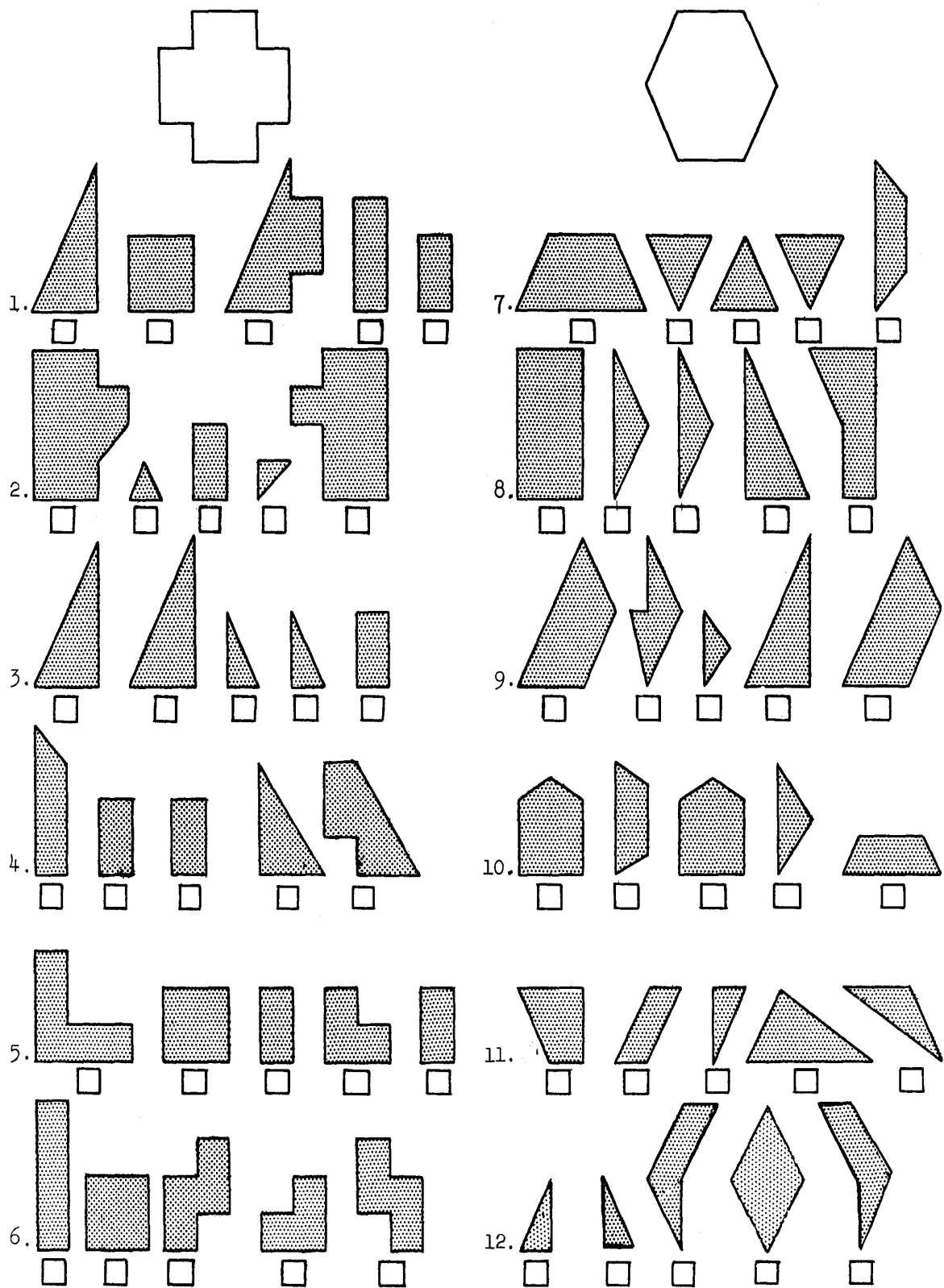


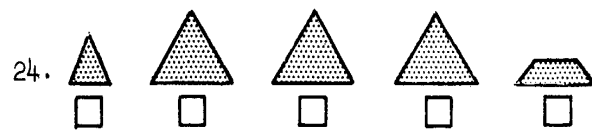
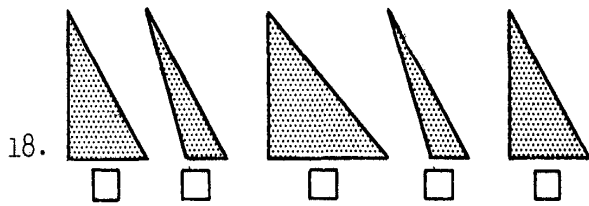
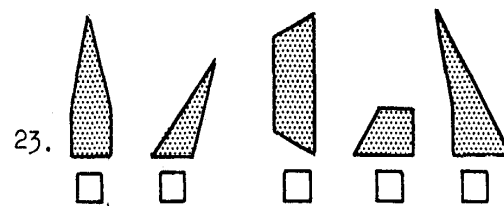
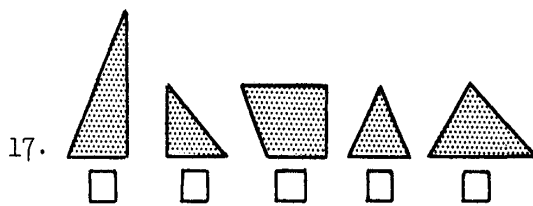
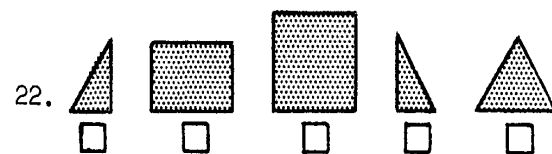
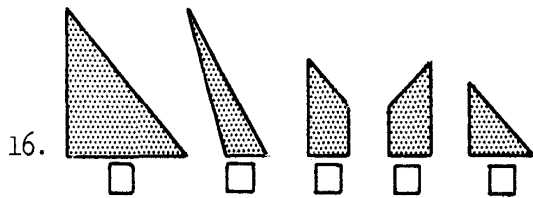
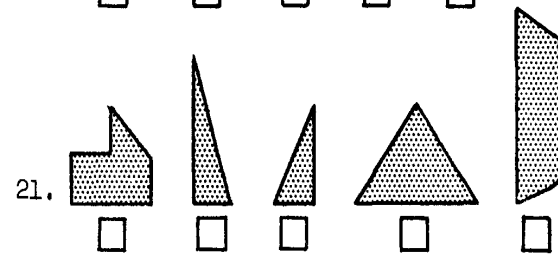
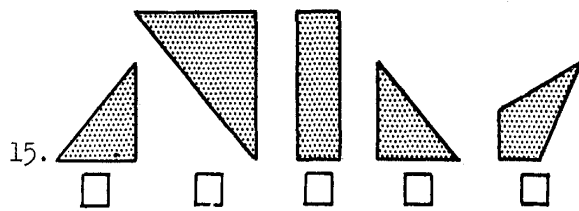
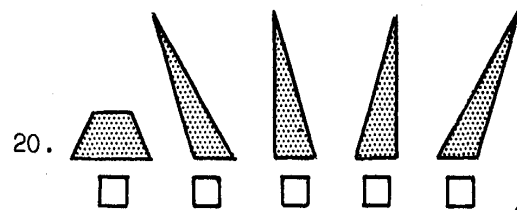
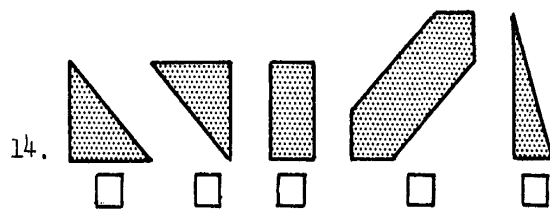
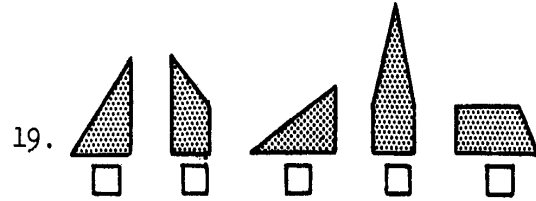
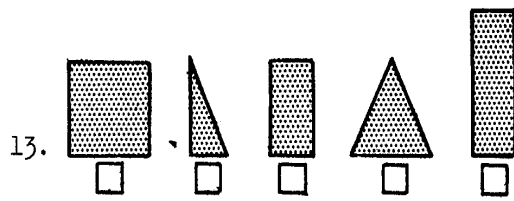
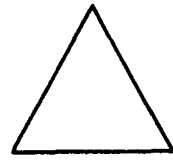
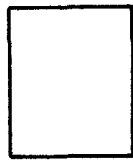
Now try to decide which pieces in Examples B and C will make the rectangle.

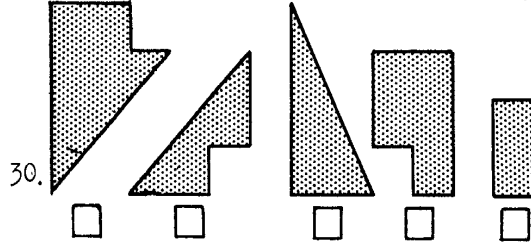
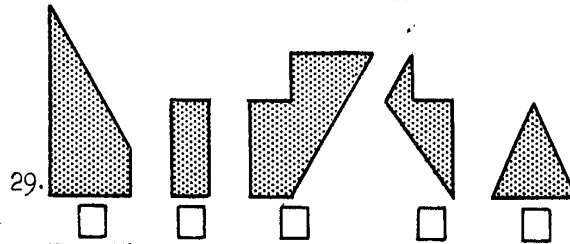
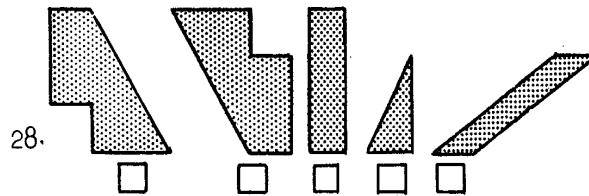
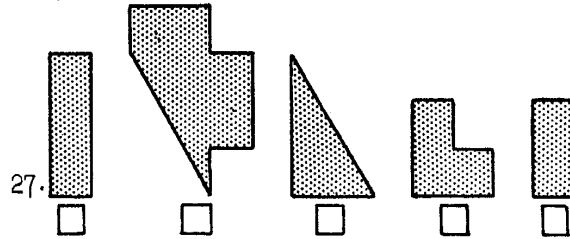
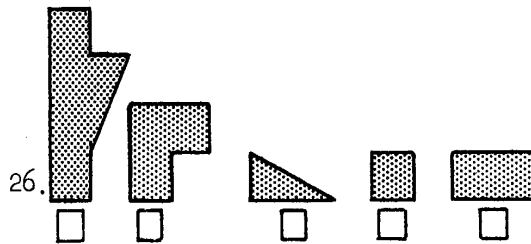
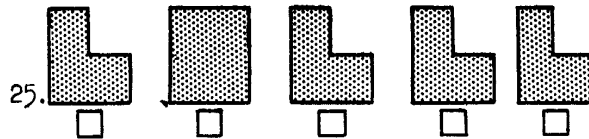
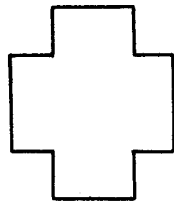


In example B, the first, fourth, and fifth pieces are needed. You should have marked a plus under these three pieces and a minus under the other two pieces. In Example C, the second, third, and fifth pieces should be marked with a plus and the first and fourth with a minus.

You have 5 minutes to complete as many questions in this section as you can.







IMPORTANT!

This following section measures aspects of your learning style. In this section you are required to choose only one answer for each question by ticking the response that you feel applies most to you. If both “a” and “b” seem to apply choose the one that you think applies more frequently. There is no right or wrong answer.

1. I would rather be considered
 - a) realistic
 - b) innovative
2. If I were a teacher, I would rather teach a course
 - a) that deals with facts and real life situations
 - b) that deals with ideas and theories
3. I find it easier
 - a) to learn facts
 - b) to learn concepts
4. In reading nonfiction, I prefer
 - a) something that teaches me new facts or tells me how to do something
 - b) something that gives me new ideas to think about
5. I prefer the idea of
 - a) certainty
 - b) theory
6. I am more likely to be considered
 - a) careful about the details of my work
 - b) creative about how to do my work
7. When I am reading for enjoyment, I like writers to
 - a) clearly say what they mean
 - b) say things in creative, interesting ways
8. When I have to perform a task, I prefer to
 - a) master one way of doing it
 - b) come up with new ways of doing it
9. I consider it higher praise to call someone
 - a) sensible
 - b) imaginative
10. I prefer courses that emphasize
 - a) concrete material (facts, data)
 - b) abstract material (concepts, theories)
11. When I am doing long calculations,
 - a) I tend to repeat all my steps and check my work carefully
 - b) I find checking my work tiresome and have to force myself to do it

IMPORTANT!

The following sections relate to the two SSA models provided describing part of SSA's recruitment process. You will first be shown the models briefly and consecutively be asked to fill in some questions about your approach of studying these models. You are required to answer each question according to the instructions or scale. Please select the answer that you feel most accurately reflects you. There is no right or wrong answer.

Please answer the next block of questions using the following scale:

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

	1	2	3	4	5
1. I feel confident in my ability to perform well on the upcoming assessment.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2. I am not confident that I will do as well on this assessment as I would like.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3. I don't feel that I am capable of performing as well on this assessment as others.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
4. I am a fast learner for these types of assessments, in comparison to other people.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
5. I would have to practice for a long time to be able to do well on this assessment.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
6. I think that my performance will be adequate on this assessment.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
7. I am sure that I can learn the techniques required for the next assessment in a short period of time.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
8. On average, other individuals are probably not as capable of doing as well on this assessment as I am.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Please answer the next block of questions using the following scale:

Never or only rarely true of me	Sometimes true of me	About half of the time true of me	Frequently true of me	Always or almost always true of me
1	2	3	4	5

	1	2	3	4	5
1. I find that at times learning makes me feel really happy and satisfied.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2. I will be discouraged by a poor result on this assessment and will worry about how I will do in future assessments.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3. I feel that nearly any topic can be highly interesting once I get into it.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
4. Even when I have prepared well for an assessment, I worry that I may not be able to do well.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
5. I desire to work hard at this assessment because I find the material interesting.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
6. Whether I like it or not, I can see that doing well in assessments is a good way to move up the corporate ladder.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
7. I spend a lot of my free time finding out more about interesting topics which have been discussed in different (refresher) courses.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
8. I desire to get good qualifications in assessments like this because I feel that I will then be able to get a reward later on.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
9. I come to most (refresher) courses with questions in mind that I want answered.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
10. I find I am continually going over my work in my mind at times like when I am on the bus, walking, or lying in bed, and so on.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
11. I like to do enough work on a topic so that I can form my own conclusions before I am satisfied.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Please answer the next block of questions by selecting the scale that you feel most accurately reflects your view:

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

	1	2	3	4	5
1. I will try to relate what I learn in this assessment to what I have learned in other situations.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2. I see no point in learning material from the models which is not likely to be questioned in the assessment.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3. I like constructing theories to fit odd things together.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
4. As long as I feel I am doing enough to finish the assessment, I will devote as little time to studying the models as I can. There are many more interesting things to do.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
5. As I am engaged in the assessment I will try to relate new material to what I already know on that topic.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
6. I will restrict learning in this assessment to what is specifically set as I think it is unnecessary to do anything extra.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
7. When I undertake this assessment I will try to understand what the modeller meant with the model.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
8. I do not think it will be helpful to study the models in depth. You don't really need to know much in order to finish such assessments.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
9. I will aim to memorise the models by repetition, going over and over them until I know them by heart even if I do not understand them.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
10. I find the best way to pass assessments is to try to remember answers to likely questions.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
11. I find I can get by in most assessments by memorising key sections rather than trying to understand them.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

IMPORTANT!

You will now be shown the two models describing SSA's recruitment process for 5 minutes. After this time elapses you will be asked to answer some questions about the models. These questions can inquire into every aspect of the recruitment process. Please use the time to learn the models in a way that you think enables you to answer these questions correctly. The survey will continue automatically after the 5 minutes have passed. Good luck!

Based on your understanding of the two SSA process models provided, please answer the next block of questions using the following scale:

True	False
1	2

	True	False
1. An Agency is required to go through the priority placement process prior to sending SSA documentation to request advertising for a vacancy.	<input type="checkbox"/>	<input type="checkbox"/>
2. SSA's Recruitment Team is responsible for identifying the priority placement phase appropriate for each vacancy in line with the documentation provided by the Agency.	<input type="checkbox"/>	<input type="checkbox"/>
3. The processes depicted in the two models each have only one possible end-point.	<input type="checkbox"/>	<input type="checkbox"/>
4. Checking for errors and checking for changes involve the same remedial action when an error or change is identified.	<input type="checkbox"/>	<input type="checkbox"/>
5. Creating an appointment vacancy within the support system is a responsibility of the SSA Recruitment Team.	<input type="checkbox"/>	<input type="checkbox"/>
6. An ad could have multiple priority placement phases but must have at least one.	<input type="checkbox"/>	<input type="checkbox"/>
7. The process 'Advertising Specific Vacancies' is a part of the 'Priority Placement' process.	<input type="checkbox"/>	<input type="checkbox"/>
8. The determination of a priority placement phase must be done at the same time as arranging the press placement for each vacancy.	<input type="checkbox"/>	<input type="checkbox"/>
9. If SSA contacts the Agency at any point after receiving a request to advertise they are unable to continue processing the vacancy until the Agency has responded.	<input type="checkbox"/>	<input type="checkbox"/>
10. A Processor can 'Conduct a Self Check' at the same time that the Checker is doing the task of 'Conduct Check' but they don't always have to be done at the same time.	<input type="checkbox"/>	<input type="checkbox"/>
11. 'Update Role Description' and 'Enter Details & Load Documents into RASP' are tasks which must be completed for every vacancy that is advertised.	<input type="checkbox"/>	<input type="checkbox"/>
12. Press ad templates are always reviewed by two parties other than the processor.	<input type="checkbox"/>	<input type="checkbox"/>
13. An error-check shows that an ad on the priority placement board does not contain any errors. This ad must have been assigned to priority phase 1.	<input type="checkbox"/>	<input type="checkbox"/>
14. The documentation of a suitable internal candidate has been forwarded to payroll. This indicates that no press ad was placed.	<input type="checkbox"/>	<input type="checkbox"/>
15. For every vacancy processed, the identification of the priority placement phase is completed before sending applications to the panel.	<input type="checkbox"/>	<input type="checkbox"/>
16. There are times when updating the support system with a review date occurs before creating an electronic file.	<input type="checkbox"/>	<input type="checkbox"/>
17. Applications can only be sent to the panel if no errors are found.	<input type="checkbox"/>	<input type="checkbox"/>
18. Ads assigned to a particular priority phase are processed in a similar way despite differing in the priority assigned.	<input type="checkbox"/>	<input type="checkbox"/>
19. For every vacancy processed the task 'Complete Details in Support System' is executed only once.	<input type="checkbox"/>	<input type="checkbox"/>
20. In the Priority Placement process an Agency may submit a request to advertise documentation with respect to each vacancy more than once.	<input type="checkbox"/>	<input type="checkbox"/>
21. If an ad prepared by TMP requires changes a new press ad template is generated and emailed back to TMP.	<input type="checkbox"/>	<input type="checkbox"/>

You have now completed this survey. Thank you for your participation.

APPENDIX H

Demographics

AGE		EDUCATION		GENDER		NATIONALITY	
<20	1	>Year12	5	Male	54	ARGENTINIAN	1
20-29	64	Year12	11	Female	37	AUSTRALIAN	42
30-39	9	ProfessionalQ	3	Total	91	AUSTRIAN	2
40-49	8	College/Tafe	15			DUTCH	42
50-59	9	TertiaryQ	55			GERMAN	2
>60	1	Other	3			INDIAN	2
Total	92	Total	92			TURKISH	1
						Total	92

APPENDIX I

Assumptions & Conditions for Factor Analysis

Assumptions to factor analysis (Hair et al., 2006, pp113-115)

1. sample size
2. data type
3. population/variable ratio
4. normality
5. factoring method

1. Sample size

With an incorporation of 88 cases the sample size exceeded the minimum threshold of 50, thereby making the data set fit for factor analysis.

2. Data type

The type of data had to be at least metric. Strictly, this would have excluded all variables from the factor analysis except for the ones inquiring into domain and modelling experience. Consequently, factor analysis was also conducted with ordinal items. This resulted in syntactic knowledge, abstraction ability, selection ability, conception ability, learning style and understanding being excluded from the analysis due to them only having two answer possibilities.

3. Population/variable ratio

All of the variables included in the factor analysis after checking for assumption two met the minimum threshold of 5 observations per variable.

4. Normality

Firstly goodness-of-fit was tested for. Although being of ordinal nature, one-sided Kolmogorov-Smirnov analysis was executed to assess the level of fit. The hypotheses used in this analysis are:

H_0 : the observed distribution of a variable is equal to the estimated standard normal distribution

H_a : the observed distribution of a variable deviates from the estimated standard normal distribution

α : .001

All items but three were regarded normally distributed therefore rejecting their null hypotheses. The alternative hypothesis was only rejected for the two semantic knowledge items and self-efficacy item one. Although acknowledging these results, near-normal distribution was accepted for the three non-normal variables due to their ordinal nature and KS-analysis being more sensitive in the centre of the distribution. Hence all items were included in the factor analysis unaltered.

5. Factoring method

Exploratory Factor Analysis was chosen using Principal Axis Factoring as the factoring method. This was decided upon based on two arguments. Firstly, the main goal of the analysis was to discover latent structures in the data, rather than exclude irrelevant items. Secondly, although most scales have been used in former research little was known about the variance structure of the variables at the time of measurement. As such, principal axis factoring best met this uncertainty allowing presence of unique variance in the variables and therefore minimising the distorting effects of unique and error variance.

Conditions for Factor Analysis (Hair et al., 2006, pp115-133)

- a. correlation
 - b. Bartlett's test of sphericity
 - c. KMO
 - d. rotation method
 - e. identification of factors
 - f. factor loading interpretation
-
- a. Correlation
A substantial number of between item correlations of above .30 needed to be present.
 - b. Bartlett's test of sphericity
The following design for the sphericity test was used:
H_o: The variables in the population correlation matrix are noncollinear.
H_a: At least two of the variables in the population matrix correlate.
 $\alpha = .001$
 - c. KMO
The KMO test had to yield a value of at least .5 indicating that at least 50% of variance is caused by underlying factors.
 - d. Rotation method
The main criteria for rotation were presence of crossloaders and a priori attempting to generate unequivocal solutions that displayed theoretical compatibility. If the unrotated solution was unproblematic to interpret and compatible with theory, no further rotation was executed. If only one or neither were the case, rotation was applied based on the level of correlation between the factors; oblique rotation was decided upon when correlation between factors $>.30$.
 - e. Factor identification
Consistent with Ford et al. (1986) and Conway and Huffcutt (2003) three methods were used for factor identification. These were:
The Kaiser criterion based on an eigenvalue > 1 .
The variance criterion based on a total percentage of variance explained $> 60\%$.
The scree plot criterion based on the amount of factors before the bent where the curve starts sloping approximately horizontally.
 - f. Factor loading interpretation
Criteria for incorporation of an item in a factor:
Items with a communality $>.5$ are incorporated
Items with a communality $< .4$ are excluded from analysis consecutively repeating factor analysis.
Items are considered crossloaders when they featured factor loadings higher than .4 on at least two factors.

APPENDIX J

Factor analysis

All Items Pattern Matrix

	Factor									
	1	2	3	4	5	6	7	8	9	10
	SE	SEK	SAL	SSL	PSE	DML	SML	DAL1	DAL2	?
SEK1		,936								
SEK2		,927								
SE1	,478				-,388					
SE2					-,709					
SE3	,308					,538				
SE4	,644									
rtSE5	,768									
rtSE6	,466				-,359					
SE7	,758									
SE8	,546			,326						
M1							,882			
M2										-,884
M3							,344			
M4			,486							-,392
M5	,327		,315						,314	
M6		-,350								
M7								,331		
M8		-,405								
M9						,320			,352	
M10					,353	,319		,371		-,319
M11						,428				-,350
ST1									,559	
ST2				,344			-,405			
ST3								,688		
ST4				,896						
ST5									,671	
ST6				,548					-,314	
ST7	,357								,407	
ST8				,586						
ST9			,747							
ST10			,456					,328		
ST11			,584							

Extraction Method: Principal Axis Factoring.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 47 iterations.

Final Solution
Pattern Matrix^a

	Factor					
	1	2	3	4	5	6
	PSE	SE	SLme	DAL	SLms	ESE
SEK1		-,943				
SEK2		-,948				
SE1	,742					
SE2	,776					
rtSE6	,597					
SE4						,523
rtSE5						,821
SE7						,662
SE8						,480
M3				,533		
M9				,590		
M10				,668		
M11				,746		
ST1				,443		
ST4					,762	
ST6					,590	
ST8					,621	
ST9			,616			
ST10			,429			
ST11			,833			

Extraction Method: Principal Axis Factoring.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 20 iterations.

APPENDIX K

Assumptions for Linear Regression Analysis

Assumptions to logistic regression analysis (Hair et al., 2006) [1/2]

- I. normality
- II. interval
- III. homoscedasticity
- IV. multicollinearity
- V. linearity

I. Normality

Normality was tested for using Kolmogorov-Smirnov analysis to assess the level of fit thereby measuring the distance between a standard normal distribution and the distribution of the variables (Field, 2009, pp145-148). Only variables of at least ordinal nature were included thereby excluding the dummy variables from this analysis.

H_0 : the observed distribution of a variable is equal to the estimated standard normal distribution

H_a : the observed distribution of a variable deviates from the estimated standard normal distribution
 α : .001

For abstraction ability (D(87)=.899, p = .394), selection ability(D(87)=.934, p = .347), conception ability (D(87)=.845, p = .473), learning style (D(87)=1.186, p = .120), achievement self-efficacy (D(87)=1.338, p = .056), deep approach to learning (D(87)=1.156, p = .138) and memorisation learning strategy (D(87)=1.334, p =.057) the alternative hypothesis was rejected suggesting these variables met the criterion of normality. For performance self-efficacy (D(87)=1.522, p <.05), minimising scope learning strategy (D(87)=1.372, p <.05) and understandability (D(87)=1.810, p < .01) the distribution was found to be significantly non-normal and consequently the skewness and kurtosis of the distributions was assessed ($z=X-\mu/SE < 1.96$ where X = skewness/kurtosis) (Field, 2009, pp138-139). Despite the non-normality, no significant skewness and kurtosis values were found for neither of the three variables, leaving them unaltered but ushering caution when testing for linearity and homoscedasticity.

II. Interval

Although the interval criterion did not have to be applied as strict for logistic regression as for linear regression, the variables were still screened accordingly. All variables met or approximated the ratio criterion, except for semantic knowledge, syntactic knowledge, approach to learning and understanding which were included as dummy variables. The cognitive ability variables were all ratio in nature. The self-efficacy and learning style variables approximate ratio because they are aggregated scales of ordinal and dichotomous variables.

III. Homoscedasticity

Homoscedasticity measured whether the variance around the estimated values of the dependent variable was, approximately, equal for all values of the independent variables. By means of scatterplot inspection all user characteristics plus deep approach to learning and minimising scope learning strategy were found approximately homoscedastic. Both performance and achievement self-efficacy plus memorisation learning strategy were subjected to further analysis using Levene's test of homogeneity. This revealed all performance self-efficacy to be convincingly homoscedastic, achievement self-efficacy only just ($F(5, 87)=1.947$, p =.096) and memorisation strategy to learning to heteroscedastic ($F(9, 77)=2.010$, p <.05). Having transformation of the latter show no improvement, no variables were transformed but caution was ushered on interpreting the results pertaining to choosing a memorisation learning strategy.

IV. Multicollinearity

Multicollinearity assessed the extent to which high correlation between the independent variables was absent or negligible. By executing linear regression analysis the Variance Inflation Factor (VIF) is obtained. Based on this number, the level of multicollinearity was assessed. The cut-off value that was used in this research is 10, hence $VIF < 10$. The results showed a maximum VIF value of 2.491 meaning the assumption of multicollinearity was met.

V. Linearity

Linearity analysis assessed whether (partial) linearity existed between the dependent and independent variables. By executing curve estimation regression analysis the linearity of the variables was checked for. Selection ability ($F(1,85)=5.174, p<.05$) and conception ability ($F(1,85)= 5.529, p<.05$) and performance self-efficacy ($F(1,85)=4.446, p<.05$) proved to be significantly non-linear whereas abstraction ability ($F(1,85)= 3.531, p=.064$) was found to be almost non-linear. These three variables were assessed on their linearity through correlation analysis using the dependent variable and five versions of the independent variable being the original, the squared, square rooted, inverted and logarithm (Schwab, 2004). The assumptions used were that absence of significant correlations indicated no relation and that, if significant correlations were present, the strongest significant correlation proved to be the most linear one. This led to squaring abstraction ability, selection ability, conception ability and performance self-efficacy.

APPENDIX L

SPSS syntax

Assumptions to Factor Analysis

```
FREQUENCIES VARIABLES=SEK_RATE1 SEK_RATE2 LS1 LS2 LS3 LS4 LS5 LS6 LS7 LS8 LS9 LS10 LS11 SE1 SE2 SE3 SE4 SE5  
SE6 SE7 SE8 M1 M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 ST1 ST2 ST3 ST4 ST5 ST6 ST7 ST8 ST9 ST10 ST11  
/STATISTICS=SKEWNESS SESKEW KURTOSIS SEKURT  
/HISTOGRAM NORMAL  
/ORDER=ANALYSIS.
```

NPAR TESTS

```
/K-S(NORMAL)=SEK_RATE1 SEK_RATE2 LS1 LS2 LS3 LS4 LS5 LS6 LS7 LS8 LS9 LS10 LS11 SE1 SE2 SE3 SE4 SE5 SE6 SE7  
SE8 M1 M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 ST1 ST2 ST3 ST4 ST5 ST6 ST7 ST8 ST9 ST10 ST11  
/MISSING ANALYSIS.
```

```
COMPUTE rtSE5=SQRT(SE5).  
EXECUTE.  
COMPUTE rtSE6=SQRT(SE6).  
EXECUTE.
```

Factor Analysis

```
FACTOR  
/VARIABLES SEK_RATE1 SEK_RATE2 SE1 SE2 SE3 SE4 rtSE5 rtSE6 SE7 SE8 M1 M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 ST1  
ST2 ST3 ST4 ST5 ST6 ST7 ST8 ST9 ST10 ST11  
/MISSING LISTWISE  
/ANALYSIS SEK_RATE1 SEK_RATE2 SE1 SE2 SE3 SE4 SE5 SE6 SE7 SE8 M1 M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 ST1 ST2  
ST3 ST4 ST5 ST6 ST7 ST8 ST9 ST10 ST11  
/PRINT INITIAL KMO EXTRACTION ROTATION  
/FORMAT BLANK(.40)  
/PLOT EIGEN  
/CRITERIA MINEIGEN(1) ITERATE(25)  
/EXTRACTION PAF  
/CRITERIA ITERATE(25)  
/ROTATION VARIMAX  
/METHOD=CORRELATION.  
/ANALYSIS SEK_RATE1 SEK_RATE2  
/PRINT INITIAL SIG KMO EXTRACTION
```

Reliability Analysis

```
RELIABILITY  
/VARIABLES=SEK_RATE1 SEK_RATE2  
/SCALE('ALL VARIABLES') ALL  
/MODEL=ALPHA  
/STATISTICS=DESCRIPTIVE  
/SUMMARY=TOTAL.
```

```
RELIABILITY  
/VARIABLES=SYK1 SYK2 SYK3 SYK4 SYK5 SYK6  
SYK7 SYK8  
/SCALE('ALL VARIABLES') ALL  
/MODEL=ALPHA  
/STATISTICS=DESCRIPTIVE  
/SUMMARY=TOTAL.
```

```
RELIABILITY  
/VARIABLES=AA1 AA2 AA3 AA4 AA5 AA6 AA7 AA8  
AA9 AA10 AA11 AA12 AA13 AA14 AA15 AA16 AA17  
AA18 AA19 AA20 AA21 AA22 AA23 AA24 AA25 AA26  
AA27  
/SCALE('ALL VARIABLES') ALL  
/MODEL=ALPHA  
/STATISTICS=DESCRIPTIVE  
/SUMMARY=TOTAL.
```

```
RELIABILITY  
/VARIABLES=SA1 SA2 SA3 SA4 SA5 SA6 SA7 SA8 SA9  
SA10 SA11 SA12 SA13 SA14 SA15 SA16 SA17 SA18 SA19  
SA20 SA21 SA22 SA23 SA24  
/SCALE('ALL VARIABLES') ALL  
/MODEL=ALPHA  
/STATISTICS=DESCRIPTIVE  
/SUMMARY=TOTAL.
```

```
RELIABILITY  
/VARIABLES=CA1 CA2 CA3 CA4 CA5 CA6 CA7 CA8 CA9  
CA10 CA11 CA12 CA13 CA14 CA15 CA16 CA17 CA18  
CA19 CA20 CA21 CA22 CA23 CA24 CA25 CA26 CA27  
CA28 CA29 CA30  
/SCALE('ALL VARIABLES') ALL  
/MODEL=ALPHA  
/STATISTICS=DESCRIPTIVE  
/SUMMARY=TOTAL.
```

```
RELIABILITY  
/VARIABLES=LS1 LS2 LS3 LS4 LS5 LS6 LS7 LS8 LS9  
LS10 LS11  
/SCALE('ALL VARIABLES') ALL  
/MODEL=ALPHA  
/STATISTICS=DESCRIPTIVE  
/SUMMARY=TOTAL.
```

```
RELIABILITY
/VARIABLES=SE1 SE2 SE6
/SCALE('ALL VARIABLES') ALL
/MODEL=ALPHA
/STATISTICS=DESCRIPTIVE
/SUMMARY=TOTAL.
```

```
RELIABILITY
/VARIABLES=SE3 SE4 SE5 SE7 SE8
/SCALE('ALL VARIABLES') ALL
/MODEL=ALPHA
/STATISTICS=DESCRIPTIVE
/SUMMARY=TOTAL.
```

```
RELIABILITY
/VARIABLES=M3 M9 M10 M11
/SCALE('ALL VARIABLES') ALL
/MODEL=ALPHA
/STATISTICS=DESCRIPTIVE
/SUMMARY=TOTAL.
```

Correlation Analysis

```
NONPAR CORR
/VARIABLES=SEK SYK AA SA CA LS PSE ESE DAL LSms LSme U
/PRINT=SPEARMAN TWOTAIL NOSIG
/MISSING=PAIRWISE.
```

Regression analysis assumptions testing

```
NPART TESTS
/K-S(NORMAL)=AA SA CA LS PSE ESE DAL LSms LSme U
/STATISTICS DESCRIPTIVES QUANTILES
/MISSING ANALYSIS.
```

```
FREQUENCIES VARIABLES=PSE DAL U
/STATISTICS=MEAN SKEWNESS SESKEW KURTOSIS
SEKURT
/HISTOGRAM NORMAL
/ORDER=ANALYSIS.
```

```
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
/CRITERIA=PIN(.05) POUT(.10)
```

Regression Analysis

```
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
Age Education MEXP DEXP
/SCATTERPLOT=(*ZPRED , *ZRESID)
/RESIDUALS DURBIN.
```

```
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER PSE ASE DAL
/SCATTERPLOT=(*ZPRED , *ZRESID)
/RESIDUALS DURBIN.
```

```
RELIABILITY
/VARIABLES=ST1 ST5 ST7
/SCALE('ALL VARIABLES') ALL
/MODEL=ALPHA
/STATISTICS=DESCRIPTIVE
/SUMMARY=TOTAL.
```

```
RELIABILITY
/VARIABLES=U1 U2 U3 U4 U5 U6 U7 U8 U9 U10 U11 U12
U14 U15 U16 U17 18 U19 U20 21
/SCALE('ALL VARIABLES') ALL
/MODEL=ALPHA
/STATISTICS=DESCRIPTIVE
/SUMMARY=TOTAL.
```

```
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
PSE ESE DAL LSms LSme
/PARTIALPLOT ALL
/SCATTERPLOT=(*ZPRED , *ZRESID)
/RESIDUALS DURBIN.
```

```
* Curve Estimation.
TSET NEWVAR=NONE.
CURVEFIT
/VARIABLES=COMPREHENSION WITH [Independent Variable]
/CONSTANT
/MODEL=LINEAR
/PLOT FIT.
```

```
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER PSE ASE LSms LSme
/SCATTERPLOT=(*ZPRED , *ZRESID)
/RESIDUALS DURBIN.
```

```
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA Age
Education MEXP DEXP [moderator]
/METHOD=ENTER [moderator*independent variable]
/PARTIALPLOT ALL
/SCATTERPLOT=(*ZPRED , *ZRESID).
```

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT DAL
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
Age Education MEXP DEXP
/SCATTERPLOT=(*ZPRED ,*ZRESID)
/RESIDUALS DURBIN.

```

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT LSms
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
Age Education MEXP DEXP
/SCATTERPLOT=(*ZPRED ,*ZRESID)
/RESIDUALS DURBIN.

```

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT LSme
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
Age Education MEXP DEXP
/SCATTERPLOT=(*ZPRED ,*ZRESID)
/RESIDUALS DURBIN.

```

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
Age Education MEXP DEXP PSE ASE DAL
/SCATTERPLOT=(*ZPRED ,*ZRESID)
/RESIDUALS DURBIN.

```

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL
CHANGE
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT U
/METHOD=ENTER DummyGr1 DummyGr2 AA SA CA LS
Age Education MEXP DEXP PSE ASE LSms LSme
/SCATTERPLOT=(*ZPRED ,*ZRESID)
/RESIDUALS DURBIN.

```

Logistic Regression Analysis

```

LOGISTIC REGRESSION VARIABLES [dimension of U]
/METHOD=BSTEP(LR) DummyGr1 DummyGr2 AA SA CA LS PSE ASE DAL LSms LSme Age Education MEXP DEXP
/CONTRAST (DummyGr1)=Indicator
/CONTRAST (DummyGr2)=Indicator
/CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

```