Università degli Studi dell'Insubria
Dipartimento di Scienze Teoriche e Applicate

PhD Dissertation

On the Quality of Web Services

by

Abbas Abdelhamid Abbas Tahir

Advisors

Prof. Sandro Morasca
Dr. Davide Tosi

External reviewer

Prof. Luciano Baresi

Doctoral program coordinator

Prof. Claudio Gentile

December 2014

Dedication

To my father Abdelhamid with love.

Acknowledgments

I am grateful to Professor Sandro Morasca for the great opportunity to work on this thesis. I deeply thank him for his attentive guidance and support throughout my PhD, not to mention all of his insightful feedback on this work. I am very thankful for having had the opportunity to learn from him. I am also deeply grateful to Dr. Davide Tosi for his support and constructive comments at different phases of my research. He was always readily available to provide support. Appreciation is extended to Professor Luciano Baresi for serving as an external reviewer and for providing valuable comments that helped me improve my doctoral thesis. I would like also to thank Dr. Davide Taibi who helped me throughout the enrolment process to the doctoral program.

Finally, I would like to thank my parents Abdelhamid and Amina, my sister and brothers from the bottom of my heart for their great support and love. They have always encouraged me throughout my PhD years. In particular, I would like to thank my brother Amjed for his emotional support and for the many scientific discussions that I have truly enjoyed with him. Very special thanks to my loving children, Shahd, Raghd, Ahmad and Aiman for their patience and understanding.

Abstract

Web Services (WSs) are gaining increasing attention as programming components and so is their quality. WSs offer many benefits, like assured interoperability, and reusability. Conversely, they introduce a number of challenges as far as their quality is concerned, seen from the perspectives of two different stakeholders: (1) the developer/provider of WSs and (2) the consumer of WSs. Developers are usually concerned about the correctness of the WS's functionality which can be assessed by functional testing. Consumers of WSs are usually careful about the reliability of WSs they are depending on (in addition to other qualities). They need to know whether the WSs are *available* (i.e., up and running), *accessible* (i.e., they actually accept requests) while available and whether they *successfully* deliver responses for the incoming requests. *Availability*, *Accessibility*, and *Successability* of WSs are directly related to WS reliability. Assessing these three factors via testing is usually only feasible at late stages of the development life-cycle. If they can be *predicted* early during the development, they can provide valuable information that may positively influence the engineering of WSs with regards to their quality.

In this thesis we focus on assessing the quality of WSs via *testing* and via *prediction*. Testing of WSs is addressed by an extensive systematic literature review that focuses on a special type of WSs, the semantic WSs. The main objective of the review is to capture the current state of the art of functional testing of semantic WSs and to identify possible approaches for deriving functional test cases from their requirement specifications. The review follows a predefined procedure that involves automatically searching 5 well-known digital libraries. After applying the selection criteria to the search results, a total of 34 studies were identified as relevant. Required information was extracted from the studies, synthesized and summarized.

The results of the systematic literature review showed that it is possible to derive test cases from requirement specifications of semantic WSs based on the different testing approaches identified in the primary studies. In more than half of the identified approaches, test cases are derived from transformed specification models. Petri Nets (and its derivatives) is the mostly used transformation. To derive test cases, different techniques are applied to the specification models. Model checking is largely used for this purpose.

Prediction of *Availability*, *Accessibility*, and *Successability* is addressed by a correlational study in which we focused on identifying possible relations between the quality attributes *Availability*, *Accessibility*, and *Successability* and other internal quality measures (e.g., cyclomatic complexity) that may allow building statistically significant predictive models for the three attributes. A total of 34 students interacted freely with 20 pre-selected WSs while internal

and external quality measures are collected using a data collection framework designed and implemented specially for this purpose. The collected data are then analyzed using different statistical approaches.

The correlational study conducted confirmed that it is possible to build statistically significant predictive models for *Accessibility* and *Successability*. A very large number of significant models was built using two different approaches, namely the binary logistic regression and the ordinal logistic regression. Many significant predictive models were selected out of the identified models based on special criteria that take into consideration the predictive power and the stability of the models. The selected models are validated using the bootstrap validation technique. The result of validation showed that only two models out of the selected models are well calibrated and expected to maintain their predictive power when applied to a future dataset. These two models are for predicting *Accessibility* based on the number of weighted methods (WM) and the number of lines of code (LOC) respectively.

The approach and the findings presented in this work for building accurate predictive models for the WSs qualities *Availability, Accessibility, and Successability* may offer researchers and practitioners an opportunity to examine and build similar predictive models for other WSs qualities, thus allowing for early prediction of the targeted qualities and hence early adjustments during the development to satisfy any requirements imposed on the WSs with regards to the predicted qualities. Early prediction of WSs qualities may help leverage trust on the WSs and reduces development costs, hence increases their adoption.

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List of Acronyms

Acronym	Description
BPEL	Business Process Execution Language
BPEL4WS	Business Process Execution Language for Web Services
DAML	DARPA Agent Markup Language
EFSM	Extended Finite State Machine
EH-CPN	Enhanced Hierarchical Color Petri Net
FTLTL	Future time Linear Temporal Logic
HPN	High-level Petri Net
HTTP	Hypertext Transfer Protocol
IEEE	Institute of Electrical and Electronics Engineers
IOPE	Inputs, Outputs, Preconditions and Effects
IPM	Input Parameter Model
LTS	Labeled Transition System
OCL	Object Constraint Language
OIL	Ontology Interchange Language
OWL-S	Web Ontology Language for Services
PRD	Production Rules Dialect
Promela	Process Meta Language
RIF	Rule Interchange Format
SLR	Systematic Literature Review
SOA	Service Oriented Architecture
SOAP	Simple Object Access Protocol
SWRL	Semantic Web Rule Language
SXM	Streamed X-Machine
TLA	Temporal Logic Actions
W3C	World Wide Web Consortium
WSDL	Web Services Description Language
WSDL-S	Web Service Semantics
WSMO	Web Service Modeling Ontology
XML	eXtensible Markup Language

Chapter 1
Introduction

Recently, Web Services (WS) have become more and more attractive as a new paradigm for building software. They play an important role in service-oriented architectures where loosely coupled programming components or services deliver their functionality over a network – often over the Internet. A WS can be defined as *"a software system designed to support interoperable machine-to-machine interaction over a network. It has an interface described in a machine-processable format (specifically WSDL). Other systems interact with the web service in a manner prescribed by its description using SOAP-messages, typically conveyed using HTTP with an XML serialization in conjunction with other web-related standards*" (W3C 2004a).

WSs offer many benefits, like assured interoperability, modularity, and reusability. Despite the great potential WSs as an essential element of service-oriented computing offer, their widespread is hindered by the issue of trust (Bozkurt, Harman, and Hassoun 2012). Trust need to be established on quality attributes of WSs including functional correctness, and reliability.

The trust issue needs to be addressed from two perspectives of two different stakeholders: (1) the developer/provider of WSs and (2) the consumer of WSs. For the developer, the main concern is that the WS is implemented as specified (functional correctness). Thus, the developer needs to take any reasonable measure to make sure that a WS is implemented correctly, including testing it. The WS consumer is mainly interested in whether the WS is the right service to use. It is therefore important to test WSs as a quality assurance measure from the consumer's perspective as well. Moreover, consumers of WSs are usually careful about the reliability of WSs they are depending on in addition to others qualities. Reliability of software is directly related to its *Availability* (Kumar, Khatter, and Kalia 2011). Actually, Malaiya (2005) listed *Availability* as one of the most common measures for reliability of software. WS consumers also need to know whether the WSs are *accessible* (i.e., they actually accept requests) while available and whether they *successfully* deliver responses for the incoming requests. These concerns (i.e., *Availability*, *Accessibility*, and *Successability* of a WS) are highly related and contribute directly to the WS's reliability. Assessing these qualities via testing is usually only feasible at late stages of the development life-cycle when the WSs are already developed, deployed and exposed to users. If the quality attributes *Availability*, *Accessibility* and *Successability* can be *predicted* early during the development, they can provide valuable information that may positively influence the engineering of WSs with regards to their quality.

In this thesis we are focusing on assessing the quality of WSs from their developers/providers as well as consumers' perspectives. Functional correctness of WS may be assured using suitable functional testing techniques. Defect detection via effective functional testing of a WS and successive removal of defects contributes positively to the reliability of the WS. WSs functional testing is addressed in this work by an extensive systematic literature review that focuses on a specific type of WSs, the semantic WSs. Early prediction of WSs qualities is addressed by establishing a methodology that involves the collection of a set of predefined internal quality measures (e.g., Cyclomatic Complexity and Distinct Method Invocations) and external quality measures (*Availability*, *Accessibility*, and *Successability*) and performing comprehensive statistical analysis to identify any possible valid relations between the internal and the external qualities that may allow for possibly accurate prediction of the external qualities based on the internal qualities.

1.1 Objectives and research questions

This thesis aims mainly at evaluating the quality of WSs, specifically by:

a) Summarizing the current state of the art of functional testing of semantic WSs. Focusing on functional testing of semantic WSs is motivated by the following:

   - Semantic WSs is a new technology that just appeared a few years ago (DAML 2000) and is a very fervid research area, while traditional WSs are already used in the industrial domain. Moreover, semantic and traditional WSs are inherently different.

   - We focused on functional testing because correctness of functionality is the primary quality of any software system and semantic WSs are no exception. Additionally, functional testing is a widely used quality assurance technique.

b) Building probabilistic predictive models for the quantification of the software sub-quality factors *Availability*, *Accessibility* and *Successability* identified in the OASIS WSQF (OASIS WSQF 2011) based on the theoretical basis provided in (Morasca 2009). These models may predict the above-mentioned factors in early development stages (design-time and deployment-time), thus allowing for early adjustments during the development to satisfy any imposed requirements with regards to the three sub-quality factors. Additionally, knowing the need of adjustments in advance may also facilitate early evaluation of the impact (costs, human resources, etc.) for implementing the adjustments.

Our Objectives (O) can be summarized as follows:

O1 - To identify possible approaches for deriving functional test cases from requirement specifications of semantic WSs;

O2 - To identify any possible challenges associated with the derivation of test cases from the specifications of semantic WSs;

O3 - To build significant probabilistic predictive models for the web services' sub-quality factors *Availability*, *Accessibility* and *Successability*;

O4 - To empirically evaluate the accuracy of the probabilistic models.

To achieve the above objectives, we formulated the following research questions (RQ):

RQ1 - Is it possible to derive functional test cases from requirement specifications of semantic WSs? What approaches are used?

RQ2 - What are the challenges associated with the derivation of test cases from the specifications of semantic WSs?

RQ3 - Is it possible to build statistically significant probabilistic predictive models for the WSs sub-quality factors *Availability*, *Accessibility* and *Successability*?

RQ4 - How accurate are these models?

1.2 Our contributions

Here we concisely list the main contributions resulting from this thesis:

- A systematic literature review that captures the current state of the art in the functional testing of semantic WSs.
- A framework for collecting internal and external quality measures of WSs.
- An approach for building probabilistic predictive models for predicting WSs' external qualities based on their internal quality measures.
- Statistically significant probabilistic predictive models for *Accessibility* and *Successability* of WSs.

1.3 Structure of the work

The remainder of this thesis is organized as follows. Chapter 2 provides the necessary background by introducing the basic concepts and the theoretical basis on which this work is based. In Chapter 3, we describe the research methodologies followed to provide reliable answers to the research questions introduced in Section 1.1. Chapter 4 reports the results of the systematic literature review and provides answers to the related research questions (RQ1 and RQ2). In Chapter 5, the results of the review and possible threats to its validity are discussed. Chapter 6 describes the approach followed for predictive model building. This includes, the set-up of the environment in which the data are collected, the WSs involved and the specification of the data need to be collected. A detailed technical description of the framework used for collecting necessary data is provided in Chapter 7. The characteristics of the dataset collected relevant for predictive models building are discussed in Chapter 8.

Chapter 9 is dedicated to comprehensively describing and comparing the different approaches followed for model building. The result of model building is discussed and an approach for model selection is established. All selected models are then validated using the bootstrap validation method. Finally, in Chapter 10, conclusions are drawn and directions for future research are proposed.

Chapter 2
Background and related work

2.1 Semantic WSs

WSs are usually described only syntactically, so only the structure of the data is specified, but not their semantics. This introduces a set of problems (such as integration inconsistencies (Denaro, Pezzè, and Tosi 2009)) that can be partially addressed by the adoption of semantic WSs, which support the semantic description of their behavior. In the semantic WS paradigm, data become machine-readable and understandable. Semantic WSs can dynamically collaborate in processing data without losing their meaning. Adding semantic description to WSs leverages their machine-processability and allows for, e.g., the automatic discovery of WSs by matching the requirement to their semantics. Ontology description languages (e.g., OWLS (W3C 2004b), WSMO (WSMO 2004) and WSDL-S (W3C 2005)) are typically used to describe WSs semantically.

There are two major initiatives in the area of semantic WSs, namely WSMO and OWL-S. WSMO is a conceptual model for semantic WSs. WSMO WSs are described explicitly in terms of their functional and non-functional properties and their interfaces using WSMO in a way that allows for automatic discovery, selection, composition, mediation and execution of the WSs. The main elements of a WSMO WSs are:

- *Capability*, which describes the functionality of the WS,
- *Interfaces*, which describes how the WS achieves its capability by means of interactions with its users (Choreography) and by using other WSs (Orchestration).

WSMO follows a goal-based approach in which the user defines her/his goals by explicitly expressing her/his requirements on the WSMO WSs. Based on user goals, the WSMO framework discovers the suitable services by automatically matching user goals to the semantically described capabilities of the published WSs. If necessary, the framework uses Mediators to handle interoperability problems or Orchestration that automatically combines services based on their capabilities to satisfy user goals.

Similar to WSMO, OWL-S provides another specification to describe WSs semantically. OWL-S WSs are described in terms of three elements, as follows.

- *Service Model* mainly describes the control flow of the service (Process Model). Additionally, it provides a process for the automatic composition and invocation of WSs.
- *Service Profile* describes the capabilities of the service, including a functionality and quality of service parameters.
- *Service Grounding* provides a mapping of the semantical description to the syntactically described implementations of WSs in WSDL. It also specifies communication protocols, transport mechanisms, and message format.

OWL-S WSs are discovered by referencing their capabilities described in the *Service Profiles*. If no single service matches the requested user service, the *Process Model* describes how an automatic composition of different services based on their semantics can be achieved to satisfy the request.

2.2 OASIS WSs Quality Factors

As a result of the increased acceptance and utilization of WSs as programming components, the OASIS (OASIS 2014) standardization body established a technical committee (OASIS WSQM 2013) to define a quality model for WSs (WSQM). The model is centered on the identified WSs quality factors [WSQF] (OASIS WSQF 2011). The quality factors are based on the functional and non-functional properties of the WSs. They are classified into 6 categories (Figure 1): Business value quality, service level measurement quality, interoperability quality, business processing quality, manageability quality, and security quality. Each category contains different related sub-quality factors. A brief description of the categories (adapted from (OASIS WSQF 2011)) follows.

Business value quality helps evaluate the suitability of WSs from business perspective. It consists of the following sub-quality factors: price, penalty and incentive, business performance, service recognition, service reputation and service provider reputation.

Interoperability quality evaluates whether the service providers and consumers can seamlessly interwork. This requires that the messages exchanged between them are correctly interpreted. Interoperability quality includes standard adoptability, standard conformability and relative proofness.

The business processing quality factors are used to guarantee a much stricter quality level when a WS is used in a mission-critical business environment. It includes messaging reliability, transaction integrity and collaborability.

Manageability quality evaluates the degree to which the WS is manageable (i.e., monitorable, controllable, etc.). It includes informability, observability and controllability.

Security quality evaluates whether the WS is safe for use. It includes the sub-factors encryption, authentication, authorization, integrity, non-repudiation, availability, audit and privacy.

Service level measurement quality measures the runtime performance of the WS. It is subdivided into five sub-quality factors: response time, maximum throughput, availability, accessibility, and successability.

Availability is defined as "*a measurement which represents the degree of which web services are available in operational status. This refers to a ratio of time in which the web services server is up and running. As the DownTime represents the time when a web services server is not available to use and UpTime represents the time when the server is available, Availability refers to ratio of UpTime to measured time.*"

$$Availability = 1 - \frac{Down\ Time}{Measured\ Time} \tag{1}$$

Accessibility "*represents the probability of which web services platform is accessible while the system is available. This is a ratio of receiving Ack message from the platform when requesting services. That is, it is expressed as the ratio of the number of returned Ack message to the number of request messages in a given time.*"

$$Accessability = \frac{number\ of\ Ack\ rmessages}{number\ of\ request\ messages} \tag{2}$$

Successability "*is a probability of returning responses after web services are successfully processed. In other words, it refers to a ratio of the number of response messages to the number of request messages after successfully processing services in a given time. 'Being successful' means the case that a response message defined in WSDL is returned. In this time, it is assumed that a request message is an error free message.*"

$$Successability = \frac{number\ of\ response\ messages}{number\ of\ request\ messages} \tag{3}$$

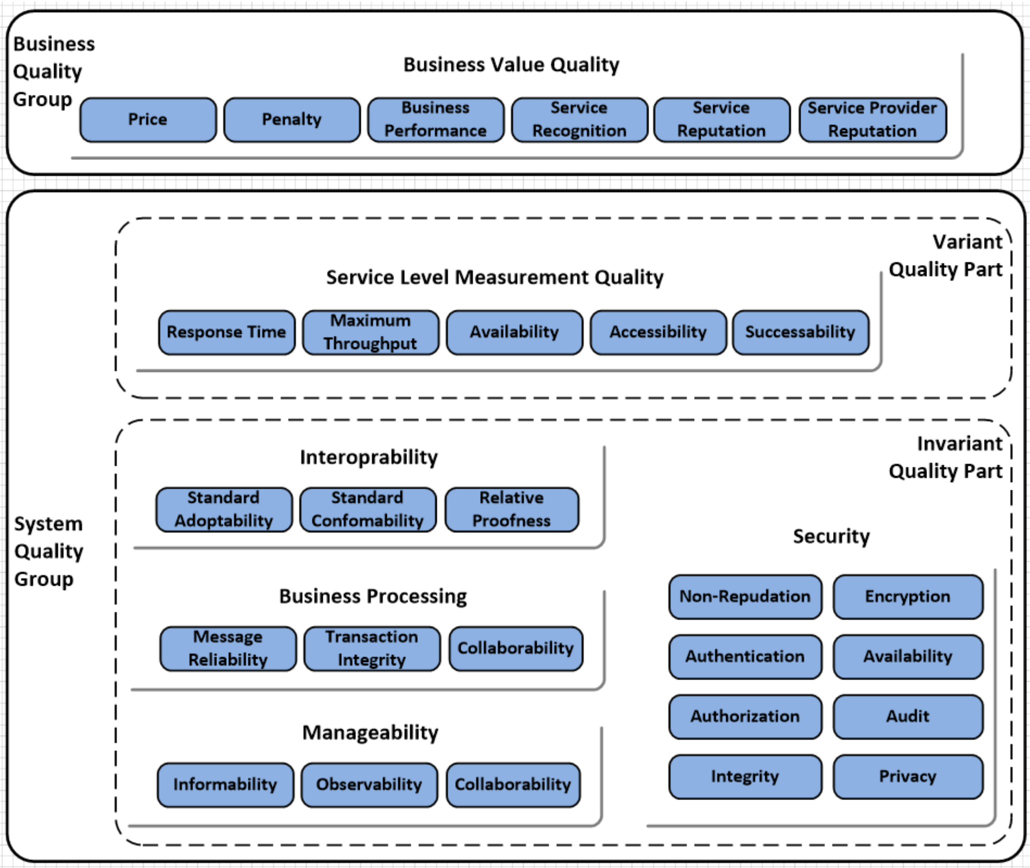

Figure 1: Structure of WSs quality factors (OASIS WSQF 2011)

One of the main goals of this thesis is to build probabilistic predictive models for the quantification of the software sub-quality factors *Availability*, *Accessibility* and *Successability* identified in the OASIS WSQF. All of these three sub-quality factors are considered external software quality measures according to the definition provided in the ISO/IEC standard 25000 (ISO 2005). On the other hand, internal software quality measures (ISO 2005) are those measures concerned with the static attributes of software products (e.g., number of lines of code). Such measures are usually related to the software architecture and design and do not require the execution of the targeted software. Measures that can only be collected by executing the software are called dynamic measures. They reflect the runtime behavior of the software. For example coupling between class objects CBO(Justus and Iyakutti 2011) is a well-known static quality measure. If it is measured in runtime, it is called dynamic coupling between objects DCBO (Justus and Iyakutti 2011) and considered as a dynamic software quality measure.

2.3 Quality evaluation via testing

Software testing plays a prominent role in the assessment and improvement of software quality, which is an essential issue for any software system and WSs are no exception. IEEE Std. 610.12-1990 (IEEE 1990) defines testing as "the process of operating a system or component under specified conditions, observing or recording the results, and making an evaluation of some aspect of the system or component." One of the main goals of testing is to trigger failures, so that, based on the occurrence and nature of the failures, software developers are guided in the identification and removal of faults. Although there is wide agreement on its importance for software quality assurance, testing is often not performed systematically enough. One possible explanation is that testing is a cost- and time-intensive process. Pezzè and Young (2007) reported that "The cost of software verification often exceeds half the overall cost of software development and maintenance." Therefore, testing techniques that help increase the efficiency of the testing activities could be very useful.

One objective of this thesis is to summarize the current state of the art of functional testing of semantic WSs. Characteristics of semantic WSs, such as dynamic service composition, raise more testing challenges compared to the syntactically described WSs. The semantical layer is one of the main differences between semantic WSs and traditional ones. Testing needs to be performed over the semantic layer and not through the lower syntactic layer as when testing traditional WSs.

Two main differences between traditional and semantic WSs may influence the approaches to be followed when testing semantic WSs:

- The presence of the semantic layer: Semantics of traditional WSs are not specified. The tester (or human user) of traditional WSs need to make her/his own interpretation of the following:
  - The capability of the only syntactically specified functionality of the service (i.e., which goals the service can fulfill).
  - The preconditions need to be fulfilled before invoking the service.
  - The state changes resulting from the execution of the service. In the case of semantic WSs, the above semantic information is pre-specified by means of ontology languages such as WSMO or OWL-S. The specified semantic information is machine-readable and understandable. Therefore, this semantic information can be used to guide testers when specifying test cases.
- Heterogeneity of standards: There are currently different initiatives and different non-compatible ontology languages (WSMO, OWL-S, WSDL-S, etc.) for semantic WSs that exhibit different levels of formality. The

more formal the description of the semantic WS, the more precise and comprehensive the testing can be (e.g., by following formal testing methods). This may also imply the use of different testing approaches depending on the level of formality of the semantic WSs description models.

2.4 Quality evaluation via prediction

Morasca (2009) introduced a probability-based approach for measuring the external qualities of software. The main assumption is that external qualities can be quantified by means of probabilities. The author proposes that "*external software attributes should not be quantified via measures, but via probabilistic estimation models.*" This implies that instead of measuring the external qualities after the deployment and the exposure of a WS, we can predict them using probabilistic models.

Additionally, the introduced probability-based approach is rooted in the *probability representations*, which are part of the well-founded Measurement Theory. Probability representation "*has not yet been used in Software Engineering Measurement*" (2009).

Based on this theory, probabilistic models for different software external qualities can be built. However, the accuracy of the models needs to be assessed by carrying out empirical studies. This thesis follows this theory and focuses on building predictive models for the sub-quality factors *Accessibility*, *Availability* and *Successability* of WSs.

2.5 Systematic literature reviews

Systematic literature reviews (SLR) are widely used by researchers in the medical domain (e.g., the Cochrane reviews (Alderson, Green, and Higgins 2003)) and were recently adopted in software engineering research (Kitchenham 2004). A systematic literature review is a form of secondary study that uses a well-defined methodology to identify, analyze, and interpret all available evidence related to a specific research question in a way that is unbiased and repeatable (Kitchenham and Charters 2007) (to a degree). A systematic literature review (Kitchenham 2004) is "*a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest. Individual studies contributing to a systematic review are called primary studies.*" Systematic reviews aim to focus on a clearly defined review topic.

2.6 Related work

Some systematic literature reviews were previously conducted in related areas like software product line testing (Engstroem and Runeson 2011) WS composition testing (Rusli, Ibrahim, and Puteh 2011) and regression test selection techniques (Engstroem, Runeson, and Skoglund 2010). Three systematic reviews appear to be more relevant to the topic of our systematic review than the others. In their review, Palacios et al. (2011) focused mainly on service-oriented architectures where the discovery and binding of the services are performed at runtime. They analyzed testing approaches, the stakeholders involved in the testing effort, and the point of time the test is done (i.e., before service publication, during execution, etc.). Semantic WSs addressed in this study and WSs in general are usually considered as the main building blocks of service-oriented architectures. A much wider scope was considered by Bozkurt et al. (2012) in their survey. They covered testing and verification in service-oriented architectures in general without restricting themselves to services with dynamic binding. Testing of both functional and nonfunctional properties was considered. Moreover, different testing techniques available in the surveyed literature were presented and discussed. Zakaria et al. (2009) presented a review on unit testing approaches for BPEL (OASIS 2007). They identified, categorized, and analyzed different BPEL unit testing approaches. BPEL describes interactions between WSs. Although both Palacios et al. (2011) and Zakaria et al. (2009) considered the identification and the description of available testing approaches (as we do), both reviews focus on different and very specific subjects. Bozkurt et al. (2012) has a much wider scope that encompasses testing service-oriented architectures in general. Our systematic literature review focuses on testing a special type of WSs: semantic WSs.

Other researchers worked towards predictive models for software quality. Ivanovic et al. (2011) proposed a methodology for predicting Service Level Agreement (SLA) violation during service composition at run-time. They used the structure of the composition and properties of the component services to derive constraints to model SLA conformance and violations. These models are used for predicting satisfaction and violation of the constraints in a specific scenario. Xing et. al. (2005) proposed an approach to predict software quality by adopting support vector machine (SVM) in the classification of software modules based on complexity metrics. A comprehensive literature review on predictive models in software engineering can be found in Hall et al. (2012).

Chapter 3
Research methods

To provide answers to the research questions introduced in Chapter 1, Section 1.1, we followed two different research methods. SLRs, by their very nature, follow a predefined procedure. For predictive model building a different approach is followed that involves collecting the required data and then carrying out correlation analysis. In the following sections, both methods are described in details.

3.1 SLR research method

The systematic review carried out to answer the research questions RQ1 and RQ2 was conducted following the procedure outlined in Kitchenham and Charters (2007).

3.1.1 Search strategy

As a necessary starting point, systematic literature reviews aim to find all primary studies related to the research questions in focus. To search for and find relevant studies, we need first to identify relevant search terms. For this purpose, we followed the approach outlined by Kitchenham and Charters (2007) in which we consider the research questions from three viewpoints: population, intervention, and outcomes. For each viewpoint, the relevant search terms in the context of this systematic literature review were identified as follows.

- *Population*: semantic web services, OWL-S, WSMO, WSDL-S.
- *Intervention*: test generation, test, testing, verification, validation, test case.
- *Outcomes*: functional properties.

In addition to these search terms, we considered synonyms, abbreviations, and alternative spellings to construct a search string. The search string was constructed as follows:

$(P_1 \text{ OR } P_2 \ldots \text{OR } P_n) \text{ AND } (I_1 \text{ OR } I_2 \ldots \text{OR } I_n)$

where P_i refers to population terms, I_i refers to intervention terms. The P_i and I_i are connected using the Boolean operators AND and OR. Purposely, we did not include the outcomes in the search string to broaden the scope of the results. Preliminary searches, which we conducted to assess the volume of potentially relevant studies, confirmed that the inclusion of outcomes in the search string remarkably reduces the volume of identified relevant studies and hence increases the risk of missing relevant studies. To compensate for not including outcomes in the search string, we filtered any study that does not address functional testing in the study selection process.

The search string was used to search the following five well-known and widely used digital libraries:

- ACM Digital library.[1]
- IEEE Xplore.[2]
- Inspec.[3]
- ScienceDirect.[4]
- SpringerLink.[5]

It was necessary to adjust the search string according to the requirements of each digital library. The search string was preliminarily checked against a list of already known primary studies (Li et al. 2010; Paradkar et al. 2007; Shaban, Dobbie, and Sun 2009; Wen-Jie and Shi 2009) as recommended by Kitchenham and Charters (2007). This preliminary check was used to examine the effectiveness of the search string before conducting the full search. The search was conducted in March[6] 2012 and was limited to studies published between the year 2000 and 2011. We decided to choose 2000 as the starting year for the search since the first ontology language for the web (DAML+OIL) was first introduced by the DAML project[7] at the end of that year (DAML 2000).

3.1.2 Study selection process

Figure 2 depicts the search stages followed and the resulting number of primary studies for each stage. In stage 1, automated search was performed by applying the search string to the digital libraries. The search was conducted on titles and abstracts of the studies. We obtained 425 studies, many of which were irrelevant, because the search was carried out only electronically. Then, in stage 2, duplicates were identified and removed. In stage 3, studies were excluded based on the title and the language according to the following two criteria:

[1] http://dl.acm.org
[2] http://ieeexplore.ieee.org
[3] http://www.theiet.org/publishing/inspec
[4] http://www.sciencedirect.com
[5] http://www.springerlink.com
[6] We checked again in late October 2012 and we could not identify any significant new publications.
[7] http://www.daml.org/

1. Studies that do not address functional testing of semantic WSs.
2. Studies that are not in the English language.

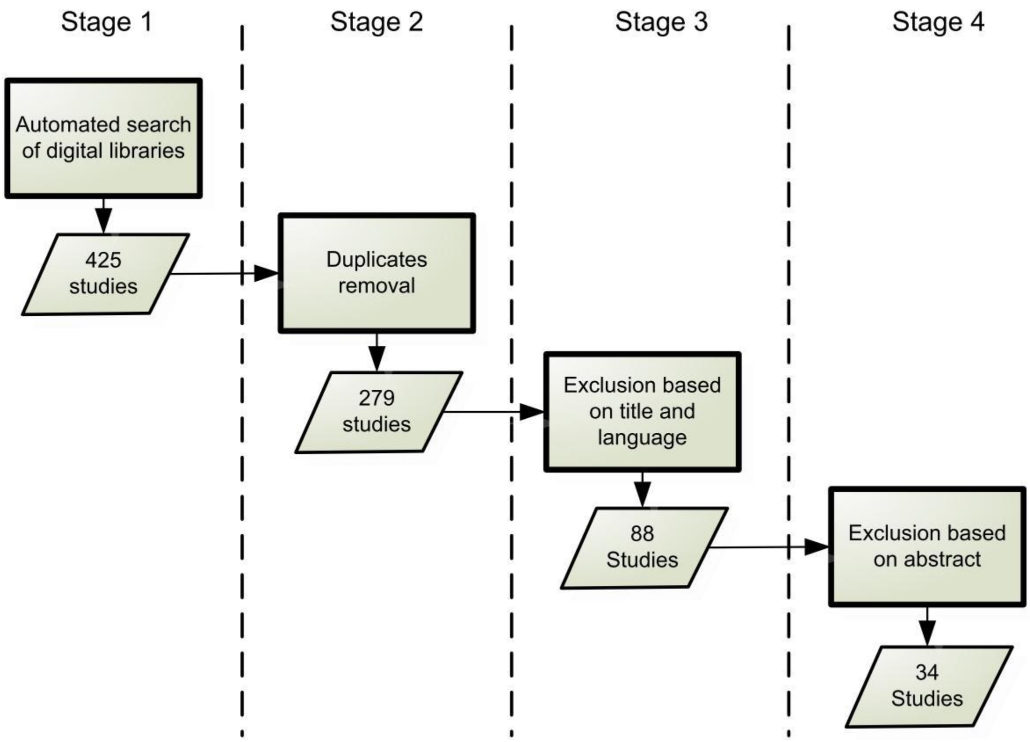

Figure 2: Stages of the search strategy.

In stage 4, only the first criterion was applied to exclude studies after studying their abstracts. After stage 4, we checked titles of references in the 34 studies selected to identify any relevant primary studies to be included.

To assess the reliability of the study inclusion/exclusion criteria, a re-evaluation of a random sample of the primary studies was performed. The re-evaluation included checking the consistency of the inclusion/exclusion decisions made. The re-evaluation was done after stage 3 and stage 4 of the selection procedure. After stage 3, we selected randomly 4 included studies (i.e., fulfilled the selection criteria of this stage) and another 4 excluded studies. We rechecked each of the 8 studies by applying the inclusion/exclusion criteria of stage 3 to them again. The same re-evaluation process was applied to another 8 randomly selected studies form stage 4.

3.1.3 Study quality assessment

Kitchenham and Charters (2007) insist on the quality assessment of the primary studies, to minimize bias and maximize validity when evaluating the primary studies. They also list five different purposes for the assessment. In this work, we use the study quality assessment as a means of weighting the importance of individual studies when results are being synthesized.

We developed a study quality questionnaire composed of 6 questions inspired to the questions presented by Dyba et al. (2007) and Kitchenham and Charters (2007). The following questions were used for the assessment of quality of the primary studies:

QA1. Are the aims and the objectives of the primary study clearly reported?

QA2. Is the context in which the research was carried out adequately described?

QA3. Is the test case derivation technique (RQ1) presented in the study clearly described?

QA4. Is there any credible validation of the technique/approach?

QA5. Are the findings clearly stated and related to the goals of the study?

QA6. Do the conclusions relate to the defined aim and purpose of study?

3.1.4 Data extraction

The data extraction phase involves collecting information relevant to the research questions from the primary studies selected. We have designed a data extraction form for this purpose (Table 1). We used the test-retest process (Kitchenham and Charters 2007) for the purpose of checking the consistency and accuracy of the extracted data with respect to the original sources. After finishing the extraction of information for all selected studies, we randomly selected 3 primary studies and performed a second extraction of the data. We noticed only one little inconsistency for one primary study (Dong 2009) where the test tool used was missing in the initial data extraction form.

No.	Data extraction category	Description	Addresses
General description			
1	Identifier	Unique identifier of the primary study	
2	Date	Date of data extraction	
Study description			
3	Title	Title of the primary study	
4	Authors	Authors of the primary study	
5	Publication year	Publication year	

6	Type	Conference paper, Journal article, book chapter, workshop paper	
7	Publication medium	Name of the publishing conference, journal, book or workshop (Including, e.g., volume number, page...)	
Study contents			
8	Objectives	What are the main objectives of the study?	RQ1, RQ2
9	Testing technique	What is the testing technique utilized?	RQ1, RQ2
10	How are the test cases derived	What is the base used for deriving test cases?	RQ1
11	Challenges identified	What challenges are associated with the chosen test derivation approach?	RQ2
12	Tool support/automation	Is the approach described in 10 or 12 supported by a tool or fully/partially automated?	RQ1
13	Validation	Which method is used for validating the study?	RQ1, RQ2

Table 1: Data extraction form.

3.2 Predictive models research method

In this section, the research method needed to provide answers to the research questions RQ3 and RQ4 is defined. The research method used for predictive model building is carried out as a correlational study. It is conducted with full control over the experimental environment. In such a context, human interactions with the WSs under examination can be easily guided and monitored.

An experimental approach was followed to collect the data necessary for predictive model building and evaluation. Students were used to interact with the WSs while quality measures are collected. Using students allowed for engaging a large group of ”users” and increased controllability over the environment. Additionally, controlled environment allows for isolating variables that are considered not relevant for the investigation and thus reducing the number of variables involved (reductionism) (Easterbrook et al. 2008).

However, one criticism on student-based studies is the reduced realism (Sjoberg et al. 2002), which may affect the external validity (Carver et al. 2010) of the outcomes of the study. We adopted two measures from Sjoberg et al. (2002) to increase realism, namely increasing the duration of the study and increasing the degree of professionalism of the involved persons. We increased the duration by running the data acquisition part of the study over multiple sessions instead of only one session. Moreover, students (graduates and undergraduates) with good background in software discipline were selected to take part in the study (Although the level of their software engineering experience was not important in this context.)

Table 2 lists the steps followed and the corresponding sections of the thesis in which they are thoroughly described.

No.	Step	Section/Chapter
1	Selection of suitable WSs for the study	Section 6.2
2	Identification and selection of related software measures to be collected besides the external qualities *Availability*, *Accessibility*, and *Successability*	Section 6.3
3	Development of a framework for collecting the selected quality measures	Chapter 7
4	Data collection	Section 6.4
5	Analysis of the collected data	Section 6.5
6	Building probabilistic models for the external qualities *Availability*, *Accessibility*, and *Successability*.	Section 9.1 to Section 9.5
7	Model selection and validation.	Section 9.6 Section 9.7

Table 2: Predictive models research method steps.

Chatterjee and Hadi (2006) proposed similar steps for general regression analysis:

1. *Statement of the Problem*
2. *Selection of Potentially Relevant Variables*
3. *Data Collection*
4. *Model Specification*
5. *Choice of fitting method*
6. *Model Fitting*
7. *Model Criticism and Selection*
8. *Using the chosen model(s) for the solution of the posed problem.*

"Statement of the Problem" in step 1 corresponds to the research questions RQ3 and RQ4 in this thesis (Section 1.1). Steps 2, 3 and 7 match steps 2, 4 and 7 in Table 2 respectively. Steps 4 to 6 correspond to step 5 and 6 in Table

2. Step 8 is about the application of the models on other datasets, which is not in focus of this thesis.

Chapter 4
SLR execution and results

4.1 Primary studies

Searching the electronic databases listed in Section 3.1.1 resulted in 425 relevant primary studies. The bibliography reference management tool JabRef (JabRef 2011) was used to manage the references to the primary studies identified. The study selection procedure described in Section 3.3 was then applied to the studies. First, a two-phase duplicate identification and removal process was followed. In the first phase, duplicate studies were identified automatically using the duplicate identification capability of JabRef. The tool identified 15 duplicates. In the second phase of duplicate identification process, we searched for duplicates manually. In this phase, 131 duplicate studies were identified. The large inconsistency between the numbers of duplicates detected automatically and those identified manually may be due to the low sensitivity of the duplicate detection algorithm utilized by JabRef. After duplicate removal only 279 primary studies remained. Afterward, the title of each study was reviewed and studies that clearly do not address functional testing of semantic WSs or that are not in the English language were excluded. For example, the search result included a study in veterinary genetics (Hull et al. 2008) titled "Development of 37 microsatellite loci for the great gray owl (Strix nebulosa) and other Strix spp. owls" which is clearly out of the scope of this review. The title- and language-based exclusion resulted in excluding additional 191 studies, with only 88 studies remaining. Subsequently, the abstract of each study was thoroughly reviewed and studies that do not address functional or self-adaptive testing of semantic WSs were filtered out. As a result, only 34 primary studies remained, listed in Appendix A. Figure 3 shows the accumulated number of selected primary studies published from the year 2000 to the year 2011. The cumulative number of publications was increasing over the years with the largest increase in the year 2009 (13 Studies). The following years (2010 and 2011) witnessed an increase of 4 publications a year.

For the 34 studies selected, we conducted a full text review including reviewing the references list of each study looking for relevant ones. We basically checked the titles of the studies in the reference lists for relevance to the purpose of this systematic review. All references that we could identify as relevant were found to be already included in the 34 studies identified previously as in Appendix A. This provided additional confidence on the effectiveness of the search process we followed.

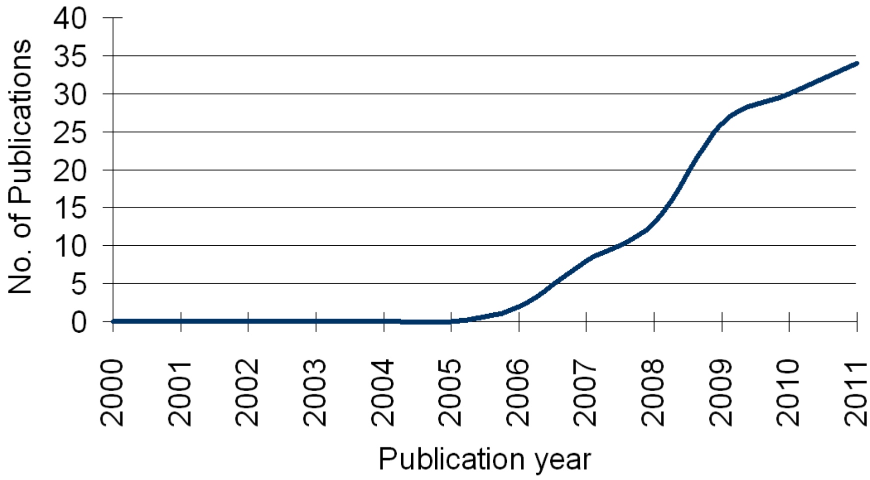

Figure 3: Cumulative number of publications.

As we mentioned in Section 3.1.3, it is essential to assess the quality of the primary studies selected. The assessment is used to weigh the importance of individual studies when results are being summarized (Kitchenham and Charters 2007). We used a simple scale of two values: (*Yes*) and (*No*) to answer the quality assessment questions as in Appendix B. Most of the questions received a positive answer (*Yes*). We here discuss only the few cases where the questions were answered negatively (*No*). For five studies (PS21, PS26, PS30, PS32, and PS33) the answer for question QA3 was negative. Specifically, studies PS21, PS26, PS32, and PS33 do not present any specific test case generation or test case derivation approach. Study PS21 presents a testing architecture based on SOA whereas study PS26 introduces a risk-based test case selection technique. Both PS32 and PS33 present test prioritization techniques. In PS30, the utilized test case derivation technique is insufficiently described because of space limitations.

For eight studies (PS1, PS11, PS20, PS21, PS24, PS26, PS28, and PS31), the answer to question QA4 was negative. Studies PS1, PS11, PS20, PS24, PS26, PS28 and PS31 do not convey any credible validation. In PS21 there is no specific test case generation or test case derivation approach presented and therefore no validation as required by QA4 is carried out. Study PS27 does not dedicate a separate section for the conclusions and in general does not discuss the conclusions.

4.2 Approaches for deriving functional test cases from requirement specifications (RQ1)

The central question in this systematic literature review, RQ1, focuses on the approaches available for deriving functional test cases from requirements specifications of semantic WSs. Functional capabilities (or requirements) of the semantic WSs are usually expressed by using an ontology description language (e.g., OWL-S, WSDL-S, etc.). Test cases can be derived from the requirements specifications of the semantic WSs to test the degree to which these requirements are satisfied. Thirty primary studies selected describe approaches for testing semantic WSs including the description of the test case derivation technique used. The primary study PS9 presents an automatic testing-based approach for the discovery of WSs based on the semantic information provided by the service requester. Additionally, it proposes exploratory testing as a test case derivation technique when the semantic WS specifications are missing or not sufficiently documented. So, the aim of PS9 is not to introduce a new testing approach for semantic WSs, but to utilize testing as a way to select a specific WS during discovery to satisfy a specific request based on the provided semantic information. Therefore, PS9 is out of the scope of RQ1. Only 3 primary studies (PS19, PS21 and PS26) do not present any testing approach. The objective of PS19 is to introduce a model for reasoning about the evolution of OWL-S requirements specification using π-calculus. PS21 presents an architecture for testing WSs. Ontologies are adapted to describe testing concepts and relations, based on which the interoperation between services are specified and implemented in semantic WSs technology. The presented architecture supports the dynamic discovery and invocation of testing services. Thus the study fulfils the search criteria but it does not provide any information about test case generation or derivation. PS26 introduces risk-based adaptive group testing for testing complex systems of semantic WSs. Test cases are categorized and scheduled according to the risks associated with the targeted WSs. The approach presented is not about test case generation or derivation but about a strategy for selecting a subset of test cases based on the risks associated with the WSs. So, the study addresses functional testing of semantic WSs, but it does not describe any test case generation or derivation approach.

Table 3 lists selected primary studies with test derivation base specifications (discussed in Section 4.2.1), transformations needed to any target model (discussed in Section 4.2.2), and the techniques followed to derive test cases from the specifications (discussed in Section 4.2.3).

4.2.1 Test case derivation base specifications

All selected primary studies (Appendix A) rely on some kind of specification models as a base for test case derivation (Table 3). The only exceptions are PS9, PS19, PS21, and PS26, which, as we mentioned before, do not present any testing approach.

Figure 4 illustrates a pie chart of the distribution of base specifications used for test case derivation presented in the selected primary studies. Eighteen of the test approaches (49%) utilize OWL-S specifications models or OWL-S models augmented with a rule-based models (SWRL, RIF-PRD) and FTLTL (Future Time Linear Temporal Logic). All test approaches (other than PS5, PS9, PS14-1,[8] PS14-4, PS19, PS21, PS26, PS27, and PS32) rely on ontology-based specifications that describe the semantics of WSs, via OWL-S, OWL, WSMO and WSDL-S. PS9, PS19, PS21, and PS26 do not introduce any testing approach and therefore are not relevant. PS5 and PS14-1 use a WSDL syntactical description model.

In PS14-4 and PS27, BPEL4WS specification models are used. BPEL4WS is an abbreviation of Business Process Execution Language for WSs. Although it can be used to semantically describe a WS (Grigorova 2006; Mandell and McIlraith 2003), BPEL4WS is basically not a semantic description language. In addition to WSDL specification, PS32 uses the IOPE (Input, Output, Precondition, and Effect) information without indicating the source of this information since such information cannot be described using WSDL.

Primary Study ID	**Test derivation base specifications**	**Model transformation into**	**Test case derivation technique**
PS1	OWL-S Specifications	Petri Net model	Path traversing & Reasoning over IOPE
PS2	WSMO Specifications	B model	Model Checking
PS3	OWL-S Specifications	Promela model	Model Checking
PS4	OWL-S “& SWRL Specifications	No	Reasoning
PS5	WSDL & OCL Specifications	WSDL-S specifications	Pair-Wise Testing and Orthogonal Array Testing
PS6	WSDL-S & SWRL Specifications	No	Random testing
PS7	WSDL-S & OCL Specifications	Input Parameter Model (IPM)	Pair-Wise Testing
PS8	OWL-S Specifications	Fault models (Testing goals)	Extended Graphplan planning algorithm
PS9	No	No	Exploratory testing

[8] PS14 represent four different techniques for testing web services. We added a suffix to the end of the primary study ID to differentiate from the test approaches presented, i.e., PS14-1, PS14-2. PS14-3 and PS14-4. PS14-1 uses WSDL specifications which do not include any semantic information. We included this approach in our systematic review for the sake of completeness.

Primary Study ID	Test derivation base specifications	Model transformation into	Test case derivation technique
PS10	OWL-S Specifications	No	Mutation testing
PS11	OWL-S Specifications	High-Level Petri Net (HPN) Model	Model Checking
PS12	OWL-S Specifications	Petri Net model	Path traversing & Reasoning over IOPE
PS13	OWL-S Specifications	Enhanced Hierarchical Color Petri Net (EH-CPN) model	Path traversing and Partition Testing
PS14-1	WSDL Specifications	no	Random testing
PS14-2	WSDL-S Specifications	no	Input and precondition analysis
PS14-3	OWL-S Specifications	no	Random testing
PS14-4	BPEL4WS Specifications	Petri Net model	Path traversing
PS15	WSMO Specifications	B model	Model Checking
PS16	OWL & RIF-PRD Specifications	Stream X-machine model	W-Method
PS17	OWL-S Specifications	Temporal Logic Actions (TLA) model	Model Checking
PS18	WSDL-S Specifications	Extended Finite State Machine (EFSM) model	One of the following: a. Full predicate coverage b. BZ-TT method c. Mutation based d. User defined test objectives
PS19	No	No	No
PS20	OWL-S Specifications	No	Mutation testing
PS21	No	No	No
PS22	OWL-S Specifications	Petri Net model	Path traversing & Reasoning over IOPE
PS23	OWL-S Specifications	No	Partition Testing
PS24	OWL-S, FTLTL and SWRL Specifications	No	Runtime analysis (code instrumentation)

Primary Study ID	Test derivation base specifications	Model transformation into	Test case derivation technique
PS25	OWL-S Specifications (extended to support the specification of mutant operators)	No	Mutation testing
PS26	No	No	No
PS27	BPEL4WS Specifications	Labeled Transition System (LTS)	Condition Checking
PS28	WSMO Specifications	No	Boundary conditions and Equivalence classes testing
PS29	WSDL-S & SWRL Specifications	No	Decision tables testing
PS30	WSDL-S & SWRL Specifications	Stream X-machine model	No clear description
PS31	OWL-S Specifications	Flow graph-based test model	Path traversing & and other traditional white-box testing techniques
PS32	WSDL Specifications and IOPE information	No	No
PS33	OWL-S Specifications	No	No
PS34	OWL-S Specifications	Markov chain diagram or Markov decision process.	Model Checking

Table 3: Approaches for deriving functional test cases from requirements specification of semantic WSs.

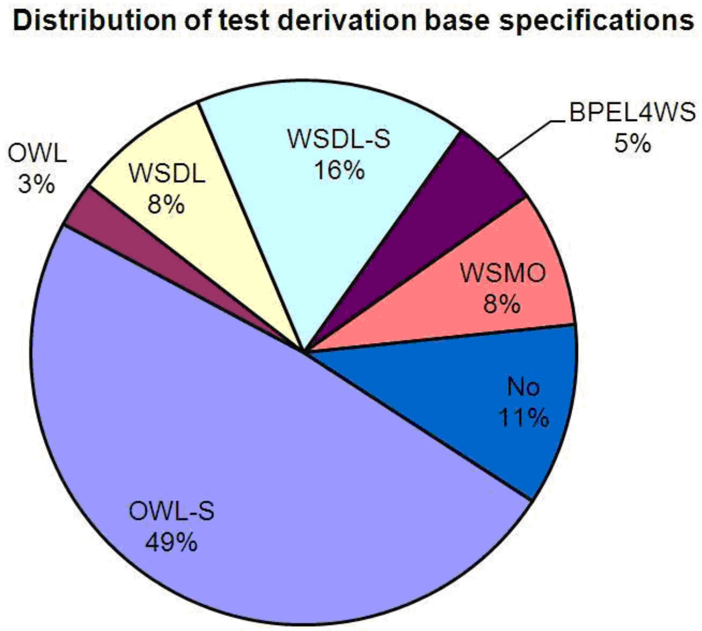

Figure 4: Distribution of test case derivation base specifications.

4.2.2 Model transformations

To simplify the automation of test case generation, it may be useful to represent the provided WS specifications in another format via model transformations. The original WS specification model is transformed into another target model that is believed to be much more efficient in terms of automatic test case generation or that is well supported by test generation tools. In the selected primary studies, the original specification model is transformed into one of the following models:

- Petri Net.
- B model.
- Promela.
- WSDL-S.
- IPM (Input Parameter Model).
- Fault model.
- HPN (High-level Petri Net).
- EH-CPN (Enhanced Hierarchical Color Petri Net).
- SXM (Stream X-machine Model).
- TLA (Temporal Logic Actions).
- EFSM (Extended Finite State Machine).
- LTS (Labeled Transition System).

- Flow graph-based test model.
- Markov chain diagram or Markov decision process.

Figure 5 depicts the distribution of the model transformations used in the different testing approaches.[9] Fourteen (43%) of the testing approaches presented in the selected primary studies do not utilize any kind of model transformation. They rather rely on the source specifications when deriving test cases. In 4 (12%) of the testing approaches, the original specifications are transformed into Petri Net models. HPN and EH-CPN models (one test approach each) can be seen as derivatives of Petri Net models and consequently we can say that about 18% of the approaches use Petri Net models and its derivatives. This makes Petri Net models and their derivatives the mostly used models, followed by B models (6%), and SXM models (6%). All other models are equally used with 3% (one test approach) each.

Table 4 represents a matrix of the source specifications model and the transformation needed as well as the IDs of the primary studies where the transformation is used. A total of 15 testing approaches use an OWL-S model as a source model. No transformations are needed and the test cases are derived directly from the source specifications in test approaches where the source specifications model is an extended OWL-S model. In the selected primary studies, OWL-S models were extended to support mutant operators or they are augmented with a rule based specification model (SWRL) as in PS4 or FTLTL specifications as in PS24. In the test approach presented in PS5, the source specification is in WSDL, which provides only a syntactical description of the web service.

The WSDL representation is then enriched with the pre- and post-conditions for the service rule, which are specified using OCL. The enriched WSDL is then used to generate a semantic WSDL (WSDL-S) representation. Similarly, the source specifications for PS32 are described in terms of WSDL supported with additional IOPE information. In PS7 and PS30, the source specifications models are in WSDL-S augmented with a rule-based model (in SWRL and OCL respectively). These models are transformed to IPM and SXM models respectively. WSMO models are used as source specification models in PS2, PS15, and PS28. In PS2 and PS15, the source model is transformed into a B model. Studies PS2 and PS15 probably represent a continuation of the same work since both studies have same first author and almost share the same context. No model transformation was used in PS28.

[9] In Figure 5 and in Table 4 we did not include the test approaches presented in PS9, PS19, PS21 and PS26 as they do not provide any test case derivation base specifications (Table 3).

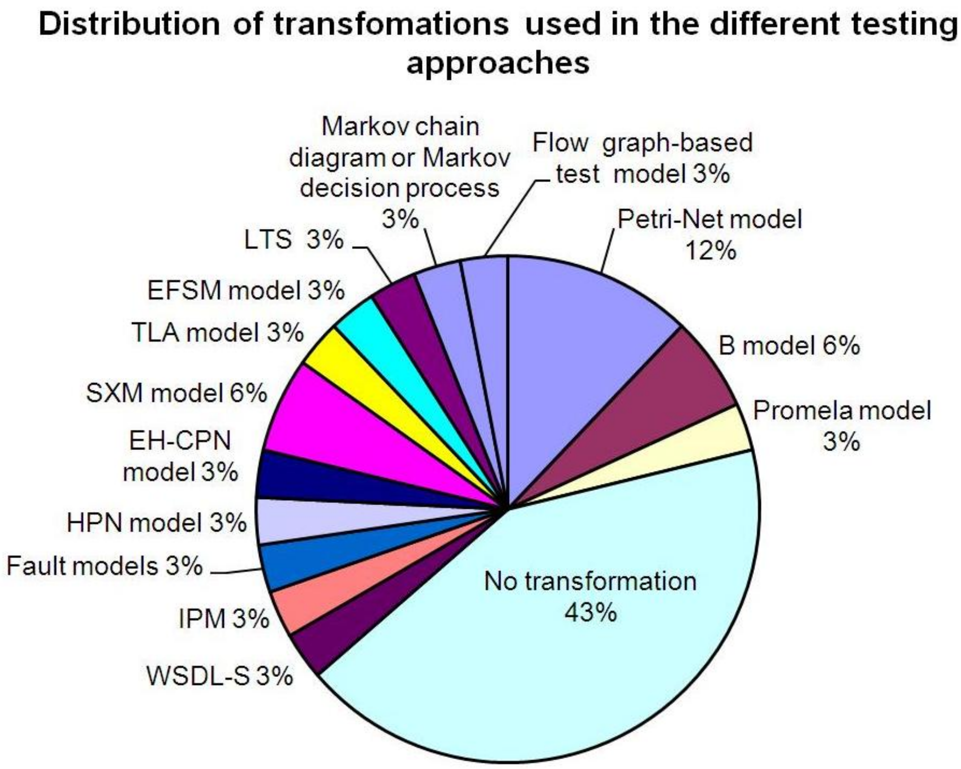

Figure 5: Distribution of the model transformation used in the different testing approaches.

Source specifications	Transformation into: Petri Net model	B model	Promela model	WSDL-S	IPM	Fault models	HPN model	EH-CPN model	SXM model	TLA model	EFSM model	LTS	Flow graph-based test model	Markov chain diagram or Markov decision process	No transformation
OWL-S Specifications	1, 12, 22		3			8	11	13		17			31	34	10, 14-3, 20, 23, 33
OWL-S & SWRL Specifications															4
OWL-S, FTLTL and SWRL Specifications															24
OWL-S Specifications (extended with mutant operators support)															25
OWL & RIF-PRD Specifications									16						
WSDL & OCL Specifications				5											
WSDL Specifications															14-1
WSDL and IOPE Information															32
WSDL-S & SWRL Specifications									30						6, 29
WSDL-S &OCL Specifications					7										
WSDL-S Specifications											18				14-2
BPEL4WS Specifications	14-4											27			
WSMO Specifications		2, 15													28

Table 4: Matrix of test derivation base specifications and transformations used for test generation in the different primary studies. Note: Numbers refer to the numerical part of the primary studies IDs.

4.2.3 Test case derivation techniques

Different test case derivation techniques are used as a part of the test approaches introduced in the primary studies (Appendix A and Table 3). Figure 6 depicts the distribution of the test case derivation techniques. With 18%, model checking is the most popular technique (used in PS2, PS3, PS11, PS15, PS17 and PS34). As mentioned in Section 4.2.2, PS15 can be considered as the continuation of the work done in PS2. In both studies, model checking is used to generate test cases from a B model. In PS3, model checking is applied to a Promela model. In PS11 and PS17, model checking is applied to High-level Petri Net (HPN) model and Temporal Logic Actions (TLA) model respectively. Path traversing and reasoning over IOPE, random testing and mutation testing come in second place in terms of popularity with 9% (3 test approaches) for each. Path traversing and reasoning over IOPE is used in the primary studies PS1, PS12, and PS22, which all use a similar approach that first transforms OWL-S specifications into a Petri Net model and applies path traversing and reasoning over IOPE techniques to derive test cases. Random testing is used in PS6, PS14-1, and PS14-3 to derive test cases. In all three approaches, random testing is applied to the base specification model and no transformation is required. Mutation testing was utilized in PS10, PS20, and PS25 to derive test cases. In all of these studies, the base specification model is either OWL-S or an extension of it and there is no transformation into another specifications model. PS30 uses a test case derivation technique that is insufficiently described because of space limitations. Each of the remaining test case derivation techniques shown in Figure 6 is used in only one primary study (3% each).

4.2.4 Test tool support

Not all test approaches presented in the selected primary studies are supported by test tools. Around half of the testing approaches presented in the studies do not use any testing tools, as can be seen in Table 5. Six approaches (17.7%) in PS2, PS3, PS11 PS15, PS17, and PS34 use model checkers. Jess[10] (Java Expert System Shell) is used in PS4 to perform automated analysis over OWL and SWRL specifications. In PS5, the test tool WebInject[11] is used as a test runner and for report generation purposes. TAG-WS (Testing by Automatically Generated Web Service semantic) is used in PS6 as a prototypical implementation tool for the testing approach presented in the study. PS16 uses a converter to convert the identified test cases into JUnit[12] format to run it using that framework. In PS18, there are four different techniques presented for test case derivation from the EFSM model. The tool

[10] http://www.jessrules.com
[11] http://www.webinject.org
[12] http://www.junit.org

Gotcha (Friedman et al. 2002) is used only for the technique "User defined test objectives." PS19 uses the tool MWB[13] (Mobility Workbench) to detect requirements evolution. Therefore, we did not consider it as a test tool. AspectJ[14], used in PS20 and PS25, is not a testing tool but a tool that supports the implementation of aspect orientation. Java-MOP[15] (Java Monitoring-Oriented Programming) is used in PS24 to support code instrumentation. In PS29 and PS30 the tools TAD (Testing by Automatically generate Decision table) and SWSDSXMGen are used respectively. Both tools are prototypically implemented to support the approaches presented in the respective papers.

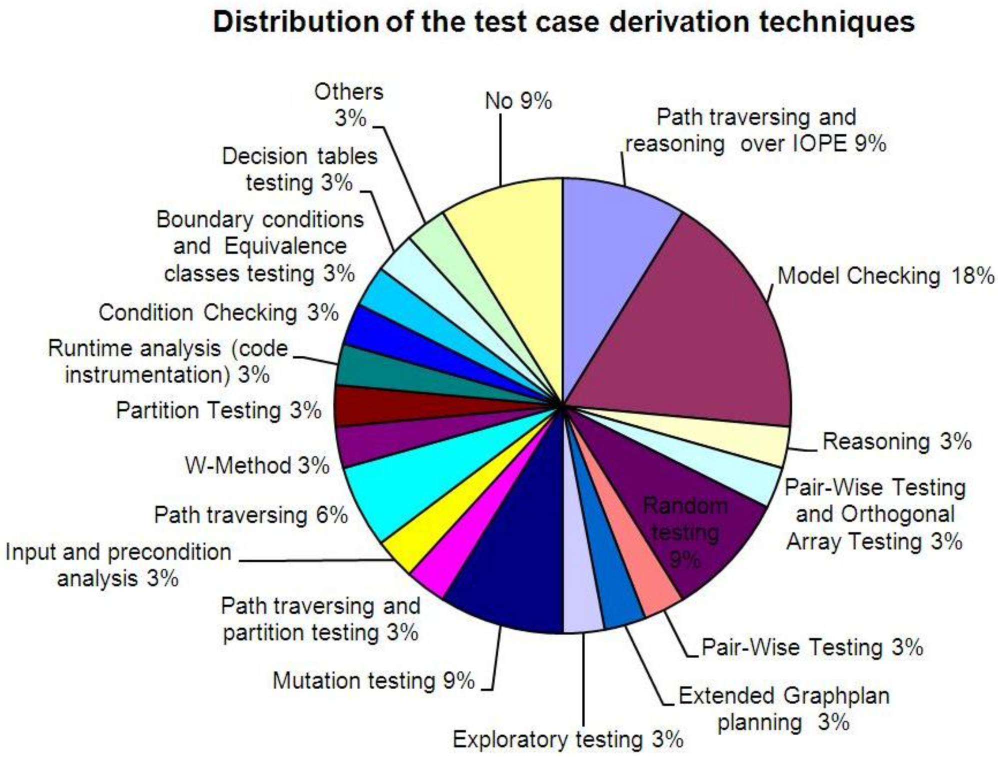

Figure 6: Distribution of the test case derivation techniques.

[13] http://www.it.uu.se/research/group/mobility/mwb.
[14] http://www.eclipse.org/aspectj
[15] http://code.google.com/p/javamop/downloads/list

Primary Study ID	Tool Support	Validation
PS1	No	No
PS2	ProB Model Checker	Example
PS3	SPIN Model Checker	Not clearly specified
PS4	Jess reasoning engine	Example
PS5	WebInject	4 Examples
PS6	TAG-WS	Example (simple)
PS7	No	Example (simple)
PS8	No	Industrial application
PS9	No	Example
PS10	No	Case Study
PS11	HPN Model Checker (Not clearly specified)	Not clearly specified
PS12	No	Example
PS13	No	Case Study
PS14	No	No credible validation
PS15	Model Checker (ProB)	Case Study
PS16	JUnit/Converter to JUnit	Example
PS17	TLC Model Checker TLC	Case Study
PS18	Gotcha	Example
PS19	MWB	Example
PS20	AspectJ	No
PS21	No	Case Study
PS22	No	Example
PS23	No	Example
PS24	Java-MOP	No credible validation
PS25	AspectJ/FIT	Case study
PS26	No	No
PS27	No	Example
PS28	No	Example
PS29	TAD	Example

Primary Study ID	Tool Support	Validation
PS30	SWSDSXMGen	Example
PS31	No	No
PS32	No	Example
PS33	No	Example
PS34	Model Checker (PRISM)	Example

Table 5: Validation approaches and tool support for the test approaches.

4.2.5 Validation of the testing approach

Most of the test approaches introduced in the selected primary studies use some kind of validation to provide confidence on the proposed approaches as shown in Table 5. Only the test approaches in primary studies PS1, PS20, PS26, and PS31 are not validated at all. Furthermore, the validation approach for PS3 and PS11 is not clearly specified. Other 19 primary studies are validated using (simple) examples mainly for the purpose of illustration of the testing approach introduced. Primary studies PS10, PS13, PS15, PS17, PS21, and PS25 use case studies to demonstrate the validity of the testing approach. PS8 validate its testing approach by applying it to a case study in an industrial environment. Hence it exhibits stronger validation than only using a simple example. We could not identify any credible validation done for the test approaches presented in PS14 and PS24. PS14 relies on the authors' opinion to claim validity of the proposed approach. PS24 is about a testing system, but it did not give any details that may make the validation done credible.

4.3 Test case derivation challenges (RQ2)

Most of the studies that discuss challenges associated with testing focus on general challenges that are applicable to the problem of testing traditional WSs as well as semantic WSs. Table 6 summarizes the WSs testing challenges introduced in the primary studies selected. As a consequence of source code invisibility (C1), structural testing techniques (white-box testing) cannot be applied to semantic WS. The absence of a (graphical) user interface (C2) prevents applying GUI-based testing approaches. This restricts noticeably the choices of the testers. Mapping from high level semantic description to low level syntactic description (C3) introduces overheads in the testing process. Traditional WSs are described in WSDL that syntactically defines operations and massages structure. Conversely, semantic WSs are described semantically using one of the ontology languages (e.g., WSMO and OWL-S). This semantical description needs to be "grounded," i.e., mapped to a technical description by defining message structure and operations of the WS in terms of WSDL. In the case of traditional WSs, testing is carried out directly at the technical layer (i.e., through the interfaces described in WSDL). On the other hand, semantic WSs are tested at the semantical layer (i.e., through the semantically described interfaces) using the available semantic information. This introduces more testing overhead than in the case of traditional WSs (e.g., test pre- and post- conditions). Additionally, the poor observability and controllability (C4) is due to the dynamic and autonomic nature of the WSs, which complicates the observation of the test results and the control of the testing process.

ID	Challenge/Issue	Primary Study
C1	Source code invisibility	PS5,13
C2	No user interface	PS15
C3	Mapping from high level semantic description to low level syntactic description	PS15
C4	The poor observability and controllability	PS21

Table 6: Challenges with testing semantic WSs.

Chapter 5
SLR discussion and threats to validity

5.1 Discussion

Most of the identified test approaches in the primary studies present approaches for deriving functional test cases from the semantic WSs requirement specifications. Some of these approaches (14) derive the test cases directly from the original specifications. Nineteen other approaches require that the original specifications be represented in a different formalism using transformations before deriving the test cases. Many of them focus on different formalisms making their research efforts scattered in different directions. Focusing on one appropriate formalism might leverage the status of research in the area of functional testing of semantic WSs. According to our review results, Petri Net is the most popular formalism, and therefore it is a good candidate for focusing on in future research. Although researchers can also investigate approaches that do not use an intermediate transformation, we do not recommend this direction. This is because semantic WSs are specified using one of the semantic WSs ontology languages (WSMO, OWL-S, WSDL-S, etc.) and most of these specifications are semi-formal. Transforming them into formal models allows for comprehensive and automated testing.

Additionally, around 18 (50%) of the primary studies do not mention any test tool support. If the techniques involved in these studies do not actually use any test tools, there may be a significant reduction in the effectiveness of the approaches presented, since many tasks need to be done manually.

In what follows, we provide a comparison of two different test approaches found in the primary studies PS13 and PS14-4. Because of space limitations, we found it necessary to restrict the comparison to two test approaches. These approaches are chosen because they share the same characteristics, as they utilize the mostly used transformations into Petri Net or its variant Enhanced Hierarchical Color Petri Net (EH-CPN) and the path traversing technique to identify the required test cases. PS13 introduces a test case derivation technique that involves transforming the OWL-S specification of a semantic WS into an EH-CPN and then analyzing control-flows and data-flows to identify all output-input-define-use chains. The chains are used to additionally identify corresponding executable paths in the EH-CPN model. Test sequences are derived from the executable paths in the model. Test data are generated using the XML-based partition testing method in which XML structures and data types are mapped to category partitions and then test data are generated randomly based on the partitions. Test cases are generated by combining test sequences and test data. In PS14-4, a test data derivation approach for composite WSs described in BPEL4WS is introduced. The approach involves converting BPEL4WS Specifications into a Petri Net model and applying path traversing to generate the test sequences. Test data are randomly generated based on the analysis of the data types available in the model.

It is clear that the test approaches presented in PS13 and PS14-4 use different transformations of their source specifications, namely, into EH-CPN and Petri Net respectively. Colored Petri Net (CPN) is a variant of Petri Net that utilizes colored tokens. Using colored tokens allows the description of more complex data objects and the removal of part of the ambiguity in Petri Net. However, CPN is not capable of representing complex composition patterns of WSs. Therefore, EH-CPN is introduced to solve this problem. As a result, EH-CPN is better than Petri Net as a target representation model for semantic WSs that are composed of other WSs (composite services). On the other hand, PS14-4 uses BPEL4WS to describe WSs that are composed of other WSs. The source specification in BPEL4WS is transformed into Petri Net which is less expressive than EH-CPN used in PS13 when it comes to composite WSs. The test derivation technique followed in PS13 allows for direct derivation of test sequences by traversing the execution paths in the EH-CPN model and generating the required test data by analyzing the input and outputs to identify category partitions and then generating test data based on them. In PS14-4, test sequences are identified by traversing the paths in Petri Net as in the approach used in PS13. However, the test data generation may result in relatively larger volume of test data compared to the test data generation approach used in PS13 which rely on the category partition technique.

5.2 Threats to validity

Validity is a main concern in empirical software engineering studies. Here, we discuss threats to construct, internal and external validities (Wohlin et al. 2000).

Construct validity is about whether the implementation of this systematic literature review matches its initial purpose. We identify the search process and search terms as the main concerns. The search terms used in this review were derived from the research questions and were tried against a list of known research studies and iteratively adjusted. However, as usually happens in systematic literature reviews, the completeness and the comprehensiveness of the terms used are not guaranteed. To reduce this risk, we searched the reference list of each selected primary study to identify additional relevant primary studies. Additionally, the search revealed three articles in the Chinese language (Ju, Di, and Bixin 2008; Xiaoyan, Ning, and Ying 2008; Ying, Maozhong, and Ning 2009) which we excluded. This may present a threat to the construct validity. Although well-known digital libraries were searched for relevant primary studies, other sources may contain relevant primary studies that have not been taken into consideration.

Internal validity is the extent to which the design and conduct of the study are likely to prevent systematic error (Kitchenham and Charters 2007). We are here concerned about the data extraction. When extracting data from the selected primary studies, we could only rely on our interpretation where the necessary data are not clearly expressed. Some required data were totally missing in a few primary studies. This may pose a threat to the internal validity.

External validity is the extent to which the effects observed in the study are applicable outside of the study (Kitchenham and Charters 2007). External validity is primarily about the generalizability of the study outcomes. Our systematic review is constrained by the following issues: (1) it is focused on a very specific problem; (2) the problem under focus is relatively new, and (3) it covers a predefined period of time (2000–2011). Taking these concerns into account, we consider our results generalizable.

Chapter 6
Predictive models empirical approach

In this chapter, the implementation of the predictive models research method introduced in Section 3.2 is explained and discussed. Primary focus is on steps 1, 2, 4 and 5 of Table 2. The other steps will be discussed in later chapters.

6.1 Experimental setup

Building and validating significant predictive models for the WSs external quality measures *Availability*, *Accessibility* and *Successability* require clearly defined experimental circumstances. Many factors may influence the time-related behavior (e.g., performance), and therefore some external qualities of the WS (e.g., network, hardware, application server, application software, etc.). In this research, we are focusing on the WSs' application software since in a typical WSs development project, only the WSs' logic is implemented and all the other elements are not developed but only used for deployment and hosting purposes. Factors other than the WSs' application software are isolated by using similar configurations for all WSs under examination. Our aim is to help predict external qualities in early stages of WSs development projects based on the observation of static internal quality measures as well as the internal dynamic behavior of WSs' application software measured through different dynamic measures.

The correlational study was conducted in a controlled environment where 34 graduate and undergraduate students interacted with a set of WSs (see Section 6.2) while the targeted dynamic quality measures are collected. This is carried out over multiple sessions as follows:

- Four sessions of length 2 hours and 30 minutes each,
- One session of length 1 hour and 30 minutes, and
- Two sessions of length 1 hour each.

Splitting data acquisition into multiple sessions was due to limitations in the capacity of the lab to accommodate all 20 WSs on server machines and at the same time to provide sufficient client machines to be used by the students. Moreover, having multiple sessions allowed to re-expose a WS to the students when problems occurred in previous sessions prevented the collection of the required data for that specific WS.

The involved students received information about the usage of the WSs before starting interacting freely with them. Each WS was installed on a separate host machine. During their interactions, relevant dynamic quality measures (Section 6.3) were collected and stored into multiple text files on the host machines.

6.2 WSs selection

The WSs needed for the study are selected based on the following criteria:

- Full access to the source code and the documentation of the WS to facilitate the evaluation of static and dynamic quality factors;
- The WSs are built using Java programming language, due to the fact that our framework is currently able to analyze Java components only;
- The WS provides the claimed functionality itself and it is not a "wrapper" for other services.

Since open source applications usually satisfy the above criteria, we focused on them.

Unfortunately, the process of identifying and selecting WSs satisfying all the aforementioned criteria ended with the availability of just one WS. Specifically, we discovered and used as case study a WS released by Yesiltepe Softwareentwicklung (Yesiltepe 2013), which satisfies all the above conditions. This WS provides a registry for artists. One issue with this WS is that the data of the artists (names, addresses, etc.) are stored on plain operating system files. This makes the application slow and not stable enough for concurrent accesses. Therefore, we modified the original WS to make use of an embedded database instead of plane files.

To overcome the limitation in the number of available Open-WSs on the net, we decided to manually convert free and open source Java applications into traditional WSs (i.e., the functionalities provided by the Java applications are exposed on the Web without any semantic annotations). To perform this conversion, we used the Apache Axis2 framework (Apache Axis2 (v1.6.2) 2014). For instance, we converted the application code2web (code2web 2013), a utility application that converts Java source code into HTML, into a WS. For uniformity, we used the Axis2 framework to expose the functionalities of all the WSs selected for the study.

To provide a statistically relevant set of WSs, we targeted 20 WSs to be used in the study as subjects. Table 7 provides a short textual description of the WSs used.

Web Service	Description	*Name* & reference to original software the WS is converted from
ArtistsRegistryWS	An Artists registry that allows searching for artists by name, part of the name, address or art type.	*artistRegistry* (Yesiltepe 2013)
Code2WebWS	Takes a folder containing Java files as input and converts them into HTML files preserving their format.	*code2web* (code2web 2013, 2)
ComputingWithUnitsWS	Converts between different units and define units.	*Computing with Units* (Redziejowski 2013)
YaHPConverterWS	Generates a PDF file from a web URL.	*YaHP-Converter* (Anciaux 2013)
NumericalConverterWS	Converts between decimal, binary and hex numbers.	*NumericalConverter* (Zona 2013)
CurrencyConverterWS	Retrieves the rate of exchange between two currencies.	*CurrencyConverter* (Aravindhan 2013)
RomanNumbersConverterWS	Bidirectional converter for Roman and Arabic numbers.	*yarc* (Mohammed 2013)
JavaToCSharpWS	Takes a Java file as input and convert it into a C# file.	*uta-java-to-csharp* (Vyas et al. 2013)
CSVGeneratorWS	Generates CSV (comma separated values) data based on a predefined XML data model.	*csvgenerator* (Jocic 2013)
SecurePasswordGeneratorWS	This WS generates unique secure password with special characteristics (length, digits, characters, etc.)	*spg2* (spg2 2013)
XMLtoRDFConverterWS	Takes a XML code file as input and converts it into RDF code file.	*XMLtoRDF* (XMLtoRDF 2013)
JavaToPythonWS	Converts Java code files into Python code files.	*j2p* (j2p 2013)
HtmlToLaTexWS	Takes HTML files as input and converts them to the LaTex forma.	*HTML to LaTeX* (michalke, srini88, and jnnnnn 2013)
HtmlToExcelWS	Converts HTML files into a	*orders-converter*

Web Service	Description	*Name* & reference to original software the WS is converted from
	Microsoft Excel file.	(Orders-Converter 2013)
ExcelToSqlWS	Generates SQL code out of a Microsoft Excel file.	*excel2sql*
		(excel2sql, n.d.)
PasswordGeneratorWS	Generates unique secure password by allowing the user to specify the length, lower and/or upper case characters, digits or special characters to be included.	*generate-password*
		(Generate-Password 2013, -)
HtmlToJspConverterWS	Takes HTML files as input and converts them to the JSP format.	*HtmlToJspConverter*
		(HtmlToJspConverter 2013)
RandomDataGeneratorWS	This WS takes a string specified in the Random Data Generation Language (RDGL) and generates random data accordingly.	*rdgl*
		(Rdgl 2013)
NumberToWordConverterWS	Delivers a plain English representation for numerical values.	*NumberConverter*
		(Zhou 2013)
MoneyToStringConverterWS	Delivers a plain English representation for money values.	*MoneyToStringConverter*
		(MoneyToStringConverter 2013)

Table 7: The 20 WSs selected for the study

6.3 Identification and selection of software measures to be collected

Building probabilistic models for the sub-quality factors *Availability*, *Accessibility*, and *Successability* involves the identification of the dependent variables and the (possibly) related independent variables. Since we aim to predict the sub-quality factors *Availability*, *Accessibility* and *Successability*, they are considered the dependent variables. The independent variables on which the prediction of the dependent variables depends are the software internal static and dynamic measures listed below. The static quality measures selected are well-known and widely accepted measures taken mainly from (Chidamber and Kemerer 2013). We also considered the dynamic behavior of the WSs by including four dynamic metrics.

- *Static software measures:*

- Lines of Code (LOC) is the number of lines of code in the WS's source code. It is a size measure that is usually used to assess the complexity of the software.
- McCabe Cyclomatic Complexity (CC) counts the number of linearly independent paths in the WS's source code.
- Weighted Methods per Class (WMC) is the sum of the McCabe Cyclomatic Complexity of all methods in a class.
- Lack of Cohesion of Methods (LCOM) "*is the number of pairs of methods in a class that don't have at least one field in common minus the number of pairs of methods in the class that do share at least one field. When this value is negative, the metric value is set to 0.*"
- Afferent Couplings (Ca) is the number of other packages that depend upon classes in a specific package.
- Efferent Couplings (Ce) is the number of other packages that the classes in the package depend upon.
- Instability (I): The ratio of efferent coupling (Ce) to total coupling (Ce + Ca)
- Abstractness (ABST): The number of abstract classes (and interfaces) divided by the total number of types in a package (Eclipse Metrics Plugin 1.3.8 2013).
- Distance (DIST): The normalized distance from the main sequence, calculated as | ABST + I - 1 | (Eclipse Metrics Plugin 1.3.8 2013).
- Weighted Methods (WM): The sum of the McCabe Cyclomatic Complexity of all methods.
- Number of Methods (NOM): Total number of methods.
- Average Lines Of Code Per Method (LCPM): The average number of lines of code in each method.
- Average Block Depth (ABD): The average of the maximum block depth for all methods.

▪ *Dynamic software measures:*

- Distinct Classes (DC) is "*the count of the distinct number of classes that a method uses within a runtime session.*" (Lavazza et al. 2012)
- Dynamic Coupling Between Objects (DCBO) is the number of distinct classes a specific class is coupled to at runtime (Justus and Iyakutti 2011).

- Object Method Invocations (OMI) is the total number of distinct methods invoked by each method in each object within a runtime session. (Lavazza et al. 2012)
- Distinct Method Invocations (DMI) is "*the count, within a runtime session, of the total number of distinct methods invoked by each method in each object.*" (Lavazza et al. 2012)

6.4 Data collection

The static software measures (e.g., LOC and WMC, etc.) were calculated for all WSs using two different tools, namely, CodePro AnalytiX (Google Inc.) and the Eclipse Metrics plugin (Eclipse Metrics Plugin 1.3.8 2013). Then, 34 students freely interacted with the 20 selected WSs through a set of clients that support all their exposed functionalities for a pre-specified period of time as described in Section 6.1. During this, the different dynamic quality measures identified in Section 6.3 were collected using the data collection framework described in details in Chapter 7. The framework collects the required data and automatically calculates the average values for all required internal dynamic quality measures.

The sub-quality factors *Availability*, *Accessibility* and *Successability* were calculated using the three formulas presented in Section 2.2. The data required for calculating *Availability* are collected from the log information of the WSs application server. This includes server's up-times and any possible down-time. The data required for calculating *Accessibility* and *Successability* were collected by capturing the HTTP messages exchanged between the WSs application server and the clients. This allows for calculating the number of requests, responses, and acknowledgment messages exchanged between the WSs and their clients. A thorough description of how *Availability*, *Accessibility* and *Successability* are calculated is provided in Section 7.1.

6.5 Data analysis

In this thesis, we follow the theory introduced by Morasca (2009) (Section 2.4) which suggests that probabilistic predictive models can be built for external quality measures based on internal quality measures. Focus is on building predictive models for the sub-quality factors *Accessibility*, *Availability* and *Successability* of WSs based on the internal quality measures identified in Section 6.3.

The data collected (Appendix C) during the study include both the independent variables (internal quality measures) and the corresponding dependent variables (*Availability*, *Accessibility* and *Successability*). One widely used approach to identify possible relations between dependent and independent variables is the statistical regression analysis. In Section 9.1, we explain in details and motivate the statistical approach followed for model building.

Chapter 7

Data collection framework

To achieve the objectives listed in Section 1.1, we designed and implemented a framework (Figure 7) for the automatic data collection and metrics calculations. The framework can support developers of WSs in assessing in a simple way the external qualities of their WSs at deployment-time, and to react promptly in case their WSs do not satisfy the expected quality requirements. Server-side, the framework simplifies the process of converting Java applications into WSs, guaranteeing a reliable message exchange between the clients and the WSs. The server-side components are also responsible for the computation of static measures, for creating the environment that is able to compute dynamic measures in a transparent way, and also for calculating *Availability*, *Accessibility* and *Successability* for the target WSs.

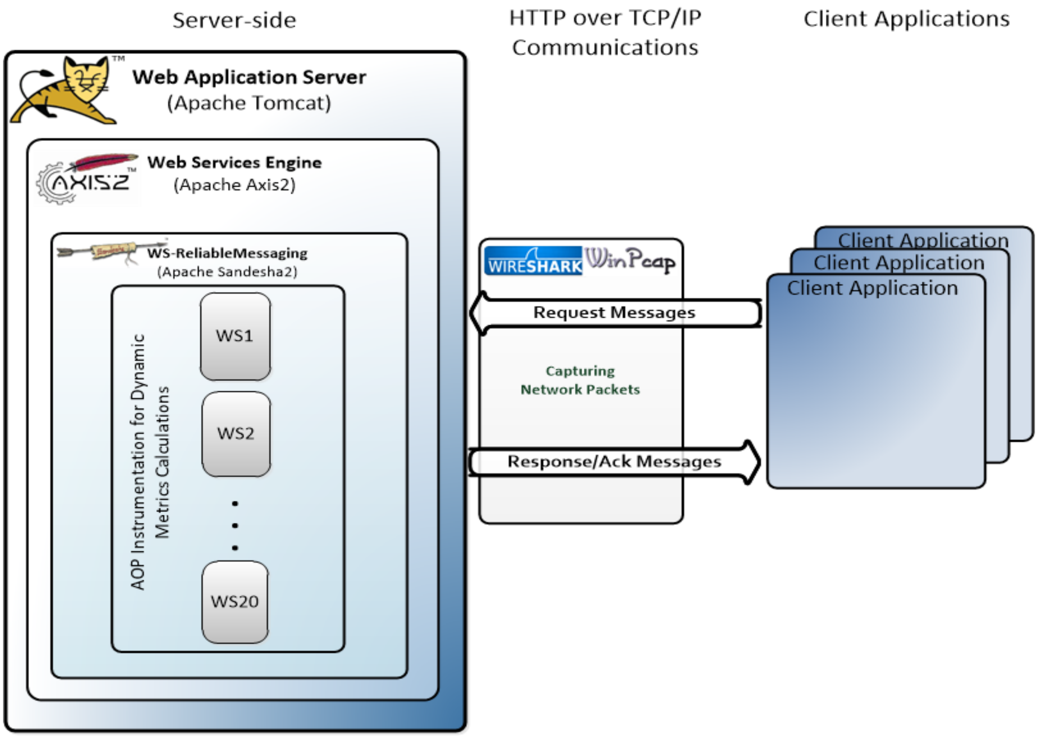

Figure 7: The data collection framework

In the following sections, the framework and its components are described in details.

7.1 Server-side

The server-side of the measurement framework is centered on the application server Apache Tomcat (Apache Tomcat 2013). First, the WS engine Apache Axis2 is deployed into Tomcat and used to expose (web) applications functionality as standard WSs that communicate using SOAP messages over the HTTP protocol. The targeted WSs are then deployed into Axis2 engine.

To assure reliable message exchange between the clients and the WSs, they were instrumented using Sandesha2 (Apache Sandesha2 (v1.6.2) 2014) (an implementation of the OASIS WS-ReliableMessages standard (OASIS WSRM 2007)). Sandesha2 provides a mechanism that can accurately track and monitor message exchanges between the WSs and their clients. It allows for the accurate determination of the correct disposition of messages only once and therefore, avoids any problems or errors associated with lost or duplicated messages. Using Sandesha2, each request received from the client is acknowledged separately. This facilitates the calculation of the *Accessibility* since it is calculated as the number of acknowledge messages received by the client divided by the number of request messages sent.

Static measures defined in Section 6.3 are calculated before the deployment of the WSs into Tomcat using CodePro AnalytiX and the Eclipse Metrics plugin. Conversely, the dynamic measures defined in Section 6.3 are collected using the Aspect-Oriented Programming (AOP) technology (Kiczales and Hilsdale 2001) at run-time. The AOP tool AspectJ was used for this purpose. Each measure is implemented as an ”Aspect” that is constructed of ”point cuts” and ”advices.” The ”point cuts” define the points in the program runtime flow that are of interest. For example, ”point cuts” can be placed to identify each ”method call” in the program flow. ”Advices” are used to collect data at the defined ”point cuts” and to use the collected data to calculated a specific measure. By placing ”point cuts” at ”method calls”, an advice can be used for example, to collect the data necessary to calculate the number of invocation of each method in the program. All dynamic metrics defined in Section 6.3 are implemented in a similar way according to their definitions and weaved into the services code during compilation. The generated byte-code is then deployed into Tomcat. When a WS is invoked during a runtime session, the weaved aspects collect all the defined dynamic measures and store the output as text files on the server-side. For each runtime session, the average values of the dynamic internal measures (i.e., DC, DCBO, DMI and OMI) are calculated and stored in a separate text file. When all interactions with the WSs completed, the average of each dynamic internal measure over all runtime sessions is calculated and added as the final value of this specific measure to the dataset to be used for model building.

During the interaction with a WS, message exchanges between the WS and its clients are captured using the network transport capturing tool WinPcap

(WinPcap (v 4.1.3) 2013) that captures outgoing and incoming TCP packets to the WS server machine. Wireshark (Wireshark (v1.8.6) 2013) is a network protocol analyzer that is used after each predefined capturing session to (1) extract all HTTP communications, and (2) calculate the number of request, response and acknowledge messages. These data are used to calculate the *Availability*, *Accessibility* and *Successability* of the WS.

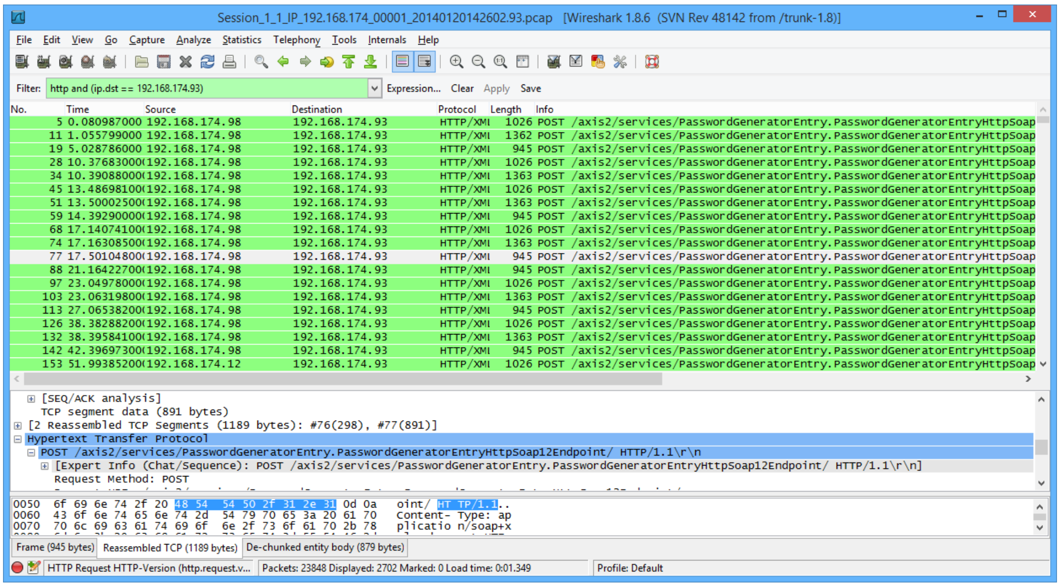

Figure 8: Wireshark used to analyze the exchanged messages between the test clients and the PasswordGenerator WS

Figure 8 presents a screenshot of Wireshark in analysis mode where a set of different filters are defined to extract the necessary information from the captured message exchanges. The following filters are used in Wireshark for this purpose:

- Number of request messages:

  http contains "SOAPAction" and (ip.dst==serverIP) (4)

  Where *SOAPAction* is replaced by the actual *SOAPAction* of the request messages of a specific WS (e.g., "generatePassword" for the PasswordGenerator WS) and *ServerIP* is replaced by the real IP address of the server hosting the WS.

- Number of acknowledgment messages:

  http and (ip.src==serverIP) and

  http.response.code==202 (5)

  Where *ServerIP* is replaced by the real IP address of the server hosting the WS.

- Number of response messages:

$$\textit{http contains "SOAPAction" and}$$
$$\textit{(ip.src == serverIP) and http.response.code == 200} \quad (6)$$

Where *SOAPAction* is replaced by the actual *SOAPAction* of the request messages of a specific WS (e.g., "generatePasswordResponse" for the WS PasswordGenerator) and *ServerIP* is replaced by the real IP address of the server hosting the WS.

7.2 Client-side

WSs clients are simple Java applications that invoke the WSs under test to deliver its specified functionality. For each WS, a web client is developed and used in experimental setup to stimulate the WSs while collecting the data necessary to calculate the targeted quality measures of the WSs. All develop clients for the WSs under evaluation rely on the Axis2 framework and are instrumented by Sandesha2 to support reliable messaging. Moreover, A graphical user interface (GUI) is implemented for each WS that facilitate its usage and provides guidance for its users. The GUI of all WS clients used throughout the study are depicted in Appendix D.

Chapter 8
Dataset Analysis

The outcome of the execution of the data collection part of the study described in Chapter 6 is a dataset (Appendix C) with the values of the 17 internal quality measures (predictors) identified in Section 6.3 and the corresponding values for the external quality measures (responses) *Availability*, *Accessibility* and *Successability*. Each row in the dataset represents the calculated values for one of the 20 WSs listed in Table 7. There are some entries missing (NAs) in row 17 (or observation 17) of the dataset, specifically the values for the dynamic measures OMI and DMI. These missing values are entries related to the *CSVGenerator* WS. This can be explained as AspectJ instruments the Java bytecode by inserting observation points into it. As a result, the size of the code increases above 64 kilobytes for OMI and DMI. But due to a Java limitation which makes it unable to handle single methods of size larger than 64 kilobytes (Itchapurapu 2013), the Java compiler throws an error. As a consequence of this technical limitation, capturing OMI and DMI for *CSVGenerator* WS was not possible.

8.1 Data reduction using PCA

The dataset used for model building consists of 20 observations with 17 predictors and 3 responses. The number of predictors is relatively high for a small number of observations. An approach for reducing the number of predictors without significantly losing information provided by the individual predictors, is Principal Components Analysis (PCA) (Rawlings, Pantula, and Hosmer 1998). PCA reduces the size of dataset by transforming the independent variables (in this case the 17 predictors) into a reduced set of variables, called principal components. Each principal component is obtained via linear combination of a subset of the original independent variables, by grouping those that are most linearly correlated to each other. The principal components are linearly uncorrelated with each other.

PCA was applied to the dataset using the following R function (The R Project 2014):

princomp(~.,dataset_pred, na.action = na.exclude, cor = TRUE)

where *dataset_pred* is the dataset containing only the 17 predictors, "*na.action = na.exclude*" means to exclude any NA entries. "*cor = TRUE*" informs R to used the correlation matrix for the calculations.

The result of the PCA analysis is presented in Table 8. The variance is a measure of the spread of the entries (numbers) in the dataset. The contribution of each PC to the variance in the dataset indicates the significance of the PC. In Table 8, the PCs are ordered according to their contribution to the variance (column 3 of the table) with PC1 contributing the most. In general, the PCs are selected according to a pre-specified level of variance coverage and the components significance. Variance coverage is the degree to which the PCs selected represent the spread of data in the original dataset. Column 4 of Table 8 shows the cumulative proportion of variance for all PCs if they are selected according to their significance starting with the most significant one (i.e. PC1). The higher the cumulative variance achieved, the better the selected PCs represent the original data. The lower the cumulative variance achieved, the higher the information lost. Therefore, variance coverage level must be sufficiently high so as not to lose information.

Assume variance coverage of 99% is targeted. To achieve this level, PC1 to PC10 need to be involved in place of the original 17 predictors. Therefore, only 10 variables (PCs) are needed to represent the original 17 predictors. However, for the calculation of these 10 PCs, all the 17 original predictors are needed as shown in Table 9. For example, PC1 is calculated as follows:

PC1 = (-0.287) DIST + (-0.285) ABST + (-0.365) WM + (-0.352) NOM + (0.171) ABD + (-0.334) LOC + (-0.208) WMC + (-0.171) LCOM + (0.225) I + (-0.210) CA + (-0.313) CE + (-0.164) DCBO + (-0.113) OMI + (-0.354) DMI

All the other PCs are calculated in the same way.

Even with a variance coverage of 90%, Six PCs are needed (PC1 to PC6) to represent the dataset. The number of PCs selected can be further reduced by reducing the variance coverage level below 90% but this may result in considerable lose of information.

The selected PCs can be used for predictive model building as the independent variables (predictors). As explained later in Section 9.6, The lower the number of predictors, the more stable the model built. The recommended number of predictors (as discussed in Section 9.6) is from 1 to 4. With PCA and a sufficient level of variance coverage, the number of variables is reduced to 6 PCs which is higher than the recommended maximum number of predictors in the model.

	Standard deviation	Proportion of variance	Cumulative proportion of variance
PC1	2.5152525	0.3721468	0.3721468
PC2	1.7771582	0.1857818	0.5579286
PC3	1.5063697	0.1334794	0.6914080

PC4	0.6914080	0.1150317	0.8064397
PC5	1.15104445	0.07793549	0.88437516
PC6	0.91627229	0.04938558	0.93376074
PC7	0.62685280	0.02311438	0.95687512
PC8	0.54543056	0.01749968	0.97437480
PC9	0.43004692	0.01087884	0.98525364
PC10	0.33007103	0.00640864	0.99166228
PC11	0.286254837	0.004820108	0.996482391
PC12	0.188549846	0.002091238	0.998573629
PC13	0.144294175	0.001224753	0.999798382
PC14	0.0446723854	0.0001173895	0.9999157717
PC15	3.332253e-02	6.531711e-05	9.999811e-01
PC16	1.784335e-02	1.872854e-05	9.999998e-01
PC17	1.762143e-03	1.826557e-07	1.000000e+00

Table 8: Principal components and their contribution to the variance in the dataset

Following the PCA approach, no sufficient dimensional reduction could be achieved. The only added value is the removal of any possible correlation between the predictors. In Section 8.2, we explain how possible correlations between the predictors are treated without using principal components.

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15	Comp.16	Comp.17
DIST	-0.287	-0.108	0.252	0.286	-0.230	0.251	0.104				-0.301		-0.140				0.714
ABST	-0.285	-0.107	0.256	0.287	-0.230	0.253	0.128				-0.333		-0.150				-0.692
WM	-0.365			-0.248		-0.113								0.238	-0.636	0.541	
NOM	-0.352	0.134	-0.121	-0.208	-0.114		-0.146	-0.171	-0.142			0.269	0.166	-0.633	0.330	0.322	
LCPM		-0.298	0.302	-0.384		0.113	0.541		-0.469		0.202	0.270					
ABD	0.171	-0.379		-0.346		-0.161	-0.242	-0.252		0.518	-0.322		-0.346			-0.163	
LOC	-0.334			-0.286		-0.293	0.258	-0.108			-0.209	-0.344	-0.108	0.364	0.564		
CC			0.489	-0.321	0.250		-0.501	0.430	-0.148	-0.280	-0.220						
WMC	-0.208		0.119	-0.122	0.592	0.392	0.123		0.459	0.324	0.139		0.227				
LCOM	-0.171	0.184	-0.388	0.151	0.382	-0.170	0.207	0.446	-0.290	0.171	-0.303	0.297	-0.171			-0.118	
I	0.225	0.212	-0.211	-0.364	-0.124	0.305	0.235		0.423	-0.402	-0.176	0.292	-0.314				
CA	-0.210	-0.268	0.219	0.153	0.148	-0.562			0.330	-0.333	0.216	0.334	-0.177	-0.137		-0.156	
CE	-0.313	0.193	-0.107	-0.283	-0.238					-0.109		-0.305	0.136	-0.244	-0.320	-0.654	
DCBO	-0.164	-0.298	-0.283		0.364	0.325		-0.432	-0.335	-0.398		-0.140	-0.260				
OMI	-0.113	-0.443	-0.262		-0.169			0.532	0.115		0.337	-0.352	-0.268	-0.172		0.217	
DC		-0.487	-0.295					0.117	0.112	-0.221	-0.361	0.152	0.634	0.165			
DMI	-0.354		-0.118		-0.209	0.186	-0.375			0.109	0.352	0.425	-0.121	0.496	0.132	-0.193	

Table 9: Vectors of weights (loadings) of the PCs

8.2 Correlation between the predictors

Collinearity exists in the dataset when one predictor can be predicted from the other predictors (i.e., the predictors are strongly correlated). Extreme correlation between the predictors may cause the regression result to be ambiguous (Chatterjee and Hadi 2006).

To check for possible correlation between the predictors, Pearson product-moment correlation (Lee Rodgers and Nicewander 1988) was used. It quantifies the strength of the linear relationship between two variables. Table 11 and Table 12 present the result of the correlation analysis (the correlation matrix). A visualization of the correlation matrix that helps visually identify any strong correlation is depicted in Figure 9. The strength of the correlation between two variables corresponds to the portion of the circle filled. The cutoff value considered for a strong correlation is 0.7 (Dancey and Reidy 2007). All identified strong correlations are listed in Table 10.

Dealing with the listed correlations is treated in Section 9.6 where recommendations for model selection are introduced.

Predictors		Correlation Coefficient
DIST	ABST	0.99974652
WM	NOM	0.93540738
WM	LOC	0.96216209
WM	CE	0.85532431
NOM	LOC	0.85346821
NOM	CE	0.93834509
LOC	CE	0.78810880
DIST	I	-0.72506909
ABST	I	-0.72389467
I	CA	-0.71705888

Table 10: Strong correlations

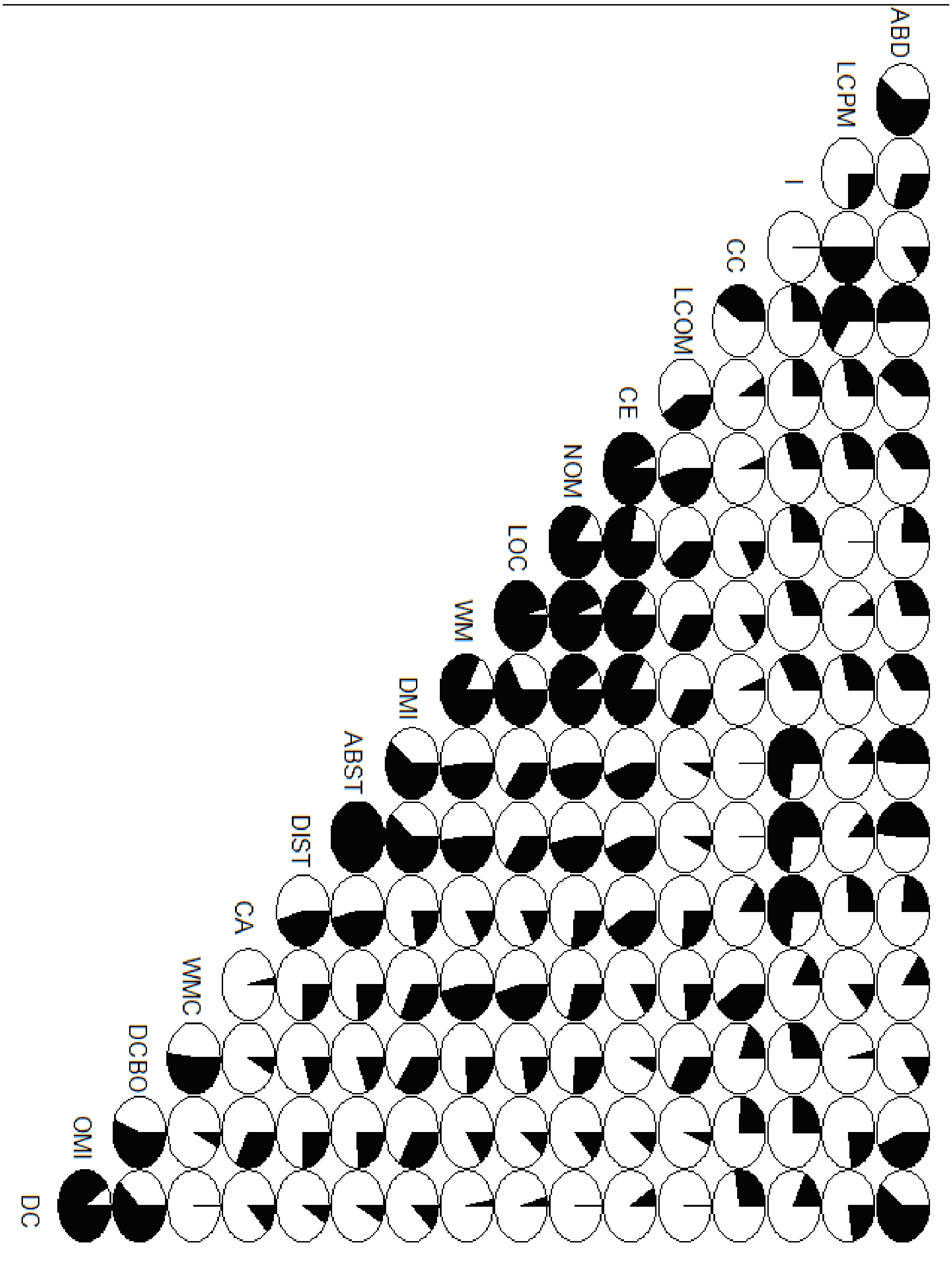

Figure 9: Visualization of the correlation information

	DIST	ABST	WM	NOM	LCPM	ABD	LOC	CC
DIST	1.00000000	0.99974652	0.48611304	0.46997585	-0.12531426	-0.4836281	0.35637353	-0.01893951
ABST	0.99974652	1.00000000	0.48050865	0.46451573	-0.12203086	-0.4869211	0.35388579	-0.02251515
WM	0.48611304	0.48050865	1.00000000	0.93540738	-0.08347339	-0.3001354	0.96216209	0.14551806
NOM	0.46997585	0.46451573	0.93540738	1.00000000	-0.29304394	-0.3762415	0.85346821	-0.05061654
LCPM	-0.12531426	-0.12203086	-0.08347339	-0.29304394	1.00000000	0.5996124	-0.02294380	0.49925386
ABD	-0.48362813	-0.48692113	-0.30013539	-0.37624151	0.59961244	1.0000000	-0.24127259	0.15035998
LOC	0.35637353	0.35388579	0.96216209	0.85346821	-0.02294380	-0.2412726	1.00000000	0.16741812
CC	-0.01893951	-0.02251515	0.14551806	-0.05061654	0.49925386	0.1503600	0.16741812	1.00000000
WMC	0.24680335	0.24204569	0.46808570	0.29967276	0.12275049	-0.1429376	0.45996627	0.40716610
LCOM	0.06500911	0.06452052	0.35403947	0.45641733	-0.65142132	-0.5055980	0.39259317	-0.40529139
I	-0.72506909	-0.72389467	-0.29727958	-0.30361515	0.24484496	0.3030531	-0.27111282	0.02270695
CA	0.45684940	0.46388005	0.16706957	0.27168938	-0.25997712	-0.2303906	0.17265483	-0.14356315
CE	0.44094468	0.43952154	0.85532431	0.93834509	-0.27941250	-0.4078535	0.78810880	-0.07819150
DCBO	0.19749816	0.19352928	0.24072245	0.26397160	-0.03747899	0.1446065	0.21093315	-0.18671567
OMI	NA	NA	NA	NA	NA	NA	NA	NA
DC	0.07992975	0.07564407	-0.02515948	-0.01910625	0.21680346	0.5974910	-0.04060479	-0.27117910
DMI	NA	NA	NA	NA	NA	NA	NA	NA

Table 11: The correlation matrix of the predictors (Part I)

	WMC	LCOM	I	CA	CE	DCBO	OMI	DC	DMI
DIST	0.24680335	0.06500911	-0.72506909	0.45684940	0.44094468	0.19749816	NA	0.07992975	NA
ABST	0.24204569	0.06452052	-0.72389467	0.46388005	0.43952154	0.19352928	NA	0.07564407	NA
WM	0.46808570	0.35403947	-0.29727958	0.16706957	0.85532431	0.24072245	NA	-0.02515948	NA
NOM	0.29967276	0.45641733	-0.30361515	0.27168938	0.93834509	0.26397160	NA	-0.01910625	NA
LCPM	0.12275049	-0.65142132	0.24484496	-0.25997712	-0.27941250	-0.03747899	NA	0.21680346	NA
ABD	-0.14293757	-0.50559797	0.30305309	-0.23039062	-0.40785351	0.14460645	NA	0.59749097	NA
LOC	0.45996627	0.39259317	-0.27111282	0.17265483	0.78810880	0.21093315	NA	-0.04060479	NA
CC	0.40716610	-0.40529139	0.02270695	-0.14356315	-0.07819150	-0.18671567	NA	-0.27117910	NA
WMC	1.00000000	0.23484244	-0.15784976	-0.03767750	0.14842948	0.52643618	NA	-0.02076746	NA
LCOM	0.23484244	1.00000000	-0.25869716	0.26338794	0.40831416	0.33693837	NA	-0.01790701	NA
I	-0.15784976	-0.25869716	1.00000000	-0.71705888	-0.24793541	-0.27598128	NA	-0.17873100	NA
CA	-0.03767750	0.26338794	-0.71705888	1.00000000	0.41399693	0.07414354	NA	0.12334146	NA
CE	0.14842948	0.40831416	-0.24793541	0.41399693	1.00000000	0.06357606	NA	-0.08321048	NA
DCBO	0.52643618	0.33693837	-0.27598128	0.07414354	0.06357606	1.00000000	NA	0.61391076	NA
OMI	NA	NA	NA	NA	NA	NA	1	NA	NA
DC	-0.02076746	-0.01790701	-0.17873100	0.12334146	-0.08321048	0.61391076	NA	1.00000000	NA
DMI	NA	NA	NA	NA	NA	NA	NA	NA	1

Table 12: The correlation matrix of the predictors (Part II)

Chapter 9
Predictive models building

Predicting the external qualities *Availability*, *Accessibility* and *Successability* for WSs is a major objective of this work. Objectives O3 and O4 and the related research questions R3 and R4 introduced in Section 1.1 are centered on building and evaluating statistically significant predictive models for WSs *Availability*, *Accessibility* and *Successability*.

We explain in the following subsections how we address building these models based on the observations collected following the approach described in Chapter 6 and using the data collection framework described in Chapter 7.

9.1 Modeling approach

A statistical predictive model is a way to reveal hidden relations between variables in a dataset. In our context the variables are the external qualities *Availability*, *Accessibility*, and *Successability* and the internal qualities collected for the correlational study.

The model is usually built using a dataset collected in a specific context. The dataset used for model building contains both the predictors (independent variables) and the responses (dependent variables). Once the model is built and validated, it can be used to predict the responses based on other datasets collected in a comparable context.

The relation reflected by a statistical model takes the form of a mathematical equation (or equations) with the predicted value (response) in one side and the predictors in the other side. For example, a linear relation with one predictor can be expressed as:

$$Y_{predicted} = b_o + b_1 X$$

where $Y_{predicted}$ is the predicted value of the response Y, b_1 is the slope of the line and b_o is the intercept.

The linear relation can be graphically represented as in the example shown in Figure 10.

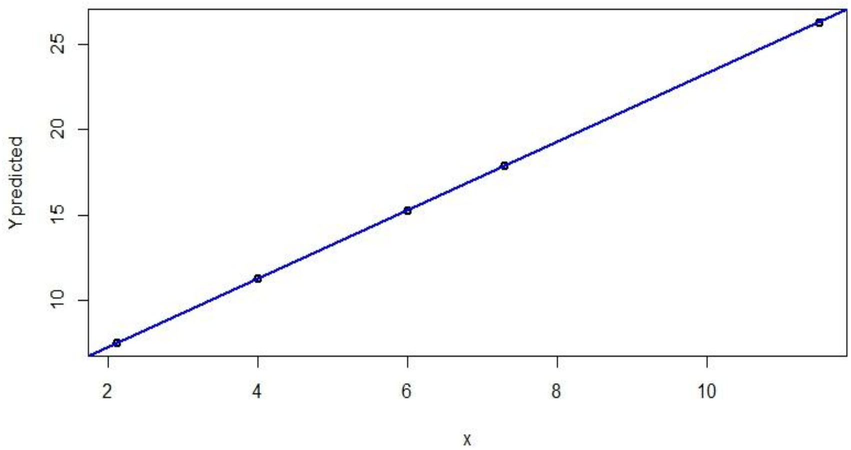

Figure 10: A linear model

Linear regression models (Kerns 2010) are widely accepted as an efficient way to predict responses when their relation to the predictors is linear. In this relation, the value of the predicted variable (response) increases linearly with the increase of X and decreases linearly with the decrease of X without having an upper or a lower limit. Such a model cannot be used to represent the relation between *Availability*, *Accessibility*, and *Successability* and the predictors (internal qualities) collected. This is because all of the three dependent variables are ratios ranging from 0 to 1 as can be seen in their formulas (Section 2.3, Equations 1-3). Therefore there is an upper limit (1) and a lower limit (0).

An alternative approach to model such a relation is the logistic regression model (Brannick 2014). As shown in Figure 11, the predicted value of logistic regression model never get above 1 or below 0.

The logistic regression model (Figure 11) with one predictor x can be represented by the following equation:

$$p = \frac{1}{1 + e^{-(b_0 + b_1 x)}}$$

where P is the probability that the predicted response is 1, b_1 is the slope of the line and b_o is the intercept.

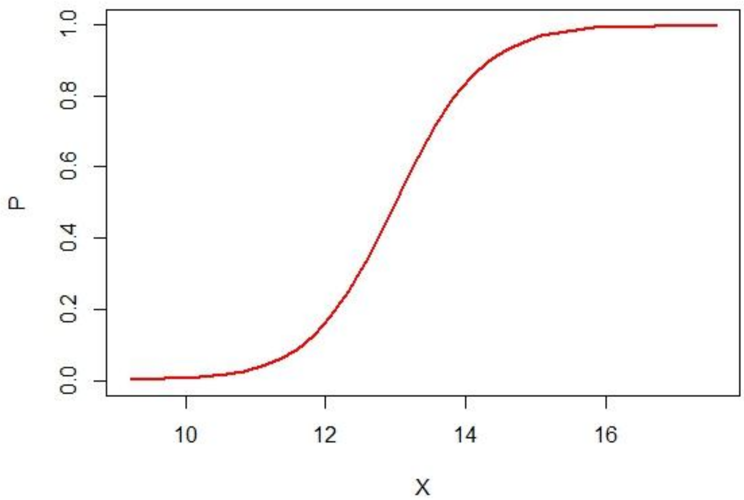

Figure 11: A logistic model

The logistic regression curve represent the responses under focus (i.e., *Availability*, *Accessibility*, and *Successability*) better than the linear model for the following reasons (Osborne and Waters 2002):

- Logistic regression can predict dependent variable values ranging for 1 to 0 whereas the linear model predicts values that get below 0 or above 1. Figure 12 compares linear and logistic regression curves.
- Logistic regression does not assume homoscedasticity (i.e., the variance of the predicted variable is not necessarily constant). Linear regression assumes homoscedasticity (Garson 2014).
- Logistic regression does not assume (or require) that the dependent variables and residuals are normally distributed. Linear regression assumes normality of distribution (Garson 2014).

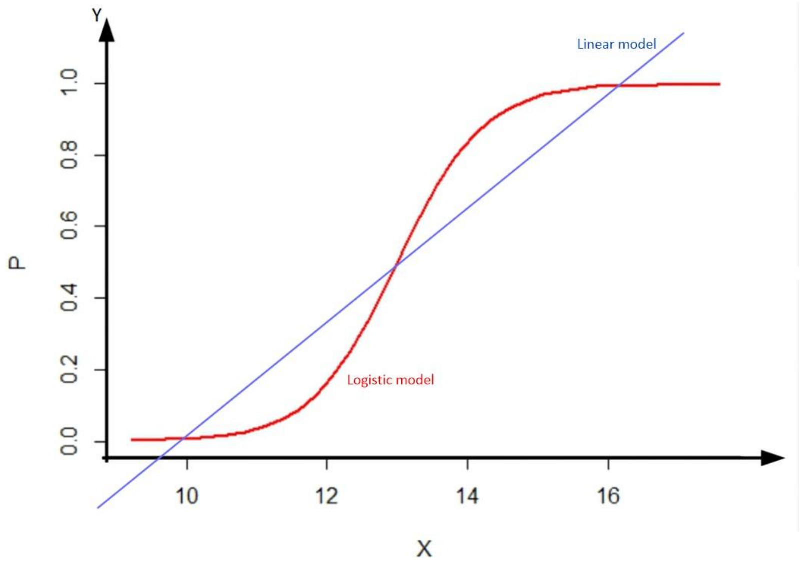

Figure 12: Linear versus logistic regression model

The Generalized Linear Model (GLM) with the *logit* link (McCulloch and Nelder 1989) is widely used when building logistic regression models. The statistics computing tool R, which is used in this work, supports the GLM. However, there are many other R packages that implement various kinds of logistic regression differently (e.g., VGAM package(Yee 2012), ordinal package (Christensen 2013) and the *rms* package (Harrell 2014)).

In Sections 9.2, 9.3 and 9.4, the approach used for detecting and treating suspicious data points (outliers) in the data collected is explained. Then model building approaches using two different types of logistic regression, namely binary logistic regression (GLM with the *logit* link) and ordinal logistic regression (ORM) are described in details.

9.2 Outliers identification

It is common in regression analysis that some observations (or data points) may have more impact on the regression results than others. Observations that have extreme values may highly influence the slope of the regression curve. Because of their high influence, they are called *influential observations*. An observation that lies far away from the other observations in the X-space is called a *leverage point* (Rousseeuw and Leroy 2005)

A leverage point is not necessarily an influential observation. Figure 13 illustrates the difference between leverage points and influential data points. As can be seen in the figure, there are two leverage points apparently away from the other observation in the X-space (labeled as ”1” and ”2”). The solid line is the regression line without considering point 1 and point 2. Point 1 has extreme value in the X- and Y-spaces. Point 2 has almost the same extreme value in the X-space as point 1 but a value in the Y-space consistent with the rest of the data points. Now, if point 1 is included, the resulting regression curve will be the upper dashed line (green). It is clear that the slope of the line is only slightly different from that of the solid line. That is to say that point 1 is not influential. If we include point 2 instead of point 1 in the regression, the resulting regression curve will be like the lower dashed line (blue). The slope of this line is clearly different from that of the solid line. Point 2 is considered to be influential. Both point 1 and point 2 have almost the same extreme X-value and therefore they are leverage points. Only point 2 is influential since it substantially change the slope of the fitted model and hence the regression results.

When a leverage point is influential, it can be considered as an outlier. A few outliers may dominate the regression results, therefore decreasing the level of confidence in the results (Rawlings, Pantula, and Hosmer 1998). As mitigation, the dataset collected to be used for model building must be investigated to identify any possible leverage points. If they are suspected to be influential (i.e., outliers) they may need to be removed. We developed a two-phase approach for outliers investigation. First, Local Outlier Factor (LOF) algorithm (Breunig et al. 2000) is used to identify potential outliers. Then, their influence is investigated by building a model once with the potential outlier and once without it. Both models are then compared to examine the influence of the outlier. If an outlier is found to be substantially influential, it is removed from the dataset used for model building.

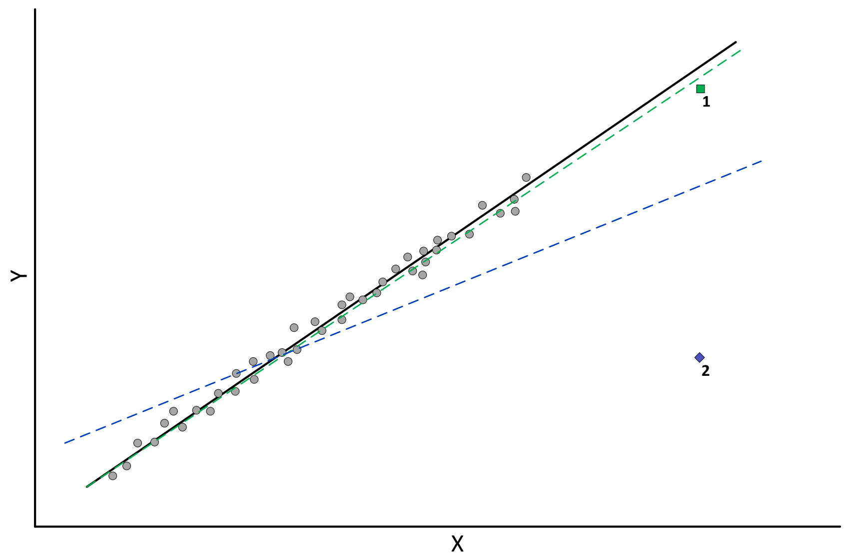

Figure 13: Outliers and influential observations

LOF is a density-based approach for outliers detection. In this approach, the density around an observation (local density) is compared to the local densities of its neighbors. If the local density of the observation is considerably lower than that of its neighbors, it is considered as an outlier. The calculated LOF indicates the degree of outlier-ness of an observation (Breunig et al. 2000).

The LOF implementation used in this work is delivered as part of the DMwR package (Torgo 2013) of the R tool (The R Project 2014). The function used is:

$$lofactor(dataset,\ k)$$

where k is the number of neighbors and the return value is a vector of outliers' scores. All data points are assigned a score that reflects the degree of their outlier-ness.

Since the size of the dataset collected is relatively small, choosing the optimal number of neighbors (k) was given a special care. Moreover, observation number 17 is omitted since it contains two missing entries (NAs). All possible values of k were used to generate the outliers' scores as shown in Table 13. Furthermore, the upper 10% of the data with the highest scores are considered to be potential influential outliers. The 10% value was chosen as a good compromise between the number of data points available and the number of possible outliers.

As it is clear from Table 13, observations 18 and 16 are most frequently reported as most influential for different values of k. Based on that, these two observations are considered to be potential outliers. To investigate how influential are these two data points, all models considered to be significant (see Section 8.3 and 8.4) are built twice with and without these data points. The resulting models are compared to investigate the influence of the outliers on the models. If it is noticed that the outliers are not influential, they are kept in the dataset used for model building. Otherwise they are removed.

k	**Potential influential outliers**
1	13 and 10
2	16 and 18
3	18 and 16
4	18 and 16
5	18 and 16
6	18 and 16
7	18 and 16
8	18 and 16
9	18 and 16

10	18 and 16
11	18 and 16
12	18 and 16
13	18 and 16
14	18 and 16
15	18 and 16
16	18 and 16
17	18 and 10
18	10 and 3

Table 13: Potential influential outliers for different number of neighbors

9.3 Models building using GLM

The Generalized Linear Model (GLM) (McCulloch and Nelder 1989) is a generalization of the linear model to accommodate different distributions of the response (including normal and non-normal distributions). Logistic regression is a special case of the GLM with the distribution family defined as *binomial* and the link function as *logit*.

The following R function is used to fit a logistic regression model:

glm(formula, family= binomial(link = "logit"))

where *formula* is a symbolic description of the model to be fitted in the form [*Response*] ~ [*Combinations of Predictors*] (e.g., *Accessibility* ~ *LOC* + *DCBO*), *family* is the assumed distribution of the dependent variable. For example, the R formula "*Accessibility* ~ *LOC* + *DCBO*" means to predict *Accessibility* using two predictors *LOC* and *DCBO* and by no means indicates that LOC and DCBO are to be summed.

The R script used for building the GLM models is listed in Appendix E. This script follows a simple logic:

> *For each of the responses (Accessibility, Availability and Successability), try to build logistic regression models using the R glm() function for all possible combinations of the predictors. Test the statistical significance of the coefficients using the p-value. If the p-value is ≤ 0.05, calculate the* R^2_N *index (Table 14) and store the model into the output file.*

The *p-value* is used to test the statistical significance of the estimated model's coefficients. This test involves comparing the response of a model containing the predictor with a model without the predictor (null hypothesis) (Hosmer Jr, Lemeshow, and Sturdivant 2013).

This test involves comparing the response of a model containing the predictors to a model containing only the intercept (constant model). If the p-values for the predictors are low enough, the model with predictors can be considered better than the constant model. The lower the p-value, the more statistically significant the predictor. Fisher (Fisher 1925) suggested that a p-value of less than or equal to 0.05 indicates significance of the predictor. This cutoff value is widely adopted as an accepted value for statistical significance (Dallal 2012).

Significance test is a relative test that compares two models with and without the variables tested for their significance. Another test is the *goodness of fit test* (Hosmer Jr, Lemeshow, and Sturdivant 2013) where the response predicted by the model is compared to the observed one. The pseudo R-Squared is a logistic regression index developed in analogy to the R-squared index used in linear regression to assess its goodness of fit. Hallett (1999) discussed the pseudo R-Squared index as a suitable goodness of fit indicator for logistic regression models. Conversely, Harrel (Harrell 2001) and Allison (Allison 2012) disagreed with Hallett as this index (in most of its variants) compares the model to the constant model. Therefore, they considered it as an index for the *Predictive Ability* (Harrell 2001) or the *Predictive Power* (Allison 2012) which shows how well responses can be predicted by the model. However, in both cases the pseudo R-Squared index gives indications of how good the model is in predicting future outcomes.

There are different variants of the pseudo R-Squared index (Table 14). Hallett (1999) considered the Nagelkerke variant of the index (R^2_N) (Nagelkerke 1991) as more appropriate for logistic regression. Therefore, R^2_N is used in this work to (1) test the goodness of fit of the models built and (2) to assess their predictive power. The value of the R^2_N index ranges from 0 to 1 with 1 indicating best fit and excellent predictive power and 0 indicating no fit and negligible predictive power.

Pseudo R-Squared variant	***Formula***
Logistic R-Squared (Hosmer Jr, Lemeshow, and Sturdivant 2013)	$R^2_L = 1 - L_M/L_0$
McFadden's R-Squared (D. McFadden 1974)	$R^2_{mcF} = 1 - \ln(L_M) / \ln(L_0)$
Nagelkerke's R-Squared (Nagelkerke 1991)	$R^2_N = [1 - (L_0/L_M)^{2/n}] / [1 - L_0^{2/n}]$

Table 14: Variant of pseudo R-Squared. [Where L_0 is the log likelihood of the constant model (i.e., without predictors), L_M is log likelihood of the full model (i.e., with predictors), ln is the natural algorithm.]

Rawling (Rawlings, Pantula, and Hosmer 1998) stated that "*Conceptually, the only way of ensuring that the best model for each subset size has been found is to compute all possible subset regressions. This is feasible when the total number of variables is relatively small, but rapidly becomes a major computing problem even for moderate numbers of independent variables.*" With only 17 predictors, the number of variables available for model building is considerably small. Therefore, the recommendation of Rawling is followed by implementing a loop in the R script that tries all possible combinations of the independent variables to build the targeted regression models.

Many significant models were identified with different combinations of predictors. Models with 4, 5, 6, 7, 8, 9, 10, 11, 12 ,13, and 14 predictors are reported in Appendix E. No significant models were identified with a number of predictors less than 4 or greater than 17. Other runs of the script after successively removing the outliers identified in Section 9.2 produced a very large number of significant models (some of them are reported in Appendix E) with 4, 5, 6, 7, 8, 9, 10, 11, 12, 13 and 14 predictors.

Figure 14, Figure 15, Figure 16 and Figure 17 show some significant models with 4 predictors built with the GLM (1) using the complete dataset, (2) after removing data point 18, (3) after removing data point 16 and (4) after removing both data points 18 and 16 respectively. The statistics shown in Figure 14 and in the following figures are explained in Table 15.

```
glm(AVAILABILITY  ~  DIST + LCPM + WMC + DC, family = binomial(link="logit"))

Coefficients:

             Estimate     Std. Error   z value      Pr(>|z|)
(Intercept)  1.137e+15    4.504e+07    25234804     <2e-16 ***
DIST        -9.132e+14    1.815e+08   -5031181      <2e-16 ***
LCPM         2.483e+14    2.302e+06    107823299    <2e-16 ***
WMC         -5.566e+12    8.440e+05   -6595174      <2e-16 ***
DC          -1.013e+15    1.492e+07   -67924460     <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R2 (Nagelkerke):  0.999999999999911
```

Figure 14: Model built with 4 predictors using GLM and the complete dataset

```
glm(AVAILABILITY Vs   DIST + LCPM + WMC + DC , family = binomial(link = "logit"))

Coefficients:

             Estimate     Std. Error    z value     Pr(>|z|)
(Intercept)  9.871e+14    4.687e+07     21060567    <2e-16 ***
```

```
DIST        -8.001e+14   1.824e+08   -4385692    <2e-16 ***
LCPM         2.450e+14   2.307e+06   106221735   <2e-16 ***
WMC         -4.058e+12   8.484e+05   -4782733    <2e-16 ***
DC          -9.474e+14   1.512e+07   -62667982   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
```

Figure 15: Model built with 4 predictors using GLM after removing the outlier point 18 from dataset

```
glm(AVAILABILITY  ~  DIST + WM + LCOM + DC, family = binomial(link = "logit"))
Coefficients:
              Estimate     Std. Error   z value     Pr(>|z|)
(Intercept)   4.943e+15    3.464e+07    142682783   <2e-16 ***
DIST         -3.341e+15    2.015e+08    -16580686   <2e-16 ***
WM           -1.594e+11    7.649e+04    -2084181    <2e-16 ***
LCOM         -2.734e+15    1.047e+08    -26120066   <2e-16 ***
DC           -1.952e+14    1.453e+07    -13430726   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
```

Figure 16: Model built with 4 predictors using GLM after removing the outlier point 16 from dataset

```
glm(AVAILABILITY  ~  DIST + LCPM + WMC + DC, family = binomial(link = "logit"))
Coefficients:
              Estimate     Std. Error   z value     Pr(>|z|)
(Intercept)   1.137e+15    4.504e+07    25234804    <2e-16 ***
DIST         -9.132e+14    1.815e+08    -5031181    <2e-16 ***
LCPM          2.483e+14    2.302e+06    107823299   <2e-16 ***
WMC          -5.566e+12    8.440e+05    -6595174    <2e-16 ***
DC           -1.013e+15    1.492e+07    -67924460   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999911
```

Figure 17: Model built with 4 predictors using GLM after removing the outliers points 18 and 16 from dataset

Statistic	*Description*
Coefficients	The regression coefficients
Estimate	The estimated regression coefficient
Std. Error	The estimated standard error for the coefficient
z value	Standard score - a score expressed in terms of standard deviations from the mean (Thomas, Nelson, and Silverman 2011).
Pr(>| z|)	The p-value for the coefficient

Table 15: Explanations of the statistics produced the *glm* function

Three models (Figure 14, Figure 15 and Figure 17) rely on the same 4 predictors to predict the response. It is noticed that models built after removing point 16 use different combinations of predictors as can be seen in the model presented in Figure 16. In general, all models showed extremely low p-values for all coefficients. This indicates very high significance of the predictors involved. Additionally, the calculated R^2_N for all the 4 models is almost 1, the highest value possible for this index. The higher the R^2_N index, the better the predictive power of the model. All the models presented in Appendix E exhibit the same level of significance of the variables involved (p-value<2e-16) and many of them with R^2_N very close to 1.

The removal of the outlier point 16 had clear influence on the generated models since it clearly affected the combinations of the predictors leading to a significant model (i.e., point 16 is an influential point). The removal of both outliers (point 16 and point 18) at the same time or only point 18 did not result in comparable effect.

Using the GLM approach, significant models could be built for *Availability* and *Successability*. On the contrary, no significant models could be built for *Accessibility*. Table 16 provides a comparison between the observed values for *Availability* and *Successability* and their predicted values based on the models presented in Figure 14 and Figure 18 respectively.

```
glm(SUCCESSABILITY ~  DIST + WM + WMC + I + CE + family = binomial(link = "logit"))

Coefficients:

              Estimate    Std. Error   z value       Pr(>|z|)

(Intercept)   2.433e+16   2.350e+08   103516381    <2e-16 ***

DIST         -9.056e+15   2.989e+08   -30294411    <2e-16 ***
```

```
WM        -1.710e+13   2.432e+05   -70291493    <2e-16 ***
WMC        2.600e+13   1.359e+06    19132634    <2e-16 ***
I         -2.499e+16   2.480e+08  -100744971    <2e-16 ***
CE         5.685e+14   7.155e+06    79460771    <2e-16 ***
OMI        1.412e+14   8.826e+06    16003379    <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R2 (Nagelkerke):  1
```

Figure 18: Model built for Successability with 6 predictors using GLM and the complete dataset

Availability Model (Figure 14)		**Successability Model** (Figure 18)	
Observed	**Predicted**	**Observed**	**Predicted**
1.00	1.00	1.000	1.000
1.00	1.00	1.000	1.000
0.95	1.00	1.000	1.000
1.00	1.00	0.442	2.220e-16
1.00	1.00	1.000	1.000
1.00	1.00	0.413	2.220e-16
1.00	1.00	1.000	1.000
1.00	1.00	1.000	1.000
1.00	1.00	1.000	1.000
1.00	1.00	0.988	1.000
1.00	1.00	0.985	1.000
1.00	1.00	0.472	2.220e-16
1.00	1.00	1.000	1.000
1.00	1.00	1.000	1.000
1.00	1.00	0.977	1.000
1.00	1.00	0.977	1.000
1.00	1.00	0.944	1.000
1.00	1.00	1.000	1.000

Availability Model (Figure 14)		Successability Model (Figure 18)	
Observed	**Predicted**	**Observed**	**Predicted**
1.00	1.00	0.844	1.000
1.00	1.00	1.000	1.000

Table 16: Observed and predicted outcomes when the GLM models applied to the training dataset

9.4 Models building using ORM

The logistic regression technique we showed in Section 9.1 is used to predict dichotomous responses. In this case the response is qualitative with only two possible values (i.e., 1 for success and 0 for failure). In many cases the response can be qualitative but with more than two categories (e.g., "very good", "good", "bad"). In such cases a variant of the logistic regression model, the *Multinomial Regression Model* (Chatterjee and Hadi 2006) can be used. The multinomial model assumes more than two categories for the response variable. If the response categories are ordered, the model is called *Ordinal Regression Model*. A popular variant of this model is the *Proportional Odds Ordinal Regression Model* (for short, the ORM model) that allows for a continuous response (Harrell 2001).

The proportional odds model allows for a continuous response by subdividing it into categories. The response is then predicted by calculating the cumulative probability that it belongs to one of these ordered categories. The proportional odds model can be described by the following model:

$$L_g = logit(P(Y \geq g)) = \beta_{0g} + \beta_1 X_1 + \cdots + \beta_p X_p \quad (g=2,\ldots,k)$$

where Y is the predicted response value of the response Y, k is the number of categories and p is the number of predictors. $P(Y \geq g)$ is the probability that $Y \geq g$.

In the dataset collected (Chapter 8), the response variables are numerical continuous ratios that range from 0 to 1. Table 17 shows an example for data categorization based on the dataset collected and a proportional odds model built for *Successability* with NOM and LCPM as predictors (Figure 19). Observed *Successability* values are presented in Table 18 with the corresponding predicted values using the model in Figure 19.

Observed Response	**Frequency**	**Category** (y is the predicted response)
0.413	1	-
0.442	1	y≥0.442
0.472	1	y≥0.472
0.844	1	y≥0.844
0.977	2	y≥0.977
0.985	1	y≥0.985
0.988	1	y≥0.988
0.994	1	y≥0.994
1.000	11	y≥1

Table 17: Categories identified for the proportional odds model

Logistic (Proportional Odds) Ordinal Regression Model

orm(formula = SUCCESSABILITY ~ NOM + LCPM, data = mydata, family = logistic)

Frequencies of Responses

0.413	0.442	0.472	0.844	0.977	0.985	0.988	0.994	1
1	1	1	1	2	1	1	1	11

		Model Likelihood Ratio Test		Discrimination Indexes		Rank Discrim. Indexes	
Obs	20	LR chi2	6.81	R2	0.301	rho	0.646
Unique Y	9	d.f.	2	g	1.312		
Median Y	1	Pr(> chi2)	0.0331	gr	3.713		
max |deriv|	0.008	Score chi2	6.94	|Pr(Y>=median)-0.5|	0.214		
		Pr(> chi2)	0.0311				

	Coef	S.E.	Wald Z	Pr(>|Z|)
y>=0.442	6.5065	1.9126	3.40	0.0007
y>=0.472	5.7814	1.7853	3.24	0.0012
y>=0.844	5.3418	1.7478	3.06	0.0022
y>=0.977	4.9805	1.7187	2.90	0.0038
y>=0.985	4.2946	1.6370	2.62	0.0087
y>=0.988	3.9403	1.5720	2.51	0.0122
y>=0.994	3.5694	1.4815	2.41	0.0160
y>=1	3.2316	1.4126	2.29	0.0222

NOM	-0.0094	0.0047	-2.02	0.0438
LCPM	-0.1485	0.0696	-2.13	0.0330

Figure 19: Model built with 4 predictors using proportional odds model and the complete dataset

Successability

Observed	Predicted
1.000	0.976
1.000	0.987
1.000	0.966
0.442	0.925
1.000	0.955
0.413	0.953
1.000	0.952
1.000	0.877
1.000	0.978
0.988	0.908
0.985	0.757
0.472	0.947
1.000	0.986
1.000	0.958
0.977	0.910
0.977	0.717
0.994	0.964
1.000	0.977
0.844	0.735
1.000	0.984

Table 18: Observed and predicted Successability based on the ORM model in Figure 19.

For ORM model building, the R package *rms* (Harrell 2014) is used. The R script used is listed in Appendix F. Similar to the script used for GLM models, this script follows a simple logic:

> *For each of the responses (Accessibility, Availability and Successability), try to build ORM models using the rms orm() function for all possible combinations of the predictors. Test the significance of*

the coefficients using the p-value. If the p-value is ≤ 0.05, store the model into the output file (R^2_N index and many other statistics are provided automatically).

In analogy to the approach used to assess the GLM models (Section 9.3), the p-value is used to check the significance of the predictors (p-value less than or equal 0.05) and R^2_N is used to (1) test the goodness of fit of the models built and (2) to assess their predictive power.

The following function of the *rms* package is used for model building:

orm(formula, family= logistic)

where *formula* is a symbolic description of the model to be fitted in the form [*Response*] ~ [C*ombinations of Predictors*] (e.g., *Successability* ~ NOM + LCPM), *family* is the assumed distribution of the response.

The output of *orm* function contains many statistics as explained in Table 19. Using the *orm* function, many significant models were identified with different combinations of predictors as reported in Appendix F. The identified models include models with 1 to 11 predictors.

orm Statistic	*Description*
Frequencies of Responses	The frequency of appearance of each listed response in the dataset.
Obs	Number of observations used for model building
LR chi2	Likelihood ratio χ^2
R2	R^2_N (Nagelkerke pseudo R-Squared)
rho	Spearman's ρ
Unique Y	Number of unique Y (response) values,
d.f.	Degrees of freedom
g	The g-index
Median Y	The median of the response
gr	The g-index on the odds ratio scale
max |deriv|	Maximum absolute value of first derivative of log likelihood
Score chi2	Score χ^2
|Pr(Y>=median)-0.5|	The mean absolute difference between 0.5 and the predicted probability that Y>= the marginal median

S.E.	Standard error
Wald Z	Z score of the Wald test
Pr(>|Z|)	P-value

Table 19; Explanations of the statistics produced the *orm* function (adapted from (Harrell 2014))

To study the influence of the identified outliers (data points 18 and 16), significant models with 2 predictors (LCPM and ABD) are built using (1) the complete dataset (2) the dataset after removing data point 18 (3) the dataset after removing data point 16 and (4) the dataset after removing data points 18 and 16 as presented in Figure 20, Figure 21, Figure 22 and Figure 23 respectively.

All four models in Figure 20, Figure 21, Figure 22 and Figure 23 are very similar. In all models the p-values of the predictors were only slightly different and always below the cutoff value of 0.05. Therefore all the coefficients are significant. The model in Figure 22 (without data point 16) shows a slight increase of the likelihood ratio based χ^2 (LR Chi2) which indicates better fit (Harrell 2001). The same applies to the R^2_N index. When removing only the outlier data point 18 from the dataset, the model (Figure 21) shows a clear decrease in χ^2 and a slight decrease in R^2_N. As can be seen in Figure 23, removing both outliers (data points 18 and 16) has negligible effects on the model. Therefore, the outlier data point 18 is clearly influential. On the contrary, data point 16 has almost no effect on the model.

The ORM approach presented in this section was used to build predictive models for the responses *Availability*, *Accessibility* and *Successability*. Only significant models for *Accessibility* and *Successability* could be built (listed in Appendix F). For the identified models, the p-values for all coefficients was sufficiently low (i.e., p $\leq$ *0.05*) to indicate significance of the coefficients. It is also noticed that the higher the number of predictors the higher the R^2_N index (i.e., the predictive power increases with the increase of the number of predictors). R^2_N index was as low as 0.224 with one predictor (*Accessibility* versus WM) and as high as 0.960 with 11 predictors (*Accessibility* versus DIST, ABST, WM, NOM, LCPM, ABD, LOC, CC, DCBO, OMI and DMI).

```
orm(SUCCESSABILITY ~  LCPM + ABD, family = logistic, maxit = 24)

Frequencies of Responses

0.413  0.442  0.472  0.844  0.977  0.985  0.988  0.994   1
  1      1      1      1      2      1      1      1     11

                        Model Likelihood        Discrimination            Rank Discrim.
                          Ratio Test               Indexes                  Indexes
Obs              20     LR chi2       8.35    R2                 0.356    rho   0.577
Unique Y          9     d.f.             2    g                  1.672
Median Y          1     Pr(> chi2)  0.0154    gr                 5.322
max |deriv|   8e-06     Score chi2    8.39    |Pr(Y>=median)-0.5| 0.241
                        Pr(> chi2) 0.0151

            Coef     S.E.     Wald Z   Pr(>|Z|)
y>=0.442    4.7350   1.6745    2.83    0.0047
y>=0.472    3.7755   1.4726    2.56    0.0104
y>=0.844    3.0965   1.3651    2.27    0.0233
y>=0.977    2.6376   1.3127    2.01    0.0445
y>=0.985    1.9002   1.2573   1.51     0.1307
y>=0.988    1.5863   1.2293   1.29     0.1969
y>=0.994    1.2655   1.1814   1.07     0.2841
y>=1        0.9491   1.1455   0.83     0.4073
LCPM       -0.2449   0.0938  -2.61     0.0090
ABD         1.9655   0.8987   2.19     0.0287
```

Figure 20: Model built with 2 predictors using ORM and the complete dataset

In Table 20, a comparison of observed and predicted values for *Accessibility* and *Successability* based on the models in Figure 24 and Figure 21 respectively. It is clear from the table that when applying the models to the training dataset, the predicted values for the outcomes were in most cases very close to the observed values.

orm(SUCCESSABILITY ~ LCPM + ABD, family = logistic, maxit = 24)

Frequencies of Responses

0.413	0.442	0.472	0.844	0.977	0.985	0.988	0.994	1
1	1	1	1	2	1	1	1	10

		Model Likelihood Ratio Test		Discrimination Indexes		Rank Discrim. Indexes	
Obs	19	LR chi2	7.37	R2	0.333	rho	0.552
Unique Y	9	d.f.	2	g	1.577		
Median Y	1	Pr(> chi2)	0.0252	gr	4.839		
max |deriv|	0.005	Score chi2	7.42	|Pr(Y>=median)-0.5|	0.228		
		Pr(> chi2)	0.0245				

	Coef	S.E.	Wald Z	Pr(>|Z|)
y>=0.442	4.6651	1.6658	2.80	0.0051
y>=0.472	3.7171	1.4631	2.54	0.0111
y>=0.844	3.0520	1.3568	2.25	0.0245
y>=0.977	2.5982	1.3046	1.99	0.0464
y>=0.985	1.8667	1.2493	1.49	0.1351
y>=0.988	1.5532	1.2212	1.27	0.2034
y>=0.994	1.2319	1.1731	1.05	0.2937
y>=1	0.9145	1.1371	0.80	0.4213
LCPM	-0.2364	0.0952	-2.48	0.0130
ABD	1.8783	0.9138	2.06	0.0398

Figure 21: Model built with 2 predictors using ORM after removing the outlier point 18 from dataset

orm(SUCCESSABILITY ~ LCPM + ABD, family = logistic, maxit = 24)

Frequencies of Responses

0.413	0.442	0.472	0.844	0.977	0.985	0.988	0.994	1
1	1	1	1	1	1	1	1	11

		Model Likelihood Ratio Test		Discrimination Indexes		Rank Discrim. Indexes	
Obs	19	LR chi2	8.45	R2	0.376	rho	0.562
Unique Y	9	d.f.	2	g	1.765		
Median Y	1	Pr(> chi2)	0.0146	gr	5.842		
max |deriv|	5e-06	Score chi2	8.35	|Pr(Y>=median)-0.5|	0.270		
		Pr(> chi2)	0.0154				

	Coef	S.E.	Wald Z	Pr(>|Z|)
y>=0.442	5.1698	1.8097	2.86	0.0043
y>=0.472	4.2245	1.6322	2.59	0.0096
y>=0.844	3.5618	1.5451	2.31	0.0212
y>=0.977	3.1075	1.5049	2.06	0.0389
y>=0.985	2.6947	1.4741	1.83	0.0675
y>=0.988	2.3069	1.4222	1.62	0.1048
y>=0.994	1.9125	1.3411	1.43	0.1538
y>=1	1.5414	1.2821	1.20	0.2293
LCPM	-0.2583	0.0995	-2.60	0.0095
ABD	1.8359	0.8953	2.05	0.0403

Figure 22: Model built with 2 predictors using ORM after removing the outlier point 16 from dataset

orm(SUCCESSABILITY ~ LCPM + ABD, family = logistic, maxit = 24)

Frequencies of Responses

0.413	0.442	0.472	0.844	0.977	0.985	0.988	0.994	1
1	1	1	1	2	1	1	1	11

		Model Likelihood Ratio Test		Discrimination Indexes		Rank Discrim. Indexes	
Obs	20	LR chi2	8.35	R2	0.356	rho	0.577
Unique Y	9	d.f.	2	g	1.672		
Median Y	1	Pr(> chi2)	0.0154	gr	5.322		
max |deriv|	8e-06	Score chi2	8.39	|Pr(Y>=median)-0.5|	0.241		
		Pr(> chi2)	0.0151				

	Coef	S.E.	Wald Z	Pr(>|Z|)
y>=0.442	4.7350	1.6745	2.83	0.0047
y>=0.472	3.7755	1.4726	2.56	0.0104
y>=0.844	3.0965	1.3651	2.27	0.0233
y>=0.977	2.6376	1.3127	2.01	0.0445
y>=0.985	1.9002	1.2573	1.51	0.1307
y>=0.988	1.5863	1.2293	1.29	0.1969
y>=0.994	1.2655	1.1814	1.07	0.2841
y>=1	0.9491	1.1455	0.83	0.4073
LCPM	-0.2449	0.0938	-2.61	0.0090
ABD	1.9655	0.8987	2.19	0.0287

Figure 23: Model built with 2 predictors using ORM after removing the outliers points 18 and 16 from dataset

```
orm(ACCESSIBILITY ~  LOC + CC, family = logistic, maxit = 24)

Frequencies of Responses

0.121  0.783  0.789  0.798  0.804  0.813  0.846   0.86  0.861  0.879  0.882  0.891  0.924  0.929  0.943
0.95

   1     1     2     1     1     1     1     1     2     1     1     1     2     1     1     1


                         Model Likelihood      Discrimination              Rank Discrim.
                            Ratio Test            Indexes                     Indexes
Obs              19   LR chi2        12.96   R2                    0.496   rho    0.610
Unique Y         16   d.f.               2   g                     1.914
Median Y      0.861   Pr(> chi2)    0.0015   gr                    6.780
max |deriv|   3e-05   Score chi2     16.66   |Pr(Y>=median)-0.5|   0.205
                      Pr(> chi2)    0.0002


         Coef     S.E.     Wald Z   Pr(>|Z|)
LOC   -0.0010   0.0003    -2.90      0.0037
CC     0.5408   0.2534     2.13      0.0328
```

Figure 24: A significant model for *Accessibility*.

Accessibility Model (Figure 24)		Successability Model (Figure 21)	
Observed	**Predicted**	**Observed**	**Predicted**
0.783	0.841	1.000	0.942
0.929	0.835	1.000	0.975
0.860	0.814	1.000	0.967
0.798	0.855	0.442	0.583
0.861	0.876	1.000	0.905
0.813	0.874	0.413	0.887
0.924	0.863	1.000	0.996
0.950	0.928	1.000	0.825
0.804	0.857	1.000	0.977
0.891	0.863	0.988	0.811
0.882	0.853	0.985	0.908
0.789	0.832	0.472	0.974

0.846	0.830	1.000	0.971
0.924	0.928	1.000	0.955
0.943	0.898	0.977	0.823
0.789	0.473	0.977	0.942
0.861	0.794	0.944	0.967
NA	NA	NA	NA
0.121	0.517	0.844	0.823
0.879	0.850	1.000	0.985

Table 20: Observed and predicted outcomes when the ORM models applied to the training dataset

9.5 Discussion

Two approaches for building significant models for *Accessibility, Availability* and *Successability* are presented in Section 9.3 and Section 9.4, namely GLM (with the distribution family defined as *binomial* and the *logit* link function) and ORM. With both approaches significant models were built. The models are evaluated using two indices, namely p-value and R^2_N. P-values are used to indicate the significance of the coefficients and hence the significance of a predictor. R^2_N is used in this work to (1) test the goodness of fit of the models built and (2) assess their predictive power. All the reported models in Appendix E and Appendix F are significant in terms of the p-values. On the other hand, the R^2_N indices vary in the range 0.1 - 1.0. The higher the R^2_N index, the better the fit and the better the predictive power of the model. However, low R^2 values are common in logistic regression (Hosmer Jr, Lemeshow, and Sturdivant 2013).

Some significant models built using the ORM approach rely only on one predictor which makes any correlation between the predictors irrelevant. For all other ORM models and models generated with the GLM approach, any correlation must be considered since it may affect the regression results. Section 9.6, introduces an approach for predictive models selection including how to deal with regressions between the predictors. Recommendations for model selection are discussed.

Although most of the models built using the GLM approach seem to be very significant with extremely low p-values for the coefficients and very high predictive power, we still have many concerns. Next, we list some of our concerns and suspiciousness with regards to the approach and the models generated.

- The p-values for all models reported is always <2e-16
- For many models R^2_N was optimal (nearly 1).
- Warning messages were thrown by the R tools during models building (Figure 25). Error message 1 was thrown for all models. The other messages (2 and 3) were thrown for many models. The first message means that the GLM expected "weights" for the responses (dependent variables) as input but could not find them. The responses are basically *not* weighted. The second warning message is raised because the default number of iterations (28) used to fit the model was not sufficient. The warning disappeared after increasing the number of iterations by setting the GLM *maxit* parameter to 200. The third warning message means that the fitted values are extremely close to 1 or zero. This is essentially an issue for *Availability* whose observed value was almost always 1.
- The GLM model with the binomial link is usually used to predict dichotomous (or binary) dependent variables. As it is clear from Table, the predicted values are either 1 or very close to 0 (2.220e-16). The dependent variables in this work (*Availability*, *Accessibility* and *Successability*) are all ratios of *continuous* nature within the interval [0,1].

```
Warning messages
1: In eval(expr, envir, enclos) :
  non-integer #successes in a binomial glm!
2: glm.fit: algorithm did not converge
3: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

Figure 25: Warning message thrown by R during model building with GLM

The ORM approach allows for modeling continuous response variables (Hosmer Jr, Lemeshow, and Sturdivant 2013; Harrell 2014; Harrell 2001) similar to the independent variables under focus in this work (*Availability*, *Accessibility* and *Successability*). This is achieved by categorizing the response into multiple ordered categories where the number of categories can be calculated as follows:

k = number of unique responses -1

Table 17 presents an example of response variable categories identified for an ORM model. This approach allows for as many categories as required to best represent a continuous response compared to the only two categories allowed for the GLM approach. When comparing the predicted values using a GLM model (Table 16) to that computed for an ORM model (Table 18), it can be noticed that unlike with GLM model, the predicted responses using the ORM model are very close to the observed values (although the p-values and the R^2_N index in the GLM model are optimal and clearly better than the corresponding values for the ORM model).

To summarize, both the GLM and the ORM approaches built significant predictive models. While using the GLM approach significant models for *Availability* and *Successability* could be built, the ORM approach resulted in significant models for *Accessibility* and *Successability*. Owing to the above mentioned concerns and the related discussion in this section, we believe that the ORM approach is more appropriate for building predictive models for the external qualities under focus.

9.6 Model selection

In Sections 9.1 to 9.5 many predictive models were built and their significance and goodness of fit were discussed. In Section 9.5, we concluded that the ORM approach is better than the GLM approach for building the targeted models. ORM models built after removing the outliers are listed in Appendix F (F.3). However, the number of significant models produced is large and they incorporate different numbers of predictors. But the question remains as to which models are more appropriate. Besides the significance of the coefficients (p-values), the goodness of fit and the predictive power (R^2_N), stability and reliability of the model are important issues. Stability and reliability of the model can be achieved by minimizing the number of predictors. Hosmer (Hosmer Jr, Lemeshow, and Sturdivant 2013) reported that "*The more variables included in a model, the greater the estimated standard errors become, and the more dependent the model becomes on the observed data.*" A model is likely to be reliable when the number of predictors is less than $n/10$, where n is the number of observations (Harrell 2001). Following this recommendation, the number of predictors must be less than 2 (for n=20 in the dataset). Accordingly, significant models with only one predictors are more likely to be reliable than other models. This applies even when the models with higher number of predictors show better predictive power (i.e., higher R^2_N). Better predictive power in this case may be an indication of over-fitting (Harrell 2001).

Following the above discussion, the following criteria are recommended for model selection:

1. The model must be significant with the p-values for the coefficients less than or equal to 0.05.
2. The model must exhibit good fit and predictive power in terms of R^2_N. Low R^2 values are the norm for logistic regression (Hosmer Jr, Lemeshow, and Sturdivant 2013). McFadden regarded values between 0.2 and 0.4 for McFaddne's R-Squared (R^2_{mcF}) to be *excellent* (Daniel McFadden 1977). R^2_{mcF} has values that range

between 0 and 1, but in practice can never be 1. R^2_N is an adjustment of McFadden's R^2 that can get to 1. Thus we regard R^2_N >= 0.2 a *good* value for the predictive power and goodness of fit.

3. The number of predictors in the model must be ≤ 4. Harrell (Harrell 2001) recommended that the number of predictors be *less than* n/10, which is 1 predictor for 20 observations. But considering only models with one predictor may be insufficient as the size of the dataset is small and it may lead to missing information hidden in other predictors. Therefore, adding more variables may help balance between the size of the dataset and the number of predictors in the model.

4. Avoid models with strong correlation between the predictors (see Table 10).

Predictive models selected following the above criteria are listed in Appendix G. The selected models include models for predicting *Accessibility* and *Successability* based on different number of predictors (1 to 4 predictors).

9.7 Model validation

Once models are built, it is necessary to ensure that the model predictive performance will be maintained when it is applied to another dataset. Rawlings (Rawlings, Pantula, and Hosmer 1998) defined model validation as "*the demonstration or confirmation that the model is sound and effective for the purpose for which it was intended.*" To assure the model fulfills its intended use, it is necessary to test the model on a dataset (test dataset) that is different from the one used for model building (the training dataset). If the test dataset is collected independently from the training datasets, the validation is considered to be external (Steyerberg et al. 2003). If the training dataset is obtained by splitting the dataset into training and test dataset, the validation is internal. Cross-validation is a popular form of internal validation in which the data are split into a training set and a test set (e.g., 80% training set and 20 percent test set). This is repeated many times such that all observations have been used at least once in the test dataset (Steyerberg et al. 2001). A drawback of the cross-validation techniques is that it does not validate the full model (i.e., the model built with the completed dataset)(Harrell 2001). The bootstrap validation is another form of internal validation where "one repeatedly fits the model in a bootstrap sample and evaluates the performance of the model on the original sample" (Harrell 2001). Bootstrap re-sampling "*replicates the process of sample generation from an underlying population by drawing samples with replacement from the original dataset, of the same size as the original dataset*" (Steyerberg et al. 2001). Steyerberg (Steyerberg et al.

2001) stated that "*internal validity could best be estimated with bootstrapping, which provides stable estimates with low bias*".

Owing to having only one dataset collected as explained in Chapter 6, it is only feasible to use internal validation to study the predictive performance of the models built. Bootstrap validation is utilized for this purpose. Validation is done as follows:

1. Build a model using the original complete dataset and calculate the predictive power index R^2_N and the calibration slope. Calibration is basically the agreement between the predicted and the observed responses. It can be graphically assessed by plotting predicted and observed responses on the x-axis and y-axis respectively. If the predicted values fully agree with the observed values, the graph will have a slope of 1 (Steyerberg et al. 2010). The slope can also be directly computed from the fitted model. For example, the column with the heading "Original sample" in Figure 26 shows the predictive power index R^2_N and the calibration slope for the model built using the original complete dataset.

2. Repeat the following steps *n*-times and calculate the mean of the R^2_N and the calibration slope over all repetitions.

   a) Draw a bootstrap dataset (training dataset) from the original dataset and build a predictive model using it. Calculate the predictive power index R^2_N and the calibration slope. For example, the column with the heading "Training sample" in Figure 26 shows the predictive power index R^2_N and the calibration slope for the model built using the training dataset.

   b) Test the model built with the bootstrap dataset using the original dataset. Measure the performance of the model in terms of the predictive power index R^2_N and the calibration slope. For example, the column with the heading "Test sample" in Figure 26 shows the predictive power index R^2_N and the calibration slope computed for the test dataset.

3. *Calculate Optimism*. It is the difference between the mean R^2_N indices and the mean calibration slopes computed in step 2. For example, optimism for the predictive power R^2_N in Figure 26 is calculated as 0.2414 - 0.2235 = 0.0180. A significant drop in R^2_N indicates over-fitting. If the calibration slope is significantly less than 1, the estimates of the responses are highly biased and there is a lack of calibration. For calibration we consider a cutoff value of 0.9. The indices calculated for the models built using the original complete dataset (second column in Figure 26) are corrected by subtracting the *optimism* from them (sixth column in Figure 26).

The *validate* method of the *rms* package of R is used to validate the models built. It supports bootstrap validation besides many other methods. The method generates a number of statistics including R^2_N and calibration slope for the original model (i.e., the model built with the complete dataset), the model built using the training set and the predictive performance of the model on the test set. Steyerberg (Steyerberg et al. 2003) recommended to set the number of bootstraps (*n* repetitions) to at least 100. This recommendation was followed by setting the number of repetitions to 100.

We now show the result of validating some models from the selected models listed in Appendix G. Only models with 1, 2, 3 and 4 predictors are presented and discussed. Validation results of all selected models are listed in Appendix H.

```
ORM Model: Accessibility ~ WM

validate(model, method="boot", B=100):
          Original  Training  Test     Optimism   Corrected  n
          sample    sample    sample              index

R2        0.2235    0.2414    0.2235   0.0180     0.2055     100
Slope     1.0000    1.0000    1.0000   0.0000     1.0000     100
```

Figure 26: Validation of a 1 predictor model

The validation result of the ORM predictive model for *Accessibility* with WM as the predictor is shown in Figure 26). The difference between the R^2_N index for the training and the test set is 0.0180 (*optimism*). The corrected R^2_N index is calculated by subtracting *optimism* from the original R^2_N index. Comparing original and corrected R^2_N indices, it is clear that there is a slight drop in the R^2_N. This indicates that the model does not suffer from over-fitting. Moreover, the slope of the test set as well as the training set is optimal (1.000). Therefore, when the model applied to future datasets, no bias is expected. Additionally, the model will exhibit a high degree of calibration.

```
ORM Model: Successability ~ LCPM + ABD

validate(model, method="boot", B=100):
          Original  Training  Test     Optimism   Corrected  n
          sample    sample    sample              index

R2        0.3334    0.3673    0.2929   0.0743     0.2591     100
Slope     1.0000    1.0000    0.8944   0.1056     0.8944     100
```

Figure 27: Validation of a 2 predictors model

The model with two predictors shown in Figure 27 experience an apparent drop in its predictive power with a 22% drop in R^2_N index. Accordingly, the model tends to be over-fitted. Also, the corrected slope (0.8944) is marginally less than the cutoff value of 0.90 which can be taken as a sign of lack of calibration and bias. The same applies to the models with 3 and 4 predictors in Figure 28 and Figure 29.

```
ORM Model: Accessibility ~ CE + DCBO + DMI

validate(model, method="boot", B=100):
          Original  Training  Test     Optimism   Corrected  n
          sample    sample    sample              index

R2        0.4324    0.5132    0.3182   0.1950     0.2374     100
Slope     1.0000    1.0000    0.4861   0.5139     0.4861     100
```

Figure 28: Validation of a 3 predictors model

```
ORM Model: Successability ~ DIST + CE + DCBO + DMI

validate(model, method="boot", B=100):
          Original  Training  Test     Optimism   Corrected  n
          sample    sample    sample              index

R2        0.3562    0.5182    0.1816   0.3366     0.0196     100
Slope     1.0000    1.0000    0.4512   0.5488     0.4512     100
```

Figure 29: Validation of a 4 predictors model

Following the validation procedure described in this section, only two models (Figure 31 and Figure 32) were found to be well calibrated and not over-fitted. The validation results of the two models are shown in Figure 26 and Figure 30. These models are valid and exhibiting high accuracy. Both models predict *Accessibility* based on WM and LOC respectively. The models are simple since they rely only on one predictor. Moreover, both predictors used are internal static measures that can be calculated directly from the WS's source code. The models in Figure 31 and Figure 32 can be represented by the equations in Figure 33 and Figure 34 respectively. As explained in Section 9.4, the response is predicted by calculating the cumulative probability that it belongs to one of the ordered categories (e.g., y≥0.783, y≥0.789, etc. in Figure 31). For example, the probability for *Accessibility* being ≥ 0.783 for WM=86 can be calculated as follows:

$$L_2 = logit(P(Y \geq 0.783)) = 4.0502 + (-0.0027) * (86) = 3.818$$

$$P(Y \geq 0.783) = exp(3.818) / (1+exp(3.818)) = 0.979$$

This can be read as the probability that the *Accessibility* be ≥ 0.783 for WM=86 is 0.979. In the same way, the probabilities for the response to belong to the other categories can be calculated.

```
ORM Model: Accessibility ~ LOC

validate(model, method="boot", B=100):
          Original  Training  Test     Optimism   Corrected  n
          sample    sample    sample              index

R2        0.3431    0.3424    0.3431   -0.0007    0.3439     100
Slope     1.0000    1.0000    0.9031    0.0969    0.9031     100
```

Figure 30: A valid model for predicting *Accessibility* based on LOC

```
ACCESSIBILITY ~  WM
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1

                     Model Likelihood          Discrimination    Rank Discrim.
                        Ratio Test                Indexes           Indexes
Obs            19    LR chi2      4.78    R2                0.223  rho    0.414
Unique Y       16    d.f.            1    g                 0.892
Median Y    0.861    Pr(> chi2) 0.0288    gr                2.441
max |deriv| 0.002    Score chi2   5.97   |Pr(Y>=median)-0.5|0.148

          Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  4.0502 1.2843  3.15  0.0016
y>=0.789  3.2207 1.0387  3.10  0.0019
y>=0.798  2.1662 0.7700  2.81  0.0049
y>=0.804  1.7519 0.6742  2.60  0.0094
y>=0.813  1.4280 0.6192  2.31  0.0211
y>=0.846  1.1567 0.5861  1.97  0.0484
y>=0.86   0.9161 0.5664  1.62  0.1057
y>=0.861  0.6843 0.5532  1.24  0.2161
y>=0.879  0.2101 0.5397  0.39  0.6970
y>=0.882 -0.0326 0.5424 -0.06  0.9520
y>=0.891 -0.2778 0.5549 -0.50  0.6166
y>=0.924 -0.5518 0.5750 -0.96  0.3372
y>=0.929 -1.2424 0.6653 -1.87  0.0618
y>=0.943 -1.7175 0.7765 -2.21  0.0270
y>=0.95  -2.4764 1.0476 -2.36  0.0181
WM       -0.0027 0.0013 -2.09  0.0363
```

Figure 31: A predictive model for predicting Accessibility based on WM

```
ACCESSIBILITY ~  LOC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                    Model Likelihood          Discrimination     Rank Discrim.
                       Ratio Test                Indexes            Indexes
Obs        19      LR chi2     7.94       R2                0.343 rho  0.444
Unique Y      16     d.f.           1      g                 1.250
Median Y   0.861     Pr(> chi2) 0.0048     gr                3.491
max |deriv| 0.05     Score chi2  10.78    |Pr(Y>=median)-0.5| 0.176

          Coef   S.E.   Wald Z Pr(>|Z|)
y>=0.783  4.9744 1.6701  2.98  0.0029
y>=0.789  3.8027 1.2324  3.09  0.0020
y>=0.798  2.5053 0.8418  2.98  0.0029
y>=0.804  2.0221 0.7166  2.82  0.0048
y>=0.813  1.6651 0.6494  2.56  0.0103
y>=0.846  1.3755 0.6100  2.26  0.0241
y>=0.86   1.1235 0.5864  1.92  0.0554
y>=0.861  0.8813 0.5705  1.54  0.1224
y>=0.879  0.3818 0.5517  0.69  0.4889
y>=0.882  0.1265 0.5521  0.23  0.8188
y>=0.891 -0.1274 0.5628 -0.23  0.8208
y>=0.924 -0.4099 0.5815 -0.70  0.4808
y>=0.929 -1.1145 0.6694 -1.66  0.0960
y>=0.943 -1.5936 0.7795 -2.04  0.0409
y>=0.95  -2.3581 1.0494 -2.25  0.0246
LOC      -0.0008 0.0003 -2.63  0.0086
```

Figure 32: A predictive model for predicting Accessibility based on LOC

```
L2 = logit(P(Y≥0.783)) = 4.0502 + (-0.0027)*(WM)
L3 = logit(P(Y≥0.789)) = 3.2207 + (-0.0027)*(WM)
L4 = logit(P(Y≥0.798)) = 2.1662 + (-0.0027)*(WM)
L5 = logit(P(Y≥0.804)) = 1.7519 + (-0.0027)*(WM)
L6 = logit(P(Y≥0.813)) = 1.4280 + (-0.0027)*(WM)
L7 = logit(P(Y≥0.846)) = 1.1567 + (-0.0027)*(WM)
L8 = logit(P(Y≥0.860)) = 0.9161 + (-0.0027)*(WM)
L9 = logit(P(Y≥0.861)) = 0.6843 + (-0.0027)*(WM)
L10 = logit(P(Y≥0.879)) = 0.2101 + (-0.0027)*(WM)
L11 = logit(P(Y≥0.882)) = -0.0326 + (-0.0027)*(WM)
L12 = logit(P(Y≥0.891)) = -0.2778 + (-0.0027)*(WM)
L13 = logit(P(Y≥0.924)) = -0.5518 + (-0.0027)*(WM)
L14 = logit(P(Y≥0.929)) = -1.2424 + (-0.0027)*(WM)
L15 = logit(P(Y≥0.943)) = -1.7175 + (-0.0027)*(WM)
L16 = logit(P(Y≥0.950)) = -2.4764 + (-0.0027)*(WM)
```

Figure 33: Formulas representing the model in Figure 31. Where P(Y≥j) is the probability that Y≥j.

```
L2 = logit(P(Y≥0.783)) = 4.9744 + (-0.0008)*(LOC)
L3 = logit(P(Y≥0.789)) = 3.8027 + (-0.0008)*(LOC)
L4 = logit(P(Y≥0.798)) = 2.5053 + (-0.0008)*(LOC)
L5 = logit(P(Y≥0.804)) = 2.0221 + (-0.0008)*(LOC)
L6 = logit(P(Y≥0.813)) = 1.6651 + (-0.0008)*(LOC)
L7 = logit(P(Y≥0.846)) = 1.3755 + (-0.0008)*(LOC)
L8 = logit(P(Y≥0.860)) = 1.1235 + (-0.0008)*(LOC)
L9 = logit(P(Y≥0.861)) = 0.8813 + (-0.0008)*(LOC)
L10 = logit(P(Y≥0.879)) = 0.3818 + (-0.0008)*(LOC)
L11 = logit(P(Y≥0.882)) = 0.1265 + (-0.0008)*(LOC)
L12 = logit(P(Y≥0.891)) = -0.1274 + (-0.0008)*(LOC)
L13 = logit(P(Y≥0.924)) = -0.4099 + (-0.0008)*(LOC)
L14 = logit(P(Y≥0.929)) = -1.1145 + (-0.0008)*(LOC)
L15 = logit(P(Y≥0.943)) = -1.5936 + (-0.0008)*(LOC)
L16 = logit(P(Y≥0.950)) = -2.3581 + (-0.0008)*(LOC)
```

Figure 34: Formulas representing the model in Figure 32. Where P(Y≥j) is the probability that Y≥j.

Chapter 10
Conclusions and future work

Web Services (WSs) are gaining more attention as programming components for different software applications. They play an important role in service-oriented architectures where loosely coupled programming components or services deliver their functionality over a network – often over the Internet. The quality of such architectures depends heavily on the quality of its individual service components, which are usually WSs. Therefore, the quality of WSs is becoming a major concern.

As with any other software component, quality of WSs can be assessed throughout different phases of the development life-cycle. Testing can be used to assess the quality of WSs. The extensive systematic literature review reported in this thesis was carried out to acquire knowledge on the state of the art in the emerging area of testing semantic WSs and identify implications for future research. The review was carried out following the procedure outlined by Kitchenham and Charters (2007) to answer two research questions, explicitly:

RQ1 - Is it possible to derive functional test cases from requirement specifications of semantic WSs? What approaches are used?

RQ2 - What are the challenges associated with the derivation of test cases from the specifications of semantic WSs?

We could identify 34 relevant primary studies. The relatively small number of the identified primary studies can be explained by the fact that semantic WSs emerged only around the end of year 2000 after the introduction of the first ontology language for the Web (DAML+OIL) (DAML, 2000). However, we believe that the identified primary studies present sufficient material to provide answers to the research questions under focus.

The results of the systematic literature review show that it is possible to derive test cases from requirements specification, based on the different testing approaches identified in the primary studies (RQ1). Around half of the test approaches analyzed start from an OWL-S specification model. For more than half of the approaches, transformation into another representation model was required. Base models are transformed to other representation models that are considered to be more efficient in terms of automatic test case generation or well supported by test case generation tools. In these approaches, test cases are derived from the transformed model. In the other approaches where transformation is not required, test cases are derived directly from the base model. The transformation used the most involves Petri Nets and its derivatives. In order to derive test cases, different techniques are applied to the specification models. Model checking is largely used to derive test cases.

As for RQ2, most of the studies that discuss challenges associated with testing semantic web services focus on general challenges that are applicable to the problem of testing traditional (syntactical) WSs as well as semantic WSs.

Assessing the external quality measures of WSs via testing is usually only feasible at late stages of the development life-cycle when the WSs are already developed, deployed and can deliver their specified functionalities. If the external quality measures can be predicted early during the development, they can provide valuable information that may positively influence the engineering of WSs with regards to their quality. Building probabilistic prediction models for the WSs sub-quality factors *Availability*, *Accessibility* and *Successability* has a strong theoretical basis but experimentation is necessary to build and empirically evaluate the accuracy of the models. Two research questions are concerned with building predictive models for three WSs external qualities, namely:

RQ3 - Is it possible to build statistically significant probabilistic predictive models for the WSs sub-quality factors *Availability*, *Accessibility* and *Successability*?

RQ4 - How accurate are these models?

An empirical approach (correlational study) was followed to collect and analyze the necessary data required for this purpose. A setup in which 34 students interacted with the targeted 20 WSs was developed and executed in multiple sessions. Twenty data points were collected representing the interactions with 20 different WSs. The dataset includes 17 different internal static and dynamic quality measures as well as the calculated values for the corresponding external qualities *Availability*, *Accessibility* and *Successability*.

The discussion presented in Chapter 9 showed that it is possible to build statistically significant predictive models for *Accessibility* and *Successability* based on the collected dataset (RQ3). Two model building approaches were examined, namely GLM and ORM. The ORM approach was found to be more appropriate for building predictive models for the targeted external qualities. A large number of significant models was built using this approach. Criteria for model selection that take into consideration the significance of the coefficients, predictive power and correlation between the predictors involved in the model were defined. The models selected using these criteria are listed in Appendix G. Although all the selected models are significant with good fit and adequate predictive power, it is necessary to ensure that the model predictive performance will be maintained when it is applied to future datasets. Therefore, all the selected models were validated using the bootstrap validation method. The result of the validation showed that only two models (first and second model in Appendix H) do not suffer from over-fitting, lack of calibration and bias. These two models showed a high degree of calibration and expected to maintain their predictive power when applied to future datasets. Therefore, we consider these models to be considerably accurate (RQ4). It is also noticed that both models rely on simple internal static quality measures (WM and LOC respectively). For collecting such measures, no execution of the software is needed. This considerably facilitates the prediction of the corresponding external qualities early during the development.

The research done in this work towards assessing the quality of WSs via prediction and testing opened many new directions for future research. Testing semantic WSs is a relatively new research area. We believe that much work remains to be done to improve the current state of research in the area of testing semantic WSs. Similarly, predictive models are well-established and widely used in many domains (e.g., medicine, psychology, economics, etc.) but they are not widely adopted in software engineering. As a result of the discussions in Sections 4.2, 4.3, 8.1, 9.5 and 9.6, we propose the following directions for future research in this area:

- Studying comparatively the different test approaches presented in the primary studies that share the same characteristics.
- Focusing on Petri Net as a common formalism for semantic WSs and developing rules for transforming OWL-S and WSMO specifications into their equivalent Petri Net representation.
- Investigating new approaches for self-adaptive testing where the test cases are automatically adapted whenever the requirements specifications of the semantic WSs change.
- Developing tools that support the research directions listed above (e.g., a tool for automating the transformation into Petri Nets).
- Executing an industrial experiment to acquire sufficient data in a realistic context and then use them for the external validation of the selected predictive models (Appendix G).
- Use the approach developed in this work to build and validate probabilistic predictive models for additional WSs external qualities.

Publications

Parts of this thesis are published in the following peer-reviewed publications:

- Tahir, A., Tosi, D., Morasca, S. 2013. "A systematic review on the functional testing of semantic web services". Journal of Systems and Software 86, 2877–2889.
- Tahir, A., Morasca, S., Tosi, D. 2013. "Towards Probabilistic models to predict Availability, Accessibility and Successability of Web Services", in: ICSEA 2013, The Eighth International Conference on Software Engineering Advances. pp. 498–503. (**Best Paper Award**)

Other peer-reviewed publications published during the course of the PhD:

- Tosi, D., Tahir, A. 2013. "A Survey on How Well-Known Open Source Software Projects Are Tested", in: Cordeiro, J., Virvou, M., Shishkov, B. (Eds.), Software and Data Technologies, Communications in Computer and Information Science. Springer Berlin Heidelberg, pp. 42–57.
- Ndem, G.C., Tahir, A., Ulrich, A., Goetz, H. 2011. "Test data to reduce the complexity of unit test automation", in: Proceedings of the 6th International Workshop on Automation of Software Test, AST '11. ACM, Waikiki, Honolulu, HI, USA, pp. 105–106.

Other peer-reviewed publications:

- Tosi D., Tahir A. 2010. "How developers test their Open Source Software products - A survey of well-known OSS projects", 5th International Conference on Software and Data Technologies, ICSOFT 2010, Athens.

Publications in preparation:

- Tahir, A., Morasca, S., Tosi, D. "Predictive models for Web Service Availability, Accessibility and Successability". IEEE Transactions on Services Computing, *in preparation.*

Patents

The following patents have been granted during the course of the PhD in a related research area:

- Ndem, G., Tahir, A. 2013. "Method for estimating testing efforts for software unit testing", US Patent 8495576, filed April 18, 2011, and issued July 23, 2013.
- Ndem, G.,Tahir, A. 2014. "Method and apparatus for the performing unit testing of software modules in software systems", US Patent 8799868, filed April 18, 2011, and issued August 05, 2014.

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Appendix A. Primary studies selected

Primary study		*Title* and Short description
ID	**Reference**	
PS1	(Bai et al. 2007)	*A framework for contract-based collaborative verification and validation of web services.* This study introduces contract-based testing where the (semantic) web service specification is regarded as a contract. Tests are derived from the OWL-S specification after transforming it into an equivalent Petri Net model and then traversing the paths in the model.
PS2	(Shaban, Dobbie, and Sun 2009)	*A framework for testing semantic web Services using model checking.* Goal-based testing is introduced. The user requirements (or goals) expressed in terms of WSMO are transformed first into a B abstract machine. A B model checker (ProB) is used then to generate test cases.
PS3	(Goli and Pathari 2006)	*A general framework for automatic verification of web services.* A method for transforming the OWL-S semantic web service specification into a Promela model is described. The model checking tool SPIN is used to perform guided simulation of the Promela model in order to detect control-flow and data-flow errors.
PS4	(Hai h. Wang and Sun 2009)	*A semantic web environment for components.* In this study, a semantic web approach to component modeling and verification is proposed. OWL-S & SWRL specifications are used to describe components and their connectors. Reasoning engines (such as Jess and Racer) are used to perform automated verification over the OWL representation of the component models.
PS5	(Askarunisa, Abirami, and MadhanMohan 2010)	*A test case reduction method for semantic based web services.* The test approach followed in this study comprises transforming the WSDL and OCL specifications of the semantic web service into WSDL-S and then generating test cases using the test reduction techniques pair-wise testing and orthogonal array testing.

Primary study		*Title* and Short description
ID	**Reference**	
PS6	(S. Noikajana and Suwannasart 2008)	*An Approach for web service test case generation based on web service semantics.* Random testing technique is applied to semantic web services specified in terms of WSDL-S & SWRL in order to generate reliable test cases.
PS7	(Siripol Noikajana and Suwannasart 2009)	*An improved test case generation method for web service testing from WSDL-S and OCL with pair-wise testing technique.* A semantic web services testing approach is introduced where the web service specifications in WSDL-S and OCL are first transformed into an Input Parameter Model (IPM) and the pair-wise testing technique is applied to the IPM in order to generate the test cases.
PS8	(Paradkar et al. 2007)	*Automated functional conformance test generation for semantic web services.* Semantic web services expressed in OWL-S. Each operation in OWL-S is defined using an Input, Output, and pairs of Precondition and an Effect (IOPE). For each operation, test objectives (test goals) and fault models are derived from each PE pair. The test goals along with the IOPE are fed into a planner that extends the Graphplan planning algorithm to generate test sequences.
PS9	(Park et al. 2009)	*Automatic discovery of web services based on dynamic black-box testing.* Test cases are generated using the exploratory testing technique based on the information provided by the service requester. The test cases are then refined by introducing test data and any missing parameters.
PS10	(Lee, Bai, and Chen 2008)	*Automatic mutation testing and simulation on OWL-S specified web services.* This study suggests input data mutation testing as a means for generating test cases from OWL-S specified semantic web services. OWL-S specification is analyzed to identify the mutants. The mutants are user for simulation testing on the services.
PS11	(Li et al. 2010)	*Construction and test of web service solution for E-government.*

Primary study ID	Primary study Reference	*Title* and Short description
		The testing approach proposed in this study involves transforming the OWL-S specifications of the semantic web services into High-Level Petri Net (HPN) model and then applying model checking to generate the required test cases.
PS12	(Bai et al. 2007)	*Contract-based testing for web services.* In the semantic web service testing approach presented in this study, the OWL-S specifications are regarded as contracts between the service requester and the provider. OWL-S specifications are first transformed into Petri Net model and then test cases are derived by traversing the different paths in the model. Test data are generated by analyzing Inputs and the Preconditions provided in the OWL-S specifications. Test oracles are generated by analyzing the Outputs and Effects in the specifications.
PS13	(Li et al. 2010)	*Generating test cases of composite services based on OWL-S and EH-CPN.* The testing approach introduced involves transforming the OWL-S specification of the semantic web service into an enhanced colored Petri Net (EH-CPN) and then analyzing the control flow and data flow to generated test cases. Partition testing is used for test data generation.
PS14	(B. Yu and Li 2010)	*Generating test data based on XML schema.* In this study 4 different approaches for generating the test data required for testing web services are presented. Three of them target semantic web services. The first approach involves generating test data by analyzing Inputs and Preconditions in the WSDL-S service specification. The second approach involves converting BPEL4WS Specifications of the web service into Petri Net and applying path traversing to generate the test cases. The third approach generates test cases directly from OWL-S specifications using the random testing technique. The last approach utilizes Inputs and Preconditions in the OWL-S service specification to generate random test data.
PS15	(Muhammad Shaban Jokhio Johkio2009)	*Goal-based testing of semantic web services.*

Primary study		*Title* and Short description
ID	**Reference**	
		The user requirements (Goals) expressed in terms of WSMO are transformed first into a B abstract machine. A B model checker is used then to generate test cases.
PS16	(Ramollari et al. 2009)	*Leveraging semantic web service descriptions for validation by automated functional testing.* The semantic web service test method introduced in this study transforms the OWL and RIF-PRD specifications of the semantic web service into Stream X-machine model (SXM). Test cases are then automatically generated from the SXM model
PS17	(Hongbing Wang et al. 2009)	*Logic-based verification for Web services composition with TLA.* Test cases for semantic web service specified in OWL-S are generated by transforming the specifications into a Temporal Logic Actions (TLA) model and then applying model checking using the tool TLC.
PS18	(Sinha and Paradkar 2006)	*Model-based functional conformance testing of web services operating on persistent data.* In this study, web service specifications in WSDL-S are transformed into Extended Finite State Machine (EFSM). Different known methods (Full predicate coverage, BZ-TT method, Mutation based and User defined test objectives) are then used to generate test cases from the EFSM model
PS19	(Wen-Jie and Shi 2009)	*Modeling requirements evolution with π-Calculus.* This paper concerned about modeling the evolution of software requirements expressed in OWL-S using π-Calculus. OWL-S requirements expressed in terms of π-Calculus. The study defines π-Calculus semantics of requirements evolution.
PS20	(X. Wang, Huang, and Wang 2009)	*Mutation test based on OWL-S requirement model.* The testing approach proposed generates test cases for semantic web services by analyzing its OWL-S specification. Mutants are then identified and introduced into the web service using the Aspect Oriented Programming technology. Tests are then applied to the web service.

Primary study		*Title* and Short description
ID	**Reference**	
PS21	(Y. Zhang and Zhu 2008)	*Ontology for service oriented testing of web services.* This study presents a framework for testing web services. For describing the different components of the framework and their relations, ontology was adapted.
PS22	(Y. Wang et al. 2007)	*Ontology-based test case generation for testing web services.* This study proposes transforming the OWL-S specifications of the semantic web service into a Petri Net model. Test cases are generated by traversing the paths in the model. The required test data are generated by reasoning over the Input, Output, and pairs of Precondition and an Effect (IOPE).
PS23	(Bai et al. 2008)	*Ontology-based test modeling and partition testing of web services.* A Test Ontology Model (TOM) that allows semantic definition of the test artifacts using classes, properties, relationships and constraints is proposed. Test cases for semantic web services are generated by analyzing its OWL-S specifications. The tests are encoded in TOM. Partition testing is used for test data generation.
PS24	(Y. Yu, Huang, and Luo 2007)	*OWL-S based interaction testing of web service-based system.* This study discusses an approach for testing the interaction among web services. The interaction requirements are expressed in terms of extended OWL-S ontology. OWL-S is extended with Future Time Linear Temporal Logic (FTLTL) which is suitable to describe temporal constraints, and SWRL which is used to describe non-temporal properties. Testing is done by comparing the interaction requirements properties specified using the extended OWL-S to the implementation properties collected through code instrumentation.
PS25	(R. Wang and Huang 2008)	*Requirement model-based mutation testing for web service.* This study introduces a mutation-based testing approach for semantic web services in which the services are specified using OWL-S extended to support the specification of mutant operators. Aspect oriented technology is used to

Primary study		*Title* and Short description
ID	**Reference**	
		transparently inject errors generated by the mutant operators.
PS26	(Bai and Kenett 2009)	*Risk-based adaptive group testing of semantic web services.* This study introduces risk-based adaptive group testing for testing complex system of semantic web services. Test cases are categorized and scheduled according to the risks associated with the targeted web services.
PS27	(Chen, Zeng, and Xu 2009)	*The binary behavioral modes based on action sequence and compliance verification for compositional web service.* This study proposes an approach for binary behavioral specification based on action sequence. The specification are expressed as behavioral modes, converted into LTS and then given operation semantic. An algorithm is utilized to check the compliance of the web service composition to the behavior modes.
PS28	(M. Shaban Jokhio, Dobbie, and Sun 2009)	*Towards specification based testing for semantic web services.* An approach for automatically generating test cases from WSMO specification of semantic web services using boundary conditions and equivalence classes techniques is proposed. Additionally, the study proposes a metric for the effectiveness of the generated test cases.
PS29	(Siripol Noikajana and Suwannasart 2008)	*Web service test case generation based on decision table.* A methodology for the automatic generation of test cases for semantic web services specified in WSDL-S & SWRL is introduced. The methodology is based on limited entry decision tables.
PS30	(Ma et al. 2010)	*Web services testing based on Stream X-Machine.* The semantic web service test method introduced in this study transforms the WSDL-S & SWRL specifications of the semantic web service into Stream X-machine model (SXM). Test cases are then automatically generated from the SXM model
PS31	(Liu et al. 2011)	*A flow graph-based test model for OWL-S web*

Primary study ID	Reference	*Title* and Short description
		services. This study proposes a flow graph-based test model to describe an abstraction of the structural test artifacts of OWL-S web services. Test paths for OWL-S web services can be generated by traversing the paths in the model and traditional path testing technique can be applied in order to achieve sufficient code-based test coverage.
PS32	(T. Zhang et al. 2011)	*An approach of end user regression testing for semantic web services.* This study proposes a web service regression testing model (WSRTM) for semantic web service. The model focuses on WSDL interface and IOPEs information changes and impacts, and proposes a test cases generation approach for operation sequences of semantic Web Service.
PS33	(Askarunisa, Punitha, and Abirami 2011)	*Black box test case prioritization techniques for semantic based composite web services using OWL-S.* In this study, composite web services are specified in OW-S and SWRL. Test cases are generated based on sequences; coverage computed for the test cases and prioritization of test cases is performed to improve the effectiveness of regression testing.
PS34	(Oghabi, Bentahar, and Benharref 2011)	*On the verification of behavioral and probabilistic web services using transformation.* OWL-S specifications of semantic web services are automatically transformed into a corresponding Markov chain diagram or Markov decision process. These are then transformed into a PRISM model. The PRISM model is used as input by the model checking tool PRISM to verify automatically the web service behavior.

Appendix B. Study quality assessment

Primary study ID	Quality assessment questions					
	QA1	QA2	QA3	QA4	QA5	QA6
PS1	Yes	Yes	Yes	No	Yes	Yes
PS2	Yes	Yes	Yes	Yes	Yes	Yes
PS3	Yes	Yes	Yes	Yes	Yes	Yes
PS4	Yes	Yes	Yes	Yes	Yes	Yes
PS5	Yes	Yes	Yes	Yes	Yes	Yes
PS6	Yes	Yes	Yes	Yes	Yes	Yes
PS7	Yes	Yes	Yes	Yes	Yes	Yes
PS8	Yes	Yes	Yes	Yes	Yes	Yes
PS9	Yes	Yes	Yes	Yes	Yes	Yes
PS10	Yes	Yes	Yes	Yes	Yes	Yes
PS11	Yes	Yes	Yes	No	Yes	Yes
PS12	Yes	Yes	Yes	Yes	Yes	Yes
PS13	Yes	Yes	Yes	Yes	Yes	Yes
PS14	Yes	Yes	Yes	Yes	No	Yes
PS15	Yes	Yes	Yes	Yes	Yes	Yes
PS16	Yes	Yes	Yes	Yes	Yes	Yes
PS17	Yes	Yes	Yes	Yes	Yes	Yes
PS18	Yes	Yes	Yes	Yes	Yes	Yes
PS19	Yes	Yes	Yes	Yes	Yes	Yes
PS20	Yes	Yes	Yes	No	Yes	Yes
PS21	Yes	Yes	No	No	Yes	Yes
PS22	Yes	Yes	Yes	Yes	Yes	Yes
PS23	Yes	Yes	Yes	Yes	Yes	Yes
PS24	Yes	Yes	Yes	No	Yes	Yes
PS25	Yes	Yes	Yes	Yes	Yes	Yes
PS26	Yes	Yes	No	No	Yes	Yes
PS27	Yes	Yes	Yes	Yes	Yes	No
PS28	Yes	Yes	Yes	No	Yes	Yes
PS29	Yes	Yes	Yes	Yes	Yes	Yes
PS30	Yes	Yes	No	Yes	Yes	Yes
PS31	Yes	Yes	Yes	No	Yes	Yes

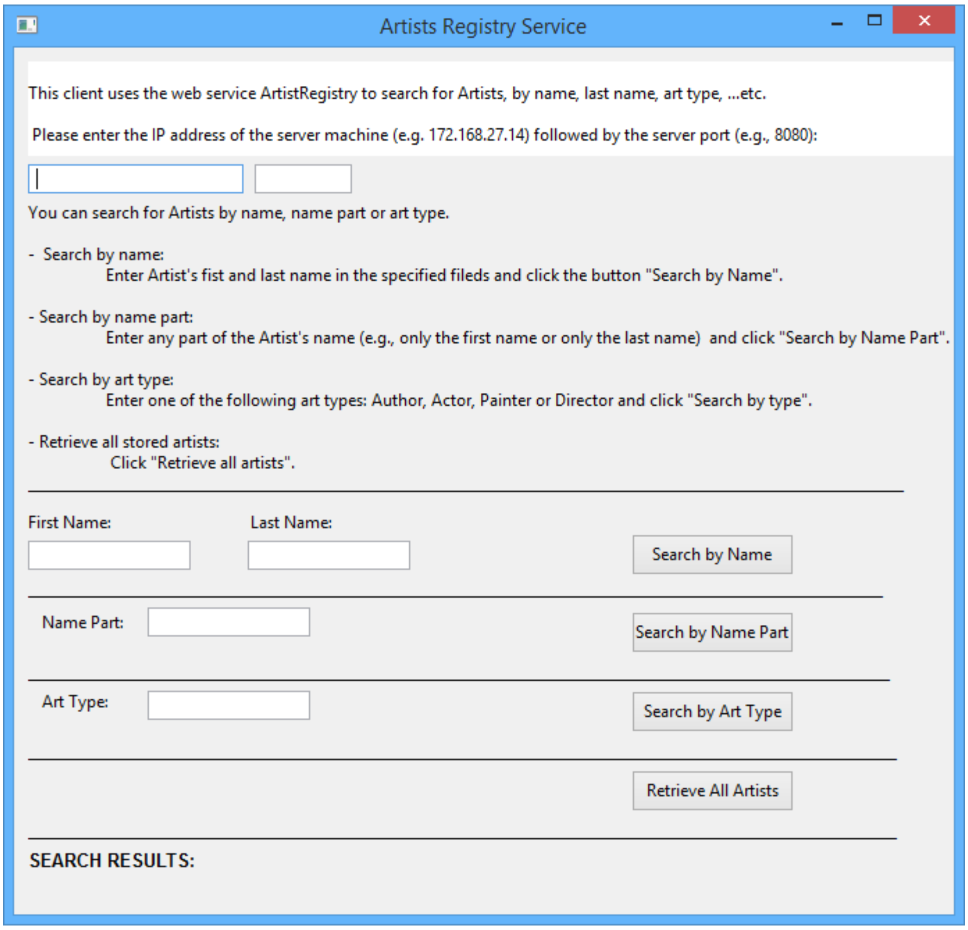
Primary study ID	Quality assessment questions					
	QA1	QA2	QA3	QA4	QA5	QA6
PS32	Yes	Yes	No	Yes	Yes	Yes
PS33	Yes	Yes	No	Yes	Yes	Yes
PS34	Yes	Yes	Yes	Yes	Yes	Yes

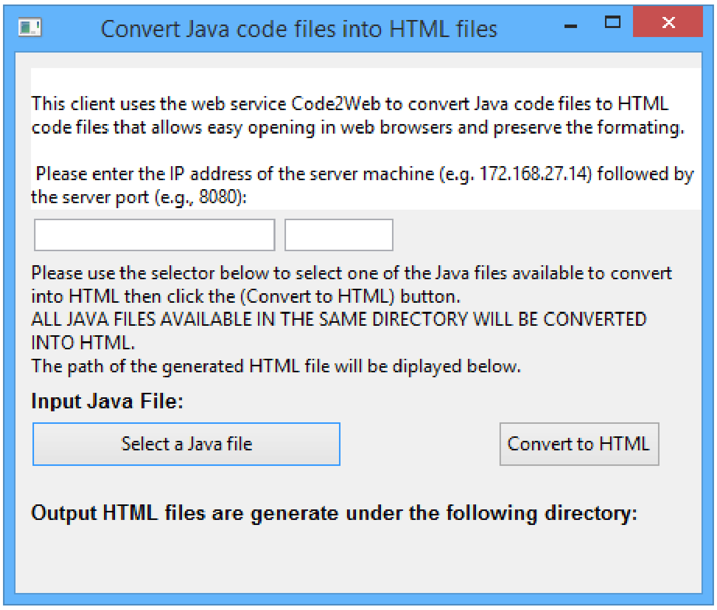
Appendix C. Dataset

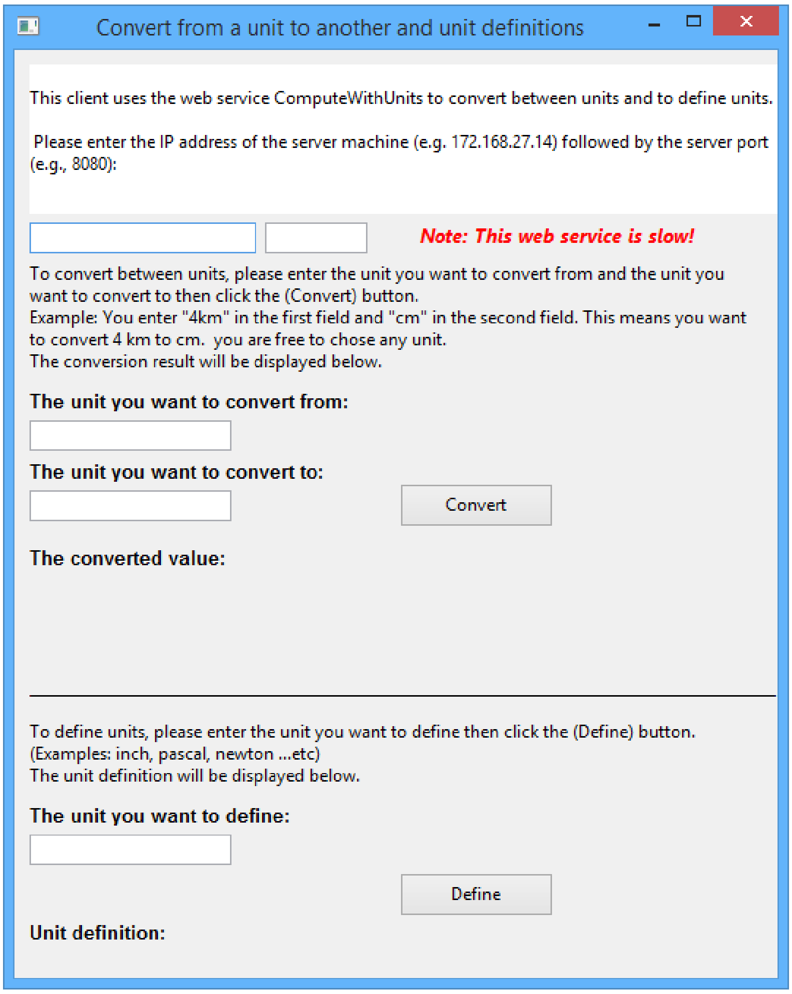
DIST	ABST	WM	NOM	LCPM	ABD	LOC	CC	WMC	LCOM	I	CA	CE	DCBO	OMI	DC	DMI	AVAILABILITY	SUCCESSABILITY	ACCESSIBILITY
0	0	86	38	11.15	1.04	565	2.26	7.6	0.24	1	0	10	2	3.375	1.5	22.998	1	1	0.783
0	0	63	32	7.5	1.08	322	1.56	14.2	0.39	1	0	4	1.5	1.846	1.707	9.864	1	1	0.929
0.19	19.2	357	114	8.94	1.1	1417	2.66	16.43	0.26	0.48	3.86	3.57	5.495	3.353	2.347	94.475	0.95	1	0.86
0.19	20	76	9	21.54	0.61	278	2.45	13.75	0	1	0	5	1.994	1.333	1	7.976	1	0.442	0.798
0	0	135	25	16.53	1.41	594	4.21	32.75	0.21	1	0	4	1.5	1.615	1.077	15.984	1	1	0.861
0	0	16	4	18.19	1.5	108	3.2	8	0	1	2	0	1	1.5	1	3	1	0.413	0.813
0	0	6	2	18.5	3.5	68	2.5	5	0	1	2	0	5	6.5	5	13	1	1	0.924
0	0	54	7	25.85	2.14	193	7.714	27	0	1	0	2	1	2.328	1.333	6.983	1	1	0.95
0	0	30	12	12.07	1,71	194	2.417	5.8	0	1	0	5	1	2	1.333	5	1	1	0.804
0.27	27.2	535	68	19.51	1,28	1842	5.778	58.5	0.062	0.666	4	8	3.661	6.047	2.649	107.961	1	0.988	0.891
0	0	17	2	33	3.5	91	2	2	0	1	0	2	4	7	4	14	1	0.985	0.882
0	0	296	87	13.87	1.86	1356	3.326	74	0.333	1	0	4	8.723	3.168	2.322	52.139	1	0.472	0.789
0	0	85	51	6.47	0.86	451	1.545	10.625	0.452	1	0	8	4.198	4.443	2.237	61.609	1	1	0.846
0	0	15	2	17.5	2	75	7.5	7.5	0	1	0	2	1	1	1	2	1	1	0.924
0	0	160	28	21.86	1.63	583	5.64	28.2	0	1	0	5	2.904	1.129	1	6.776	1	0.977	0.943
0.16	16	1310	395	10	0.9	4947	3.02	25.604	0.251	1	0	48	3.178	3.679	1.551	256.915	1	0.977	0.789
0.18	18.7	323	151	6.9	0.84	1395	1.897	10.433	0.334	0.537	25	29	2.83		2.043		1	0.994	0.861
0	0	19	5	12.83	2.16	92	3.167	9.5	0	1	0	2	1	1	1	4	1	1	0.879
0.03	3.3	1001	180	22.8	1.75	6058	5.542	42.652	0.317	0.852	4	23	2.75	2.579	1.527	38	1	0.844	0.121
0	0	18	8	10.33	1.72	110	1.875	7.5	0.25	1	0	2	1	2	1	2	1	1	0.879

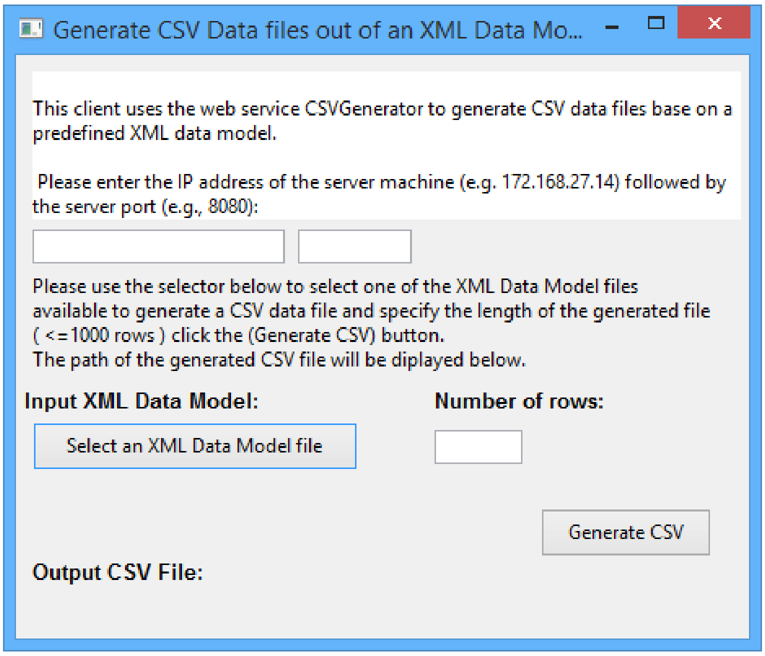
Table 21: Dataset collected during the study

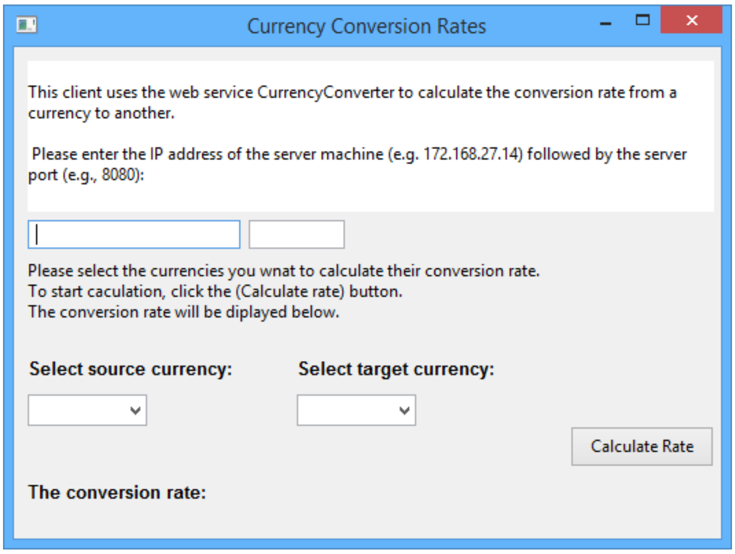
Appendix D. WSs clients GUIs

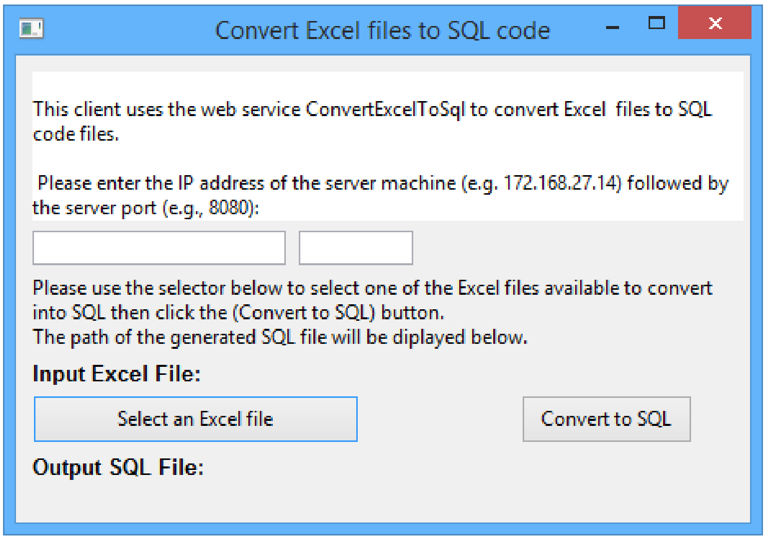


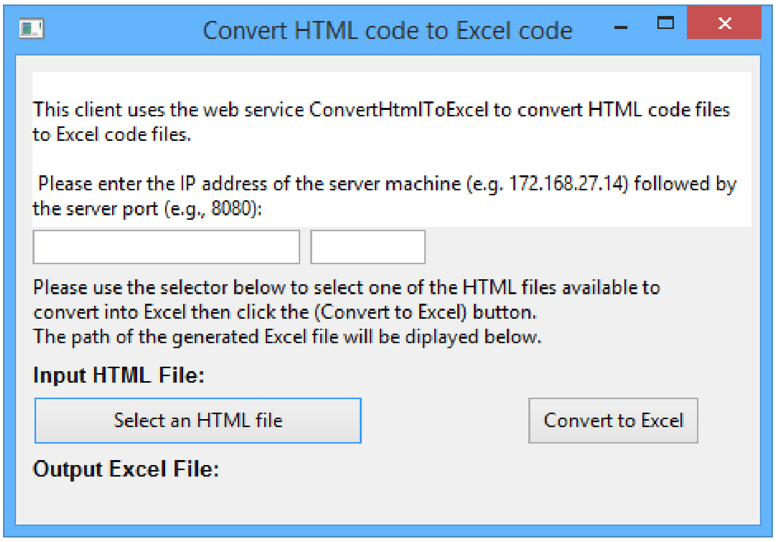


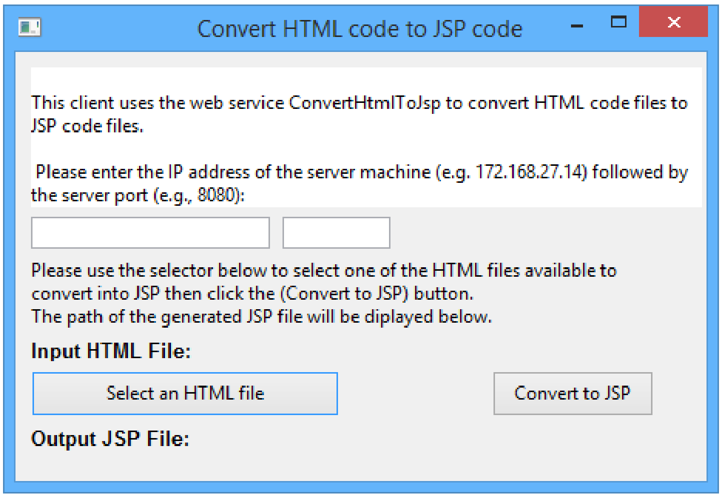

Convert from a unit to another and unit definitions
This client uses the web service ComputeWithUnits to convert between units and to define units.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Note: This web service is slow!
To convert between units, please enter the unit you want to convert from and the unit you want to convert to then click the (Convert) button.
Example: You enter "4km" in the first field and "cm" in the second field. This means you want to convert 4 km to cm. you are free to chose any unit.
The conversion result will be displayed below.
The unit you want to convert from:
The unit you want to convert to:
Convert
The converted value:
To define units, please enter the unit you want to define then click the (Define) button.
(Examples: inch, pascal, newton ...etc)
The unit definition will be displayed below.
The unit you want to define:
Define
Unit definition:

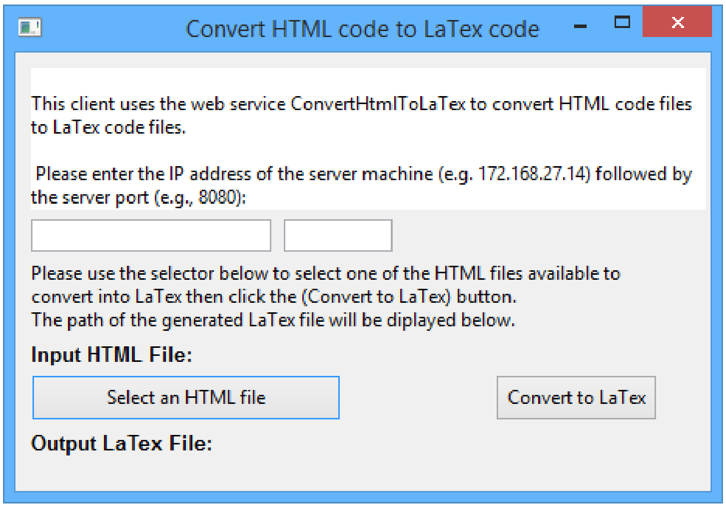

Generate CSV Data files out of an XML Data Mo...
This client uses the web service CSVGenerator to generate CSV data files base on a predefined XML data model.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the XML Data Model files available to generate a CSV data file and specify the length of the generated file (<=1000 rows) click the (Generate CSV) button.
The path of the generated CSV file will be diplayed below.
Input XML Data Model:
Number of rows:
Select an XML Data Model file
Generate CSV
Output CSV File:

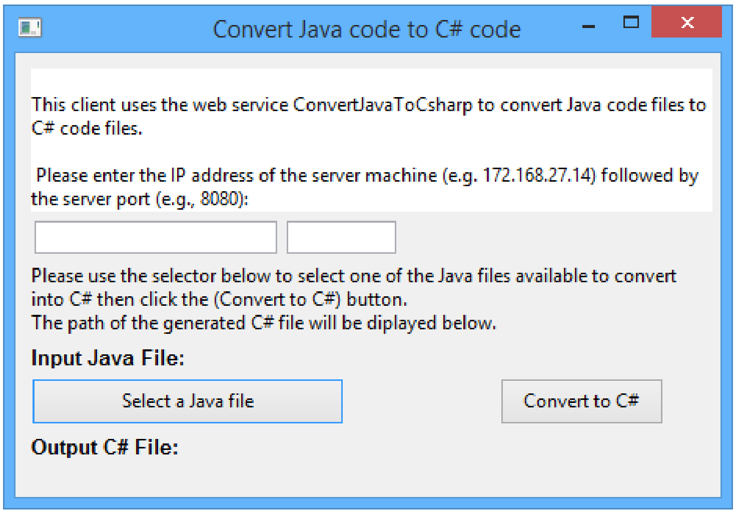

Currency Conversion Rates
This client uses the web service CurrencyConverter to calculate the conversion rate from a currency to another.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please select the currencies you wnat to calculate their conversion rate.
To start caculation, click the (Calculate rate) button.
The conversion rate will be diplayed below.
Select source currency:
Select target currency:
Calculate Rate
The conversion rate:

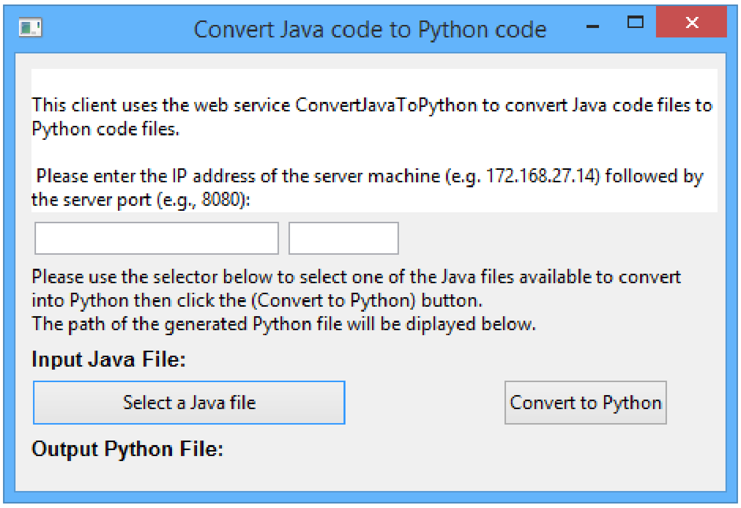

Convert Excel files to SQL code
This client uses the web service ConvertExcelToSql to convert Excel files to SQL code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the Excel files available to convert into SQL then click the (Convert to SQL) button.
The path of the generated SQL file will be diplayed below.
Input Excel File:
Select an Excel file
Convert to SQL
Output SQL File:

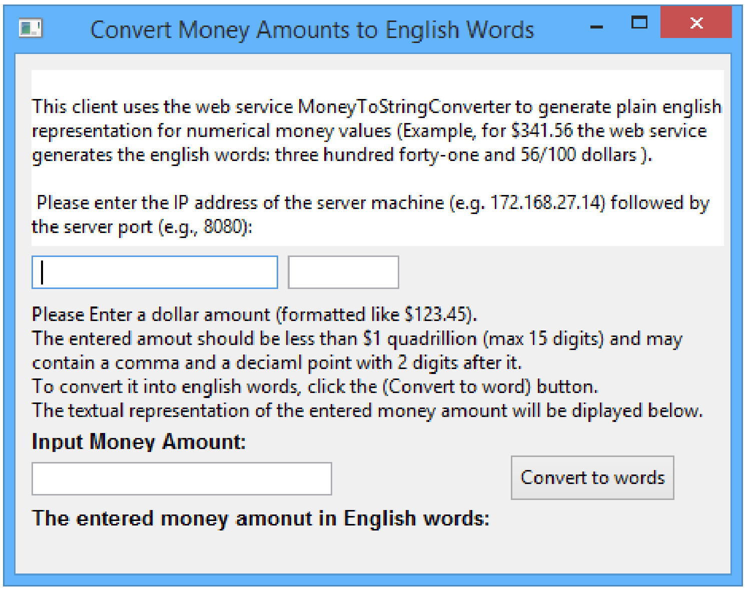

Convert HTML code to Excel code
This client uses the web service ConvertHtmlToExcel to convert HTML code files to Excel code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the HTML files available to convert into Excel then click the (Convert to Excel) button.
The path of the generated Excel file will be diplayed below.
Input HTML File:
Select an HTML file
Convert to Excel
Output Excel File:

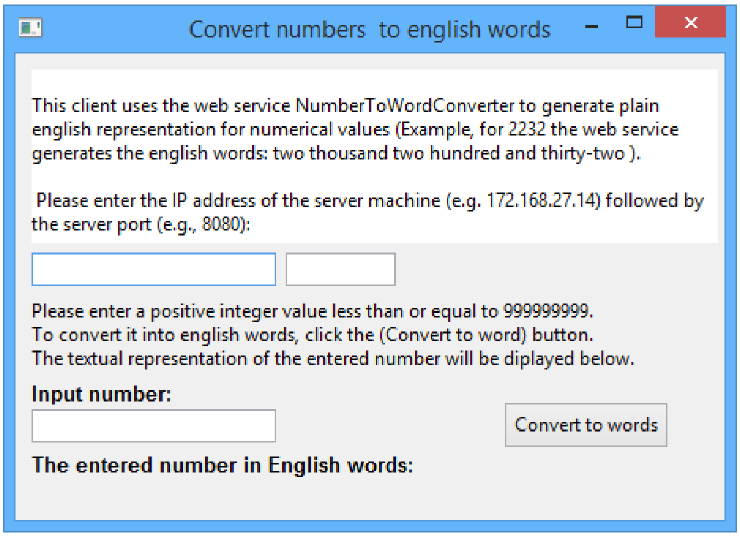

Convert HTML code to JSP code
This client uses the web service ConvertHtmlToJsp to convert HTML code files to JSP code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the HTML files available to convert into JSP then click the (Convert to JSP) button.
The path of the generated JSP file will be diplayed below.
Input HTML File:
Select an HTML file
Convert to JSP
Output JSP File:

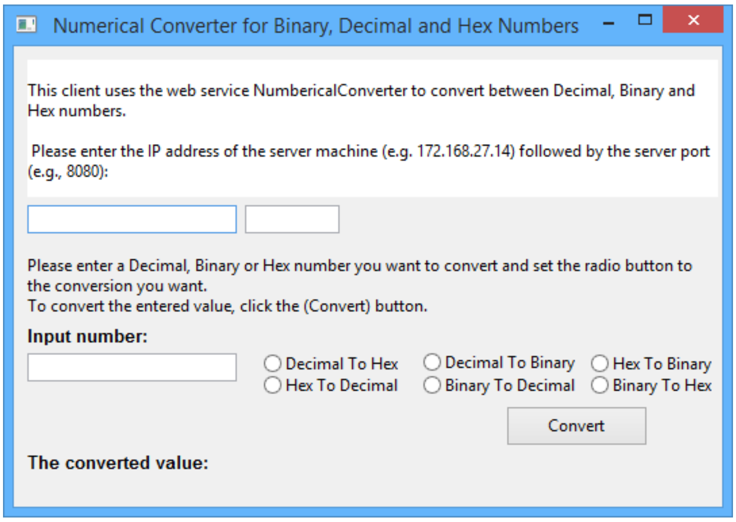

Convert HTML code to LaTex code
This client uses the web service ConvertHtmlToLaTex to convert HTML code files to LaTex code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the HTML files available to convert into LaTex then click the (Convert to LaTex) button.
The path of the generated LaTex file will be diplayed below.
Input HTML File:
Select an HTML file
Convert to LaTex
Output LaTex File:

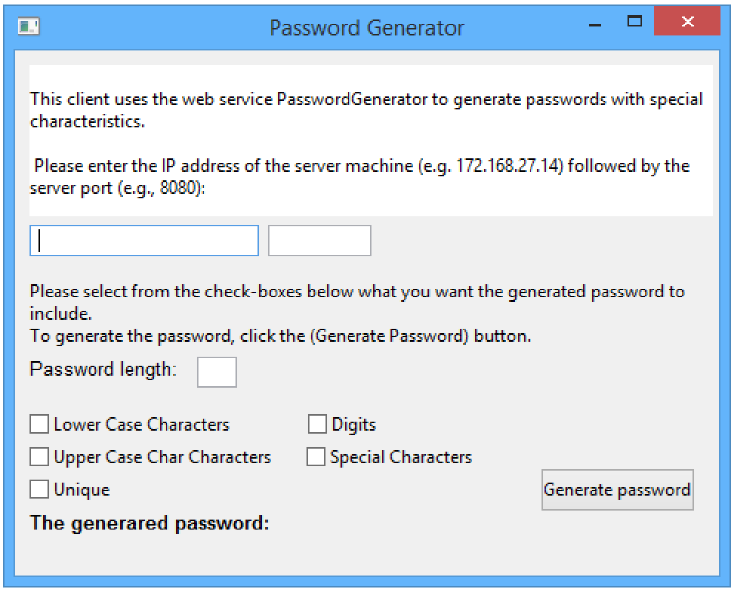

Convert Java code to C# code
This client uses the web service ConvertJavaToCsharp to convert Java code files to C# code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the Java files available to convert into C# then click the (Convert to C#) button.
The path of the generated C# file will be diplayed below.
Input Java File:
Select a Java file
Convert to C#
Output C# File:

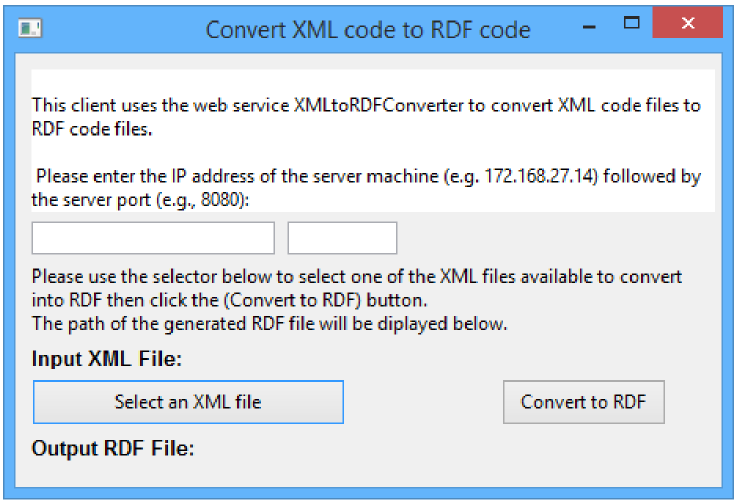

Convert Java code to Python code
This client uses the web service ConvertJavaToPython to convert Java code files to Python code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the Java files available to convert into Python then click the (Convert to Python) button.
The path of the generated Python file will be diplayed below.
Input Java File:
Select a Java file
Convert to Python
Output Python File:

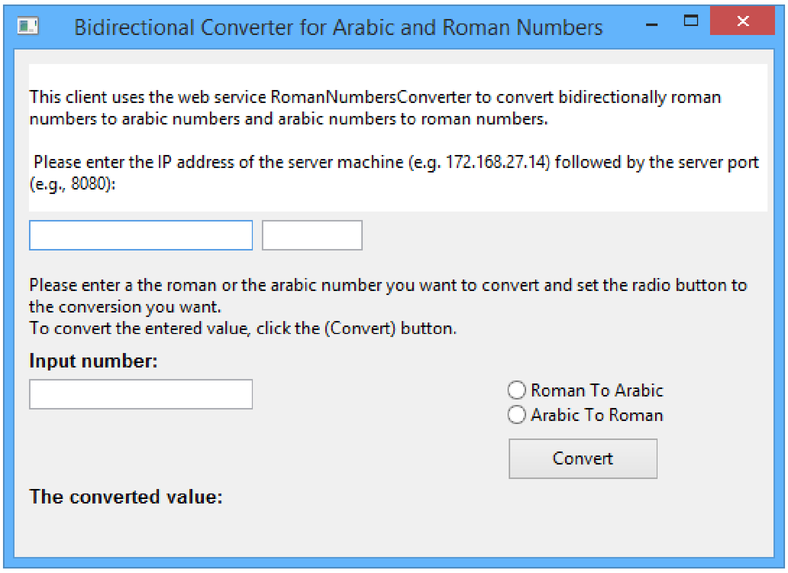

Convert Money Amounts to English Words
This client uses the web service MoneyToStringConverter to generate plain english representation for numerical money values (Example, for $341.56 the web service generates the english words: three hundred forty-one and 56/100 dollars).
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please Enter a dollar amount (formatted like $123.45).
The entered amout should be less than $1 quadrillion (max 15 digits) and may contain a comma and a deciaml point with 2 digits after it.
To convert it into english words, click the (Convert to word) button.
The textual representation of the entered money amount will be diplayed below.
Input Money Amount:
Convert to words
The entered money amonut in English words:

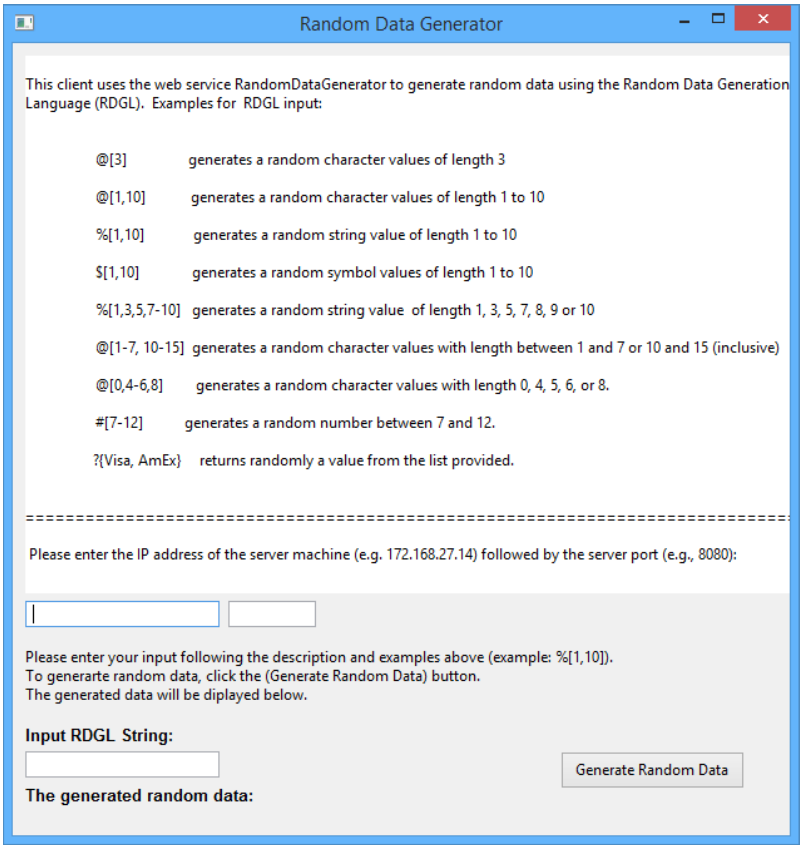

Convert numbers to english words
This client uses the web service NumberToWordConverter to generate plain english representation for numerical values (Example, for 2232 the web service generates the english words: two thousand two hundred and thirty-two).
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please enter a positive integer value less than or equal to 999999999.
To convert it into english words, click the (Convert to word) button.
The textual representation of the entered number will be diplayed below.
Input number:
Convert to words
The entered number in English words:

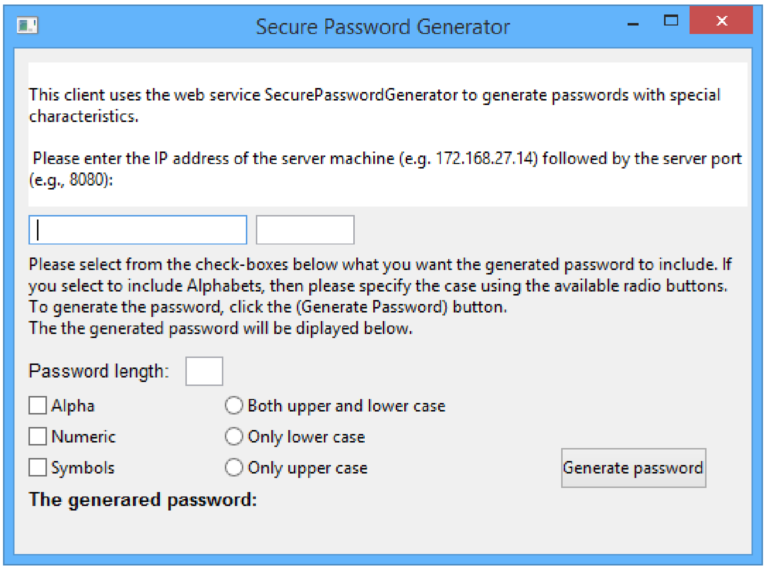

Numerical Converter for Binary, Decimal and Hex Numbers
This client uses the web service NumbericalConverter to convert between Decimal, Binary and Hex numbers.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please enter a Decimal, Binary or Hex number you want to convert and set the radio button to the conversion you want.
To convert the entered value, click the (Convert) button.
Input number:
Decimal To Hex
Decimal To Binary
Hex To Binary
Hex To Decimal
Binary To Decimal
Binary To Hex
Convert
The converted value:

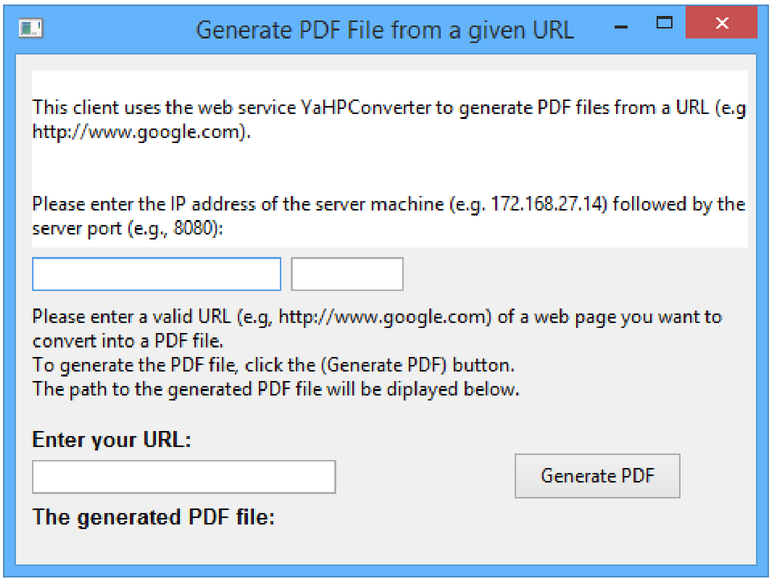

Password Generator
This client uses the web service PasswordGenerator to generate passwords with special characteristics.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please select from the check-boxes below what you want the generated password to include.
To generate the password, click the (Generate Password) button.
Password length:
Lower Case Characters
Digits
Upper Case Char Characters
Special Characters
Unique
Generate password
The generared password:


Convert XML code to RDF code
This client uses the web service XMLtoRDFConverter to convert XML code files to RDF code files.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please use the selector below to select one of the XML files available to convert into RDF then click the (Convert to RDF) button.
The path of the generated RDF file will be diplayed below.
Input XML File:
Select an XML file
Convert to RDF
Output RDF File:


Bidirectional Converter for Arabic and Roman Numbers
This client uses the web service RomanNumbersConverter to convert bidirectionally roman numbers to arabic numbers and arabic numbers to roman numbers.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please enter a the roman or the arabic number you want to convert and set the radio button to the conversion you want.
To convert the entered value, click the (Convert) button.
Input number:
Roman To Arabic
Arabic To Roman
Convert
The converted value:


Random Data Generator
This client uses the web service RandomDataGenerator to generate random data using the Random Data Generation Language (RDGL). Examples for RDGL input:
@[3] generates a random character values of length 3
@[1,10] generates a random character values of length 1 to 10
%[1,10] generates a random string value of length 1 to 10
$[1,10] generates a random symbol values of length 1 to 10
%[1,3,5,7-10] generates a random string value of length 1, 3, 5, 7, 8, 9 or 10
@[1-7, 10-15] generates a random character values with length between 1 and 7 or 10 and 15 (inclusive)
@[0,4-6,8] generates a random character values with length 0, 4, 5, 6, or 8.
#[7-12] generates a random number between 7 and 12.
?{Visa, AmEx} returns randomly a value from the list provided.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please enter your input following the description and examples above (example: %[1,10]).
To generarte random data, click the (Generate Random Data) button.
The generated data will be diplayed below.
Input RDGL String:
Generate Random Data
The generated random data:


Secure Password Generator
This client uses the web service SecurePasswordGenerator to generate passwords with special characteristics.
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please select from the check-boxes below what you want the generated password to include. If you select to include Alphabets, then please specify the case using the available radio buttons.
To generate the password, click the (Generate Password) button.
The the generated password will be diplayed below.
Password length:
Alpha
Numeric
Symbols
Both upper and lower case
Only lower case
Only upper case
Generate password
The generared password:


Generate PDF File from a given URL
This client uses the web service YaHPConverter to generate PDF files from a URL (e.g http://www.google.com).
Please enter the IP address of the server machine (e.g. 172.168.27.14) followed by the server port (e.g., 8080):
Please enter a valid URL (e.g, http://www.google.com) of a web page you want to convert into a PDF file.
To generate the PDF file, click the (Generate PDF) button.
The path to the generated PDF file will be diplayed below.
Enter your URL:
Generate PDF
The generated PDF file:

Appendix E. GLM models

1. R script used for building the GLM models

```
#########
# R script to build models for the Accessibility, Availability and
#Successability using the GLM package (glm())
#########

# Read all data points from .csv file
dataset <-read.csv("D:/Experiment/Analysis/Dataset.csv")
attach(dataset)

internalmetrics.array <- c("DIST","ABST", "WM", "NOM","LCPM","ABD","LOC","CC",
                           "WMC","LCOM","I","CA","CE","DCBO","OMI","DC","DMI")

externalmetrics.array <- c("ACCESSIBILITY","AVAILABILITY","SUCCESSABILITY")

require(combinat)
require(pscl)

numberOfindpVar = length(internalmetrics.array)

counter = 1

for (t in 1:numberOfindpVar) {

  # combination of numberOfindpVar independent variable at the time
  internalmetrics<- combn(internalmetrics.array, t)

  myFile <- paste("D:/Experiment/Analysis/Output/Output_",t,".txt")

  # output directed to file (appended to existing file) and sent to terminal.
  sink(myFile,append=TRUE, split=TRUE)

  for (n in 1:length(externalmetrics.array)) {
        dependent.var <- externalmetrics.array[n]

        length1 <- (length(internalmetrics)/t)

        for (i in 1: length1 )  {

          indpVar <- ""
          if (t == length(internalmetrics.array)){
            for (k in 1: t )  {
              if (k<t)
               indpVar <- paste (indpVar,internalmetrics.array[k], "+")
           else {
             indpVar <- paste (indpVar,internalmetrics.array[k])

           }
         }
      }

      else {

          for (k in 1: t )  {
            if (k<t)
              indpVar <- paste (indpVar, internalmetrics[k,i], "+")
            else
              indpVar <- paste (indpVar, internalmetrics[k,i])
          }

      }
          formulastr <- paste ( dependent.var, "~" , indpVar)
```

```
            lregression.model <- glm(as.formula(formulastr),
                                                 family=binomial(link = "logit"))

            # Check significance of the coefficients (p-value must be <= 0.05)
            p.valueLow = TRUE
            for (m in 1: t )  {
           tmpBoolean <- summary(lregression.model)$coefficients[m+1,4] <= 0.05
           p.valueLow = p.valueLow && tmpBoolean
            }

          if (p.valueLow ){
              cat("==============================================","\n\n")
              cat(paste(dependent.var, "Vs " ,indpVar, "\n\n"))
              cat(paste("Counter: ",counter,  "\n\n"))

               # calculate Nagelkerke (Cragg & Uhler's) R2 (pscl package)
               # and paste it into the output file after the summary
                R2pseudo <- pR2(lregression.model)

              capture.output(summary(lregression.model),
                                         file = myFile, append = TRUE)
              cat(paste("R2 (Nagelkerke): ",as.numeric(R2pseudo[6]),  "\n"))

            }
            counter = counter+1
       }
     }
     closeAllConnections()
     sink()
  }
```

2. GLM models built with the complete dataset

Note: Since the number of identified significant models (7178) is very large and more than 192130 lines will be needed to accommodate all models in this document, we listed only three models for each combination of predictors of specific size (i.e., where possible, three models with 2 predictors, three models with 3 predictors, etc.)

```
================================================================================
AVAILABILITY Vs   DIST + LCPM + WMC + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.137e+15  4.504e+07  25234804   <2e-16 ***
DIST        -9.132e+14  1.815e+08  -5031181   <2e-16 ***
LCPM         2.483e+14  2.302e+06 107823299   <2e-16 ***
WMC         -5.566e+12  8.440e+05  -6595174   <2e-16 ***
DC          -1.013e+15  1.492e+07 -67924460   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999911
================================================================================
AVAILABILITY Vs   ABST + LCPM + WMC + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  4.303e+15  4.505e+07  95523172   <2e-16 ***
ABST        -6.564e+13  1.775e+06 -36970494   <2e-16 ***
LCPM        -7.184e+13  2.300e+06 -31235097   <2e-16 ***
WMC          3.540e+13  8.426e+05  42010800   <2e-16 ***
DC          -1.117e+14  1.491e+07  -7491260   <2e-16 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999911
===============================================================================
AVAILABILITY Vs   WM + LCPM + DCBO + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -2.529e+14  4.938e+07  -5122312   <2e-16 ***
WM          -2.306e+12  8.396e+04 -27462021   <2e-16 ***
LCPM         1.595e+14  2.551e+06  62504038   <2e-16 ***
DCBO        -5.125e+13  8.327e+06  -6154190   <2e-16 ***
DMI          1.079e+13  5.309e+05  20327671   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  0.999999999999894
===============================================================================
SUCCESSABILITY Vs   LOC + I + CA + CE + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  6.795e+15  2.045e+08  33222304   <2e-16 ***
LOC         -9.883e+11  2.885e+04 -34257505   <2e-16 ***
I           -5.910e+15  2.016e+08 -29314631   <2e-16 ***
CA           2.003e+14  2.573e+07   7783914   <2e-16 ***
CE           1.504e+14  3.814e+06  39449939   <2e-16 ***
OMI          8.924e+13  9.505e+06   9389210   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -57998.8314775996
===============================================================================
AVAILABILITY Vs   ABST + ABD + LOC + CC + LCOM

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  3.902e+15  8.145e+07  47900792   <2e-16 ***
ABST         2.393e+13  2.217e+06  10795532   <2e-16 ***
ABD         -2.779e+13  2.760e+07  -1007091   <2e-16 ***
LOC          3.167e+11  1.241e+04  25513796   <2e-16 ***
CC          -4.183e+14  9.832e+06 -42547020   <2e-16 ***
LCOM        -4.014e+15  1.473e+08 -27242472   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999911
===============================================================================
SUCCESSABILITY Vs   LOC + I + CA + CE + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  6.795e+15  2.045e+08  33222304   <2e-16 ***
LOC         -9.883e+11  2.885e+04 -34257505   <2e-16 ***
I           -5.910e+15  2.016e+08 -29314631   <2e-16 ***
CA           2.003e+14  2.573e+07   7783914   <2e-16 ***
CE           1.504e+14  3.814e+06  39449939   <2e-16 ***
OMI          8.924e+13  9.505e+06   9389210   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -57998.8314775996
===============================================================================
SUCCESSABILITY Vs   DIST + WM + WMC + I + CE + OMI

Coefficients:
              Estimate Std. Error    z value Pr(>|z|)
(Intercept)  2.433e+16  2.350e+08  103516381   <2e-16 ***
DIST        -9.056e+15  2.989e+08  -30294411   <2e-16 ***
WM          -1.710e+13  2.432e+05  -70291493   <2e-16 ***
WMC          2.600e+13  1.359e+06   19132634   <2e-16 ***
I           -2.499e+16  2.480e+08 -100744971   <2e-16 ***
```

```
CE           5.685e+14  7.155e+06   79460771   <2e-16 ***
OMI          1.412e+14  8.826e+06   16003379   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

  (1 observation deleted due to missingness)
R2 (McFadden):  0.999999999999999
R2 (Nagelkerke): 1
================================================================================
AVAILABILITY Vs   WM + ABD + LOC + WMC + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  1.396e+14  4.979e+07   2803436   <2e-16 ***
WM           1.202e+13  5.524e+05  21765714   <2e-16 ***
ABD          6.473e+14  3.095e+07  20915584   <2e-16 ***
LOC         -1.647e+12  8.498e+04 -19381448   <2e-16 ***
WMC          2.291e+13  9.973e+05  22967676   <2e-16 ***
OMI          3.437e+14  1.408e+07  24405879   <2e-16 ***
DMI         -2.445e+13  1.332e+06 -18362727   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  0.999999999999894
================================================================================
AVAILABILITY Vs   NOM + LOC + CC + WMC + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -1.705e+15  5.647e+07 -30197079   <2e-16 ***
NOM          2.882e+13  1.067e+06  27009355   <2e-16 ***
LOC         -8.893e+11  3.282e+04 -27101116   <2e-16 ***
CC           6.354e+14  1.014e+07  62675683   <2e-16 ***
WMC          4.762e+13  1.052e+06  45278059   <2e-16 ***
OMI          2.423e+14  1.201e+07  20182265   <2e-16 ***
DMI         -1.639e+13  1.121e+06 -14619521   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  0.999999999999894
================================================================================
AVAILABILITY Vs   NOM + ABD + LOC + CC + WMC + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  3.057e+13  5.671e+07    539116   <2e-16 ***
NOM          6.690e+13  1.342e+06  49863869   <2e-16 ***
ABD          2.369e+14  3.836e+07   6174948   <2e-16 ***
LOC         -1.637e+12  3.867e+04 -42338251   <2e-16 ***
CC           3.774e+14  1.259e+07  29967083   <2e-16 ***
WMC          2.671e+13  1.054e+06  25326897   <2e-16 ***
OMI          4.368e+14  2.090e+07  20897503   <2e-16 ***
DMI         -7.022e+13  1.564e+06 -44893599   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  0.999999999999916
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + LCPM + LOC + I + CE

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  1.452e+16  2.031e+08  71514287   <2e-16 ***
DIST        -4.522e+16  1.764e+10  -2563227   <2e-16 ***
ABST         2.538e+14  1.687e+08   1503815   <2e-16 ***
WM           1.502e+12  5.528e+05   2717884   <2e-16 ***
LCPM         6.850e+13  2.623e+06  26115405   <2e-16 ***
LOC         -9.733e+11  9.089e+04 -10708941   <2e-16 ***
I           -1.524e+16  2.052e+08 -74302532   <2e-16 ***
CE           1.695e+14  4.011e+06  42264782   <2e-16 ***
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -963.609277456143
================================================================================
SUCCESSABILITY Vs   ABST + LOC + CC + I + CA + CE + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.118e+16  2.426e+08  46092544   <2e-16 ***
ABST        -6.692e+12  3.049e+06  -2194652   <2e-16 ***
LOC         -9.783e+09  3.212e+04   -304565   <2e-16 ***
CC           1.587e+14  9.110e+06  17420579   <2e-16 ***
I           -1.214e+16  2.400e+08 -50576698   <2e-16 ***
CA          -4.933e+14  2.615e+07 -18865903   <2e-16 ***
CE           4.371e+13  4.550e+06   9606031   <2e-16 ***
OMI          4.364e+14  9.834e+06  44376109   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1303.57350606885
================================================================================
AVAILABILITY Vs   WM + LCPM + ABD + LOC + CC + WMC + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -9.282e+14  6.476e+07 -14333194   <2e-16 ***
WM          -2.325e+12  6.988e+05  -3327186   <2e-16 ***
LCPM         7.998e+13  4.261e+06  18770964   <2e-16 ***
ABD          9.315e+14  3.212e+07  28998019   <2e-16 ***
LOC          3.429e+11  1.043e+05   3287949   <2e-16 ***
CC           1.543e+14  1.191e+07  12956074   <2e-16 ***
WMC          1.631e+13  1.089e+06  14974581   <2e-16 ***
OMI         -6.882e+13  1.756e+07  -3919380   <2e-16 ***
DMI          1.575e+13  1.765e+06   8921974   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  0.999999999999916
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + I + CE

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  2.767e+16  2.868e+08  96484090   <2e-16 ***
DIST        -8.752e+17  2.010e+10 -43532714   <2e-16 ***
ABST         8.014e+15  1.908e+08  42000536   <2e-16 ***
WM           4.797e+13  8.762e+05  54745494   <2e-16 ***
NOM         -5.558e+13  1.127e+06 -49306665   <2e-16 ***
ABD         -8.102e+14  2.482e+07 -32638627   <2e-16 ***
LOC         -7.023e+12  1.296e+05 -54199329   <2e-16 ***
I           -2.494e+16  2.719e+08 -91737372   <2e-16 ***
CE           1.093e+14  4.441e+06  24614242   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -35481.9898019734
================================================================================
SUCCESSABILITY Vs   ABST + ABD + LOC + WMC + I + CA + CE + DCBO

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.318e+16  2.367e+08  55708594   <2e-16 ***
ABST         4.186e+12  3.125e+06   1339580   <2e-16 ***
ABD          2.063e+14  2.631e+07   7838520   <2e-16 ***
LOC         -5.701e+11  2.463e+04 -23144278   <2e-16 ***
WMC         -4.837e+13  1.270e+06 -38094788   <2e-16 ***
I           -1.248e+16  2.428e+08 -51390344   <2e-16 ***
CA          -2.512e+14  5.659e+06 -44380205   <2e-16 ***
CE           1.252e+14  3.705e+06  33795364   <2e-16 ***
DCBO         1.790e+14  1.048e+07  17085332   <2e-16 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -1304320.61142356
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + LOC + CC + WMC + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -5.644e+14  7.103e+07  -7945889   <2e-16 ***
DIST        -6.620e+17  1.740e+10 -38035992   <2e-16 ***
ABST         6.345e+15  1.683e+08  37699178   <2e-16 ***
WM           1.529e+13  7.405e+05  20653753   <2e-16 ***
NOM         -2.135e+13  1.248e+06 -17105119   <2e-16 ***
LCPM        -3.292e+14  4.566e+06 -72096885   <2e-16 ***
LOC         -1.644e+12  9.039e+04 -18186199   <2e-16 ***
CC           1.485e+15  1.443e+07 102879325   <2e-16 ***
WMC         -8.622e+13  1.123e+06 -76752192   <2e-16 ***
OMI          1.457e+15  1.439e+07 101238386   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  1
================================================================================
=
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + LOC + CC + CE + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -6.117e+14  6.386e+07  -9579022   <2e-16 ***
DIST         3.698e+17  1.636e+10  22598588   <2e-16 ***
ABST        -3.481e+15  1.582e+08 -22008483   <2e-16 ***
WM          -2.861e+13  6.116e+05 -46775148   <2e-16 ***
NOM          9.328e+12  1.114e+06   8374410   <2e-16 ***
LCPM        -1.218e+14  4.054e+06 -30035462   <2e-16 ***
LOC          3.546e+12  8.141e+04  43559438   <2e-16 ***
CC           7.157e+14  1.212e+07  59067013   <2e-16 ***
CE           2.766e+14  4.452e+06  62125235   <2e-16 ***
DC           1.001e+15  2.026e+07  49376281   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -35481.9898019734
================================================================================
SUCCESSABILITY Vs   WM + NOM + LCPM + ABD + WMC + LCOM + CE + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.826e+15  9.835e+07  18562669   <2e-16 ***
WM           6.704e+12  2.278e+05  29430080   <2e-16 ***
NOM         -8.056e+13  1.627e+06 -49525601   <2e-16 ***
LCPM        -6.964e+13  4.551e+06 -15300024   <2e-16 ***
ABD          6.090e+14  4.579e+07  13300470   <2e-16 ***
WMC         -2.341e+13  1.367e+06 -17122597   <2e-16 ***
LCOM         3.881e+15  2.392e+08  16224483   <2e-16 ***
CE           1.774e+14  5.841e+06  30376459   <2e-16 ***
OMI         -3.256e+14  2.209e+07 -14740929   <2e-16 ***
DMI          7.233e+13  1.501e+06  48183614   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -57998.8314775996
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + CC + CE + DCBO + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -5.622e+14  6.927e+07  -8115765   <2e-16 ***
DIST         1.253e+17  1.537e+10   8152696   <2e-16 ***
ABST        -1.110e+15  1.502e+08  -7394111   <2e-16 ***
WM          -2.289e+12  1.902e+05 -12030057   <2e-16 ***
NOM         -3.236e+13  1.372e+06 -23586407   <2e-16 ***
LCPM        -3.435e+14  4.652e+06 -73838133   <2e-16 ***
```

```
ABD          2.911e+15  4.243e+07  68607940   <2e-16 ***
CC           7.961e+14  1.450e+07  54893413   <2e-16 ***
CE           3.223e+14  9.078e+06  35502406   <2e-16 ***
DCBO        -9.038e+13  1.689e+07  -5352844   <2e-16 ***
OMI          2.433e+14  2.165e+07  11233679   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1303.57350606885
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + CC + CE + DCBO + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  2.022e+14  6.433e+07   3143070   <2e-16 ***
DIST        -2.107e+17  1.118e+10 -18855422   <2e-16 ***
ABST         2.182e+15  1.093e+08  19970738   <2e-16 ***
WM          -8.928e+10  1.711e+05   -521783   <2e-16 ***
NOM         -2.663e+13  1.132e+06 -23523487   <2e-16 ***
LCPM        -2.907e+14  4.075e+06 -71324596   <2e-16 ***
ABD          2.216e+15  5.058e+07  43807907   <2e-16 ***
CC           4.330e+14  1.255e+07  34505519   <2e-16 ***
CE           2.076e+14  6.144e+06  33786446   <2e-16 ***
DCBO        -4.621e+14  1.523e+07 -30331888   <2e-16 ***
DC           1.123e+15  3.681e+07  30505313   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -35481.9898019734
================================================================================
SUCCESSABILITY Vs   ABST + LOC + CC + WMC + LCOM + I + CA + CE + DCBO + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  4.870e+14  2.997e+08   1624817   <2e-16 ***
ABST         2.025e+13  3.814e+06   5308129   <2e-16 ***
LOC         -3.663e+11  2.417e+04 -15153126   <2e-16 ***
CC           5.517e+14  1.385e+07  39832164   <2e-16 ***
WMC         -6.570e+13  1.775e+06 -37015311   <2e-16 ***
LCOM         1.157e+16  1.630e+08  71020079   <2e-16 ***
I           -1.348e+15  2.729e+08  -4938768   <2e-16 ***
CA          -8.298e+13  5.808e+06 -14286114   <2e-16 ***
CE           5.379e+13  3.779e+06  14236196   <2e-16 ***
DCBO        -2.697e+14  1.659e+07 -16251223   <2e-16 ***
DC           7.534e+14  2.347e+07  32105854   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -963.609277456143
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + LCOM + I +
DCBO

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -3.036e+15  3.846e+08  -7894558   <2e-16 ***
DIST        -1.678e+17  2.437e+10  -6885499   <2e-16 ***
ABST         1.714e+15  2.313e+08   7412826   <2e-16 ***
WM           7.932e+11  1.199e+06    661846   <2e-16 ***
NOM          1.102e+13  1.487e+06   7409362   <2e-16 ***
LCPM        -1.530e+14  4.704e+06 -32538280   <2e-16 ***
ABD          3.108e+15  4.246e+07  73217442   <2e-16 ***
LOC         -7.914e+11  1.669e+05  -4741184   <2e-16 ***
CC           8.216e+14  1.329e+07  61822458   <2e-16 ***
LCOM         1.170e+16  2.089e+08  55995635   <2e-16 ***
I            3.294e+13  3.262e+08    100970   <2e-16 ***
DCBO        -9.255e+14  1.064e+07 -87020861   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -24.5469146533793
================================================================================
```

```
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + LCOM + CE +
DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -1.525e+15  1.058e+08 -14420218   <2e-16 ***
DIST         1.640e+17  1.656e+10   9903405   <2e-16 ***
ABST        -1.438e+15  1.605e+08  -8958864   <2e-16 ***
WM          -1.704e+13  6.367e+05 -26762563   <2e-16 ***
NOM         -1.217e+13  1.159e+06 -10498381   <2e-16 ***
LCPM        -1.619e+14  4.763e+06 -33999044   <2e-16 ***
ABD          2.090e+15  6.149e+07  33986221   <2e-16 ***
LOC          1.793e+12  8.773e+04  20440770   <2e-16 ***
CC           6.552e+14  1.228e+07  53351623   <2e-16 ***
LCOM         2.506e+15  2.159e+08  11608097   <2e-16 ***
CE           3.281e+14  4.542e+06  72241252   <2e-16 ***
DC          -1.055e+14  3.357e+07  -3143855   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -35481.9898019734
==============================================================================
SUCCESSABILITY Vs   LCPM + LOC + WMC + LCOM + I + CA + CE + DCBO + OMI + DC +
DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.698e+16  3.067e+08  55373242   <2e-16 ***
LCPM        -5.032e+14  5.343e+06 -94176747   <2e-16 ***
LOC          4.446e+12  7.968e+04  55801057   <2e-16 ***
WMC          3.939e+13  1.786e+06  22049672   <2e-16 ***
LCOM        -1.634e+16  2.281e+08 -71638681   <2e-16 ***
I           -6.799e+15  3.165e+08 -21483155   <2e-16 ***
CA          -2.576e+15  3.809e+07 -67626567   <2e-16 ***
CE          -4.645e+14  1.491e+07 -31144764   <2e-16 ***
DCBO        -1.308e+15  1.846e+07 -70867136   <2e-16 ***
OMI          8.574e+14  3.214e+07  26676828   <2e-16 ***
DC           1.986e+15  5.741e+07  34600235   <2e-16 ***
DMI         -5.803e+12  1.439e+06  -4034282   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1303.57350606885
==============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + WMC + CE +
DCBO + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -4.831e+15  1.157e+08 -41751427   <2e-16 ***
DIST         1.343e+18  2.975e+10  45148457   <2e-16 ***
ABST        -1.272e+16  2.849e+08 -44640150   <2e-16 ***
WM          -6.552e+13  1.435e+06 -45643557   <2e-16 ***
NOM         -1.319e+13  1.957e+06  -6742510   <2e-16 ***
LCPM        -1.533e+14  5.438e+06 -28194664   <2e-16 ***
ABD          3.855e+15  5.566e+07  69263914   <2e-16 ***
LOC          8.209e+12  1.649e+05  49767302   <2e-16 ***
CC           8.368e+14  1.512e+07  55331838   <2e-16 ***
WMC          6.063e+12  2.707e+06   2240123   <2e-16 ***
CE           9.406e+14  1.360e+07  69138323   <2e-16 ***
DCBO         4.517e+14  2.533e+07  17835531   <2e-16 ***
OMI         -1.044e+15  2.818e+07 -37048855   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  1
==============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + LCOM + CA +
OMI + DMI

Coefficients:
```

```
             Estimate Std. Error    z value Pr(>|z|)    
(Intercept)  6.078e+15  1.072e+08   56674097   <2e-16 ***
DIST         2.593e+18  2.433e+10  106572662   <2e-16 ***
ABST        -2.482e+16  2.334e+08 -106369971   <2e-16 ***
WM          -8.342e+13  9.332e+05  -89385363   <2e-16 ***
NOM          7.242e+13  2.002e+06   36182004   <2e-16 ***
LCPM        -1.323e+14  5.766e+06  -22941825   <2e-16 ***
ABD         -4.405e+14  5.360e+07   -8219423   <2e-16 ***
LOC          1.458e+13  1.643e+05   88751840   <2e-16 ***
CC           6.942e+13  1.571e+07    4420158   <2e-16 ***
LCOM        -1.372e+16  2.181e+08  -62922396   <2e-16 ***
CA          -2.669e+15  2.820e+07  -94645042   <2e-16 ***
OMI          4.760e+14  2.963e+07   16065778   <2e-16 ***
DMI         -4.532e+13  3.042e+06  -14899387   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -27.7118031256598
================================================================================
SUCCESSABILITY Vs   WM + NOM + LCPM + ABD + LOC + CC + WMC + CE + DCBO + OMI +
DC + DMI

Coefficients:
             Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  6.633e+14  7.468e+07   8881768   <2e-16 ***
WM          -6.049e+11  9.982e+05   -606033   <2e-16 ***
NOM         -4.258e+13  2.173e+06 -19596093   <2e-16 ***
LCPM        -1.975e+14  5.019e+06 -39356064   <2e-16 ***
ABD         -2.398e+14  4.701e+07  -5101874   <2e-16 ***
LOC          5.880e+10  1.574e+05    373599   <2e-16 ***
CC           5.954e+14  1.547e+07  38496981   <2e-16 ***
WMC         -3.208e+13  2.300e+06 -13949945   <2e-16 ***
CE           4.116e+14  8.049e+06  51139268   <2e-16 ***
DCBO         5.288e+14  2.517e+07  21008560   <2e-16 ***
OMI         -1.217e+14  5.044e+07  -2413648   <2e-16 ***
DC           1.168e+15  7.136e+07  16371111   <2e-16 ***
DMI         -5.114e+12  3.419e+06  -1495544   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1303.57350606885
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + WMC + LCOM + I +
CE + DCBO + DC

Coefficients:
             Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.317e+15  4.336e+08   3037193   <2e-16 ***
DIST        -2.806e+17  3.237e+10  -8669797   <2e-16 ***
ABST         2.788e+15  3.065e+08   9096477   <2e-16 ***
WM           5.964e+13  1.655e+06  36026515   <2e-16 ***
NOM         -1.333e+14  2.430e+06 -54872766   <2e-16 ***
LCPM        -1.623e+14  4.685e+06 -34643208   <2e-16 ***
ABD          5.329e+15  6.881e+07  77439544   <2e-16 ***
LOC         -6.816e+12  2.195e+05 -31048026   <2e-16 ***
WMC         -1.014e+14  2.376e+06 -42681691   <2e-16 ***
LCOM         1.926e+16  2.491e+08  77302756   <2e-16 ***
I           -3.441e+15  3.688e+08  -9331528   <2e-16 ***
CE           2.258e+14  6.697e+06  33722781   <2e-16 ***
DCBO         6.815e+14  2.513e+07  27123967   <2e-16 ***
DC          -2.891e+15  4.964e+07 -58240503   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -24.5469146533793
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + WMC + LCOM + CA
+ CE + DCBO + DC

Coefficients:
             Estimate Std. Error   z value Pr(>|z|)
```

```
(Intercept) -3.502e+15  1.173e+08 -29864357   <2e-16 ***
DIST         5.216e+17  2.035e+10  25632619   <2e-16 ***
ABST        -4.815e+15  1.946e+08 -24745552   <2e-16 ***
WM           5.010e+12  1.337e+06   3746582   <2e-16 ***
NOM         -8.676e+13  2.095e+06 -41420652   <2e-16 ***
LCPM        -1.564e+14  4.538e+06 -34460855   <2e-16 ***
ABD          6.803e+15  6.887e+07  98790038   <2e-16 ***
LOC          3.673e+11  1.620e+05   2267010   <2e-16 ***
WMC         -1.160e+14  2.738e+06 -42350706   <2e-16 ***
LCOM         1.355e+16  2.511e+08  53979547   <2e-16 ***
CA          -1.190e+14  7.647e+06 -15565719   <2e-16 ***
CE           5.124e+14  8.374e+06  61183253   <2e-16 ***
DCBO         9.216e+14  2.600e+07  35451693   <2e-16 ***
DC          -3.835e+15  4.758e+07 -80603039   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R2 (Nagelkerke):  1
==============================================================================
SUCCESSABILITY Vs   ABST + WM + NOM + ABD + LOC + CC + WMC + LCOM + CA + CE +
DCBO + OMI + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.156e+15  2.491e+08   4641068   <2e-16 ***
ABST        -9.820e+13  7.368e+06 -13327518   <2e-16 ***
WM           4.063e+13  1.168e+06  34797184   <2e-16 ***
NOM         -5.822e+13  2.279e+06 -25547997   <2e-16 ***
ABD         -2.015e+14  1.265e+08  -1593682   <2e-16 ***
LOC         -3.539e+12  1.103e+05 -32081391   <2e-16 ***
CC           3.339e+14  1.311e+07  25473273   <2e-16 ***
WMC         -1.198e+14  3.303e+06 -36266476   <2e-16 ***
LCOM         8.124e+15  3.705e+08  21925108   <2e-16 ***
CA          -7.662e+14  5.387e+07 -14223340   <2e-16 ***
CE          -1.831e+14  2.422e+07  -7556638   <2e-16 ***
DCBO        -1.526e+14  2.895e+07  -5271639   <2e-16 ***
OMI         -5.054e+14  3.577e+07 -14126913   <2e-16 ***
DC           1.977e+15  7.122e+07  27757763   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -27.7118031256598
==============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + LCOM + I +
CA + OMI + DC + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  2.366e+16  7.284e+08  32475321   <2e-16 ***
DIST         8.831e+17  6.263e+10  14099819   <2e-16 ***
ABST        -8.458e+15  5.978e+08 -14148668   <2e-16 ***
WM          -2.214e+12  2.029e+06  -1091146   <2e-16 ***
NOM          3.490e+13  2.562e+06  13623927   <2e-16 ***
LCPM        -4.653e+14  9.293e+06 -50063737   <2e-16 ***
ABD          2.661e+14  7.495e+07   3549779   <2e-16 ***
LOC          2.273e+12  3.445e+05   6597932   <2e-16 ***
CC           7.411e+13  1.781e+07   4162296   <2e-16 ***
LCOM        -1.553e+16  2.711e+08 -57284981   <2e-16 ***
I           -1.535e+16  6.497e+08 -23626285   <2e-16 ***
CA          -2.184e+15  3.923e+07 -55673085   <2e-16 ***
OMI          2.232e+15  7.414e+07  30103542   <2e-16 ***
DC          -1.440e+15  9.878e+07 -14580005   <2e-16 ***
DMI         -1.277e+14  3.514e+06 -36342734   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -27.7118031256598
==============================================================================
SUCCESSABILITY Vs   ABST + WM + NOM + LCPM + ABD + LOC + WMC + LCOM + CA + CE +
DCBO + OMI + DC + DMI
```

```
Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -1.517e+15  4.079e+08  -3718683   <2e-16 ***
ABST         4.639e+13  8.299e+06   5590351   <2e-16 ***
WM           3.718e+13  1.330e+06  27959882   <2e-16 ***
NOM         -1.321e+14  2.942e+06 -44888161   <2e-16 ***
LCPM         2.647e+13  7.597e+06   3483710   <2e-16 ***
ABD          1.805e+15  1.628e+08  11084034   <2e-16 ***
LOC         -2.159e+12  1.766e+05 -12224501   <2e-16 ***
WMC         -8.251e+13  3.503e+06 -23552971   <2e-16 ***
LCOM         1.982e+16  6.258e+08  31679399   <2e-16 ***
CA          -8.586e+14  8.639e+07  -9938937   <2e-16 ***
CE           4.451e+12  3.587e+07    124101   <2e-16 ***
DCBO        -4.112e+14  3.203e+07 -12837964   <2e-16 ***
OMI         -1.263e+15  6.656e+07 -18980294   <2e-16 ***
DC           2.033e+15  8.256e+07  24620548   <2e-16 ***
DMI          5.224e+13  3.043e+06  17171354   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -27.7118031256598
===============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + WMC + LCOM + I +
DCBO + OMI + DC + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.177e+16  6.537e+08  18001343   <2e-16 ***
DIST        -1.126e+17  4.663e+10  -2414546   <2e-16 ***
ABST         9.340e+14  4.419e+08   2113646   <2e-16 ***
WM           4.047e+13  1.574e+06  25713427   <2e-16 ***
NOM          1.941e+13  2.991e+06   6489338   <2e-16 ***
ABD         -1.599e+14  6.643e+07  -2407608   <2e-16 ***
LOC         -7.435e+12  2.212e+05 -33614118   <2e-16 ***
CC           4.141e+14  1.534e+07  26996208   <2e-16 ***
WMC         -2.883e+13  3.064e+06  -9408452   <2e-16 ***
LCOM         1.020e+16  2.631e+08  38766269   <2e-16 ***
I           -1.270e+16  6.110e+08 -20788592   <2e-16 ***
DCBO        -8.176e+14  3.012e+07 -27149263   <2e-16 ***
OMI         -1.953e+13  3.710e+07   -526511   <2e-16 ***
DC           2.096e+15  6.485e+07  32326915   <2e-16 ***
DMI         -7.820e+13  3.249e+06 -24071395   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -27.7118031256598
===============================================================================
```

3. GLM models built after removing the outlier data point 16

Note: Since the number of identified significant models (7697) is very large and more than 202422 lines will be needed to accommodate all models in this document, we listed only three models for each combination of predictors of specific size (i.e., where possible, three models with 2 predictors, three models with 3 predictors, etc.)

```
===============================================================================
AVAILABILITY Vs   DIST + WM + LCOM + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  4.943e+15  3.464e+07 142682783   <2e-16 ***
DIST        -3.341e+15  2.015e+08 -16580686   <2e-16 ***
WM          -1.594e+11  7.649e+04  -2084181   <2e-16 ***
LCOM        -2.734e+15  1.047e+08 -26120066   <2e-16 ***
```

```
DC          -1.952e+14  1.453e+07 -13430726   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
================================================================================
AVAILABILITY Vs   DIST + LCPM + LOC + CC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  2.433e+15  4.223e+07  57602349   <2e-16 ***
DIST        -6.564e+15  1.864e+08 -35207585   <2e-16 ***
LCPM        -8.984e+12  2.582e+06  -3479251   <2e-16 ***
LOC          2.830e+11  1.222e+04  23152555   <2e-16 ***
CC           3.019e+14  9.559e+06  31582823   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
================================================================================
AVAILABILITY Vs   DIST + ABD + LOC + CC

Coefficients:
             Estimate Std. Error  z value Pr(>|z|)
(Intercept) 6.701e+14  5.057e+07 13251859   <2e-16 ***
DIST        1.547e+15  2.056e+08  7526944   <2e-16 ***
ABD         2.761e+14  2.292e+07 12045439   <2e-16 ***
LOC         7.529e+11  1.227e+04 61383195   <2e-16 ***
CC          1.304e+13  8.481e+06  1538020   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
================================================================================
AVAILABILITY Vs   ABST + WM + NOM + LCOM + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -1.517e+15  3.506e+07 -43249851   <2e-16 ***
ABST         2.482e+12  2.097e+06   1183318   <2e-16 ***
WM           3.131e+12  1.454e+05  21535117   <2e-16 ***
NOM          4.635e+12  8.535e+05   5430406   <2e-16 ***
LCOM         2.842e+15  1.463e+08  19424893   <2e-16 ***
DC           9.456e+14  1.458e+07  64868805   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -1457120398776.47
================================================================================
AVAILABILITY Vs   DIST + NOM + LOC + LCOM + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  4.799e+15  3.501e+07 137072678   <2e-16 ***
DIST        -1.059e+16  2.331e+08 -45445334   <2e-16 ***
NOM          3.073e+13  8.560e+05  35898186   <2e-16 ***
LOC         -2.233e+11  2.453e+04  -9102868   <2e-16 ***
LCOM        -1.018e+16  1.471e+08 -69206887   <2e-16 ***
DC          -6.888e+14  1.463e+07 -47075706   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
================================================================================
AVAILABILITY Vs   ABST + NOM + LOC + LCOM + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  3.464e+15  3.505e+07  98825400   <2e-16 ***
ABST        -9.200e+12  2.283e+06  -4030029   <2e-16 ***
NOM         -2.371e+13  8.571e+05 -27658207   <2e-16 ***
LOC          6.696e+11  2.454e+04  27288928   <2e-16 ***
LCOM        -6.334e+14  1.472e+08  -4301396   <2e-16 ***
DC           9.286e+13  1.463e+07   6347376   <2e-16 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  0.999999999999916
================================================================================
SUCCESSABILITY Vs   ABST + WM + WMC + CA + CE + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  2.088e+15  4.537e+07  46018409   <2e-16 ***
ABST        -1.215e+14  2.745e+06 -44268470   <2e-16 ***
WM           1.096e+13  3.629e+05  30199747   <2e-16 ***
WMC         -8.068e+13  1.868e+06 -43197486   <2e-16 ***
CA          -1.287e+15  3.138e+07 -41027711   <2e-16 ***
CE          -9.503e+13  1.023e+07  -9292548   <2e-16 ***
DMI          5.191e+13  8.920e+05  58196245   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -103142.750425021
================================================================================
SUCCESSABILITY Vs   WM + CC + WMC + LCOM + CE + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -3.371e+14  5.055e+07  -6667498   <2e-16 ***
WM          -5.196e+12  1.873e+05 -27750190   <2e-16 ***
CC           7.484e+14  1.131e+07  66163807   <2e-16 ***
WMC         -9.801e+13  1.293e+06 -75803644   <2e-16 ***
LCOM         7.726e+15  1.448e+08  53364454   <2e-16 ***
CE           1.596e+14  7.397e+06  21577221   <2e-16 ***
DMI          4.990e+13  7.388e+05  67546005   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1878.38961267511
================================================================================
SUCCESSABILITY Vs   DIST + WM + LCPM + CC + CE + DCBO + OMI

Coefficients:
              Estimate Std. Error    z value Pr(>|z|)    
(Intercept)  1.804e+15  6.759e+07   26686806   <2e-16 ***
DIST        -3.717e+15  2.390e+08  -15553450   <2e-16 ***
WM          -6.250e+12  1.826e+05  -34237423   <2e-16 ***
LCPM        -3.240e+14  3.039e+06 -106633764   <2e-16 ***
CC           8.452e+14  1.162e+07   72743491   <2e-16 ***
CE           3.571e+14  7.402e+06   48247857   <2e-16 ***
DCBO        -5.602e+14  1.147e+07  -48856238   <2e-16 ***
OMI          1.276e+15  1.203e+07  106062727   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  1
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + CA + CE + OMI

Coefficients:
              Estimate Std. Error    z value Pr(>|z|)    
(Intercept) -9.387e+14  3.570e+07  -26294234   <2e-16 ***
DIST         7.281e+17  1.113e+10   65400731   <2e-16 ***
ABST        -7.100e+15  1.085e+08  -65439302   <2e-16 ***
WM          -2.842e+13  2.486e+05 -114314937   <2e-16 ***
NOM          3.175e+13  9.137e+05   34745113   <2e-16 ***
CA           1.024e+15  2.167e+07   47263219   <2e-16 ***
CE           9.388e+14  7.311e+06  128406036   <2e-16 ***
OMI          2.981e+14  9.730e+06   30634846   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -32.6424632733131
================================================================================
SUCCESSABILITY Vs   DIST + WM + LCPM + CA + DCBO + OMI + DMI
```

```
Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  5.071e+15  5.192e+07  97676651   <2e-16 ***
DIST        -2.761e+15  3.471e+08  -7953424   <2e-16 ***
WM           2.172e+12  1.226e+05  17709242   <2e-16 ***
LCPM        -1.691e+14  3.449e+06 -49031670   <2e-16 ***
CA          -9.911e+14  1.978e+07 -50105884   <2e-16 ***
DCBO        -1.091e+15  1.151e+07 -94744121   <2e-16 ***
OMI          9.158e+14  1.406e+07  65138528   <2e-16 ***
DMI          4.926e+13  1.404e+06  35075752   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -103142.750425021
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + I + CE

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  3.951e+15  4.051e+08   9753459   <2e-16 ***
DIST         2.122e+17  1.477e+10  14366979   <2e-16 ***
ABST        -2.053e+15  1.420e+08 -14457565   <2e-16 ***
WM          -5.090e+12  2.403e+05 -21180793   <2e-16 ***
NOM         -2.581e+13  1.556e+06 -16593982   <2e-16 ***
LCPM        -1.268e+14  4.102e+06 -30910313   <2e-16 ***
ABD          1.823e+15  3.390e+07  53771724   <2e-16 ***
I           -4.116e+15  3.624e+08 -11359590   <2e-16 ***
CE           3.764e+14  4.485e+06  83927088   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -1338.47757579276
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + LOC + CC + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -1.166e+15  6.387e+07 -18251979   <2e-16 ***
DIST         3.962e+16  1.622e+10   2443182   <2e-16 ***
ABST        -1.843e+14  1.558e+08  -1182954   <2e-16 ***
WM          -3.268e+13  8.342e+05 -39177077   <2e-16 ***
NOM         -1.671e+13  9.695e+05 -17240720   <2e-16 ***
LCPM        -2.946e+14  4.177e+06 -70516673   <2e-16 ***
LOC          5.466e+12  1.280e+05  42706850   <2e-16 ***
CC           1.389e+15  1.289e+07 107823936   <2e-16 ***
DC           1.939e+15  2.068e+07  93793656   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -2646314.35646031
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + CE + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -1.455e+15  9.751e+07 -14920088   <2e-16 ***
DIST         4.060e+17  1.346e+10  30172132   <2e-16 ***
ABST        -3.675e+15  1.302e+08 -28223104   <2e-16 ***
WM          -5.675e+12  3.821e+05 -14849442   <2e-16 ***
NOM         -4.889e+13  1.370e+06 -35677739   <2e-16 ***
LCPM        -3.513e+14  4.155e+06 -84537350   <2e-16 ***
ABD          5.249e+15  5.164e+07 101637918   <2e-16 ***
CE           7.466e+14  1.020e+07  73211324   <2e-16 ***
OMI         -6.405e+14  1.635e+07 -39173590   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  1
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + CE + OMI + DMI
```

```
Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -2.173e+15  1.056e+08 -20578916   <2e-16 ***
DIST         1.162e+18  1.850e+10  62777372   <2e-16 ***
ABST        -1.099e+16  1.782e+08 -61697835   <2e-16 ***
WM          -2.175e+13  3.835e+05 -56717464   <2e-16 ***
NOM          4.098e+13  1.737e+06  23592856   <2e-16 ***
LCPM        -1.554e+14  4.156e+06 -37402802   <2e-16 ***
ABD          4.335e+15  6.103e+07  71026471   <2e-16 ***
CE           9.095e+14  1.065e+07  85366574   <2e-16 ***
OMI         -9.598e+14  2.329e+07 -41215081   <2e-16 ***
DMI         -4.691e+13  2.397e+06 -19570450   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  1
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CA + OMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.881e+15  6.681e+07  28148554   <2e-16 ***
DIST         1.226e+18  2.373e+10  51669006   <2e-16 ***
ABST        -1.167e+16  2.270e+08 -51407773   <2e-16 ***
WM          -3.358e+13  9.669e+05 -34727703   <2e-16 ***
NOM         -4.542e+12  1.254e+06  -3623102   <2e-16 ***
LCPM        -1.135e+13  4.380e+06  -2590726   <2e-16 ***
ABD          2.005e+15  4.235e+07  47351053   <2e-16 ***
LOC          6.855e+12  1.645e+05  41672751   <2e-16 ***
CA          -1.672e+15  2.746e+07 -60888912   <2e-16 ***
OMI         -6.864e+14  1.284e+07 -53458144   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -103142.750425021
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + LOC + CC + WMC + DMI

Coefficients:
              Estimate Std. Error    z value Pr(>|z|)    
(Intercept)  2.149e+15  6.975e+07   30806258   <2e-16 ***
DIST        -2.376e+18  2.767e+10  -85875756   <2e-16 ***
ABST         2.246e+16  2.629e+08   85432957   <2e-16 ***
WM           1.414e+14  1.735e+06   81525523   <2e-16 ***
NOM         -2.653e+13  1.670e+06  -15882933   <2e-16 ***
LCPM        -1.309e+14  3.386e+06  -38651957   <2e-16 ***
LOC         -2.205e+13  2.702e+05  -81613491   <2e-16 ***
CC           6.262e+14  1.153e+07   54324812   <2e-16 ***
WMC         -2.550e+14  2.430e+06 -104911124   <2e-16 ***
DMI          1.146e+14  1.766e+06   64880249   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -32.6424632733131
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + LOC + WMC + LCOM + CA + CE

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.757e+15  8.293e+07  21189308   <2e-16 ***
DIST         1.171e+18  2.516e+10  46542619   <2e-16 ***
ABST        -1.125e+16  2.390e+08 -47073452   <2e-16 ***
WM          -4.472e+13  1.778e+06 -25151975   <2e-16 ***
NOM          6.618e+13  1.441e+06  45907543   <2e-16 ***
LCPM         2.134e+12  3.857e+06    553227   <2e-16 ***
LOC          4.503e+12  2.667e+05  16885770   <2e-16 ***
WMC          2.012e+13  2.544e+06   7909023   <2e-16 ***
LCOM        -7.540e+15  2.076e+08 -36328626   <2e-16 ***
CA          -5.691e+14  8.225e+06 -69187206   <2e-16 ***
CE           5.768e+14  7.237e+06  79709028   <2e-16 ***
```

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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -59550.6261081451
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + WMC + CA

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.918e+15  7.503e+07  25566526   <2e-16 ***
DIST        -3.294e+17  2.583e+10 -12754783   <2e-16 ***
ABST         3.181e+15  2.468e+08  12890790   <2e-16 ***
WM           4.104e+13  1.774e+06  23138443   <2e-16 ***
NOM         -1.398e+13  1.246e+06 -11220204   <2e-16 ***
LCPM        -3.213e+14  4.866e+06 -66027336   <2e-16 ***
ABD          2.668e+15  3.893e+07  68526405   <2e-16 ***
LOC         -6.089e+12  2.742e+05 -22203520   <2e-16 ***
CC           5.755e+14  1.172e+07  49114654   <2e-16 ***
WMC         -1.195e+14  2.444e+06 -48889545   <2e-16 ***
CA          -5.849e+13  6.663e+06  -8778075   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -1338.47757579276
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + LOC + WMC + LCOM + CA + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  7.300e+15  8.229e+07  88704013   <2e-16 ***
DIST         4.703e+17  3.258e+10  14433881   <2e-16 ***
ABST        -4.722e+15  3.094e+08 -15261744   <2e-16 ***
WM           4.142e+12  1.814e+06   2283794   <2e-16 ***
NOM         -8.406e+13  1.702e+06 -49397866   <2e-16 ***
LCPM        -2.007e+14  4.049e+06 -49567974   <2e-16 ***
LOC          3.748e+12  2.902e+05  12917391   <2e-16 ***
WMC         -7.389e+13  2.424e+06 -30487969   <2e-16 ***
LCOM        -6.185e+15  2.258e+08 -27398917   <2e-16 ***
CA          -2.276e+15  2.792e+07 -81517034   <2e-16 ***
DMI          1.104e+14  1.879e+06  58742630   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -32.6424632733131
===============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + WMC + LCOM + CA
+ DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -8.470e+14  1.025e+08  -8266823   <2e-16 ***
DIST        -6.601e+17  2.567e+10 -25716351   <2e-16 ***
ABST         6.198e+15  2.451e+08  25291574   <2e-16 ***
WM           1.047e+14  1.785e+06  58651766   <2e-16 ***
NOM         -5.209e+13  1.423e+06 -36617295   <2e-16 ***
LCPM        -2.824e+12  4.733e+06   -596567   <2e-16 ***
ABD          2.409e+15  6.435e+07  37434700   <2e-16 ***
LOC         -1.521e+13  2.753e+05 -55267155   <2e-16 ***
WMC         -1.968e+14  2.460e+06 -79985994   <2e-16 ***
LCOM         1.742e+16  2.450e+08  71124696   <2e-16 ***
CA          -5.566e+13  6.629e+06  -8397481   <2e-16 ***
DC          -8.932e+14  3.158e+07 -28278147   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  1
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + WMC + I +
CA

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  1.445e+14  6.512e+08    221868   <2e-16 ***
```

```
DIST        -2.952e+17  3.061e+10  -9644285   <2e-16 ***
ABST         2.778e+15  2.909e+08   9549761   <2e-16 ***
WM           4.250e+13  1.777e+06  23915204   <2e-16 ***
NOM          6.251e+13  2.265e+06  27598563   <2e-16 ***
LCPM        -1.063e+14  4.869e+06 -21825588   <2e-16 ***
ABD          1.340e+15  4.098e+07  32689904   <2e-16 ***
LOC         -8.172e+12  2.746e+05 -29764306   <2e-16 ***
CC           7.129e+14  1.351e+07  52769901   <2e-16 ***
WMC         -1.047e+14  2.840e+06 -36860542   <2e-16 ***
I           -1.877e+15  5.932e+08  -3163666   <2e-16 ***
CA          -2.707e+14  6.679e+06 -40538003   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -28.4799919425685
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + WMC + LCOM + CE
+ DCBO

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -1.159e+15  9.376e+07 -12361474   <2e-16 ***
DIST        -4.494e+17  2.696e+10 -16667440   <2e-16 ***
ABST         4.400e+15  2.573e+08  17101677   <2e-16 ***
WM           4.225e+13  1.825e+06  23149224   <2e-16 ***
NOM         -1.129e+13  1.516e+06  -7447644   <2e-16 ***
LCPM        -1.389e+14  4.622e+06 -30044352   <2e-16 ***
ABD          3.224e+15  4.390e+07  73452847   <2e-16 ***
LOC         -7.524e+12  2.705e+05 -27814903   <2e-16 ***
WMC          2.061e+13  2.657e+06   7757600   <2e-16 ***
LCOM         1.380e+16  2.090e+08  66040348   <2e-16 ***
CE           1.860e+13  6.311e+06   2946754   <2e-16 ***
DCBO        -1.008e+15  1.655e+07 -60915818   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -59550.6261081451
================================================================================
SUCCESSABILITY Vs   ABST + WM + NOM + ABD + LOC + CC + WMC + I + CA + DCBO + OMI
+ DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -5.529e+15  1.764e+09  -3135116   <2e-16 ***
ABST         4.408e+13  1.148e+07   3839530   <2e-16 ***
WM           2.717e+13  1.676e+06  16208121   <2e-16 ***
NOM          1.041e+14  9.288e+06  11211477   <2e-16 ***
ABD          2.513e+15  1.369e+08  18351735   <2e-16 ***
LOC         -6.519e+12  4.557e+05 -14305916   <2e-16 ***
CC           6.074e+14  1.368e+07  44409223   <2e-16 ***
WMC         -6.538e+13  3.404e+06 -19204816   <2e-16 ***
I            2.278e+15  1.548e+09   1471497   <2e-16 ***
CA          -1.013e+15  4.366e+07 -23195271   <2e-16 ***
DCBO        -1.014e+15  5.362e+07 -18912560   <2e-16 ***
OMI          5.417e+13  2.676e+07   2024267   <2e-16 ***
DMI          1.821e+13  2.622e+06   6947177   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  1
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + WMC + LCOM
+ CE + DCBO

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -8.079e+14  1.051e+08  -7686498   <2e-16 ***
DIST        -9.441e+16  2.703e+10  -3492370   <2e-16 ***
ABST         8.795e+14  2.581e+08   3407923   <2e-16 ***
WM           1.981e+13  1.826e+06  10846243   <2e-16 ***
NOM         -4.573e+13  1.591e+06 -28742881   <2e-16 ***
LCPM        -1.210e+14  4.825e+06 -25082031   <2e-16 ***
```

```
ABD          6.299e+14  4.408e+07  14289839   <2e-16 ***
LOC         -3.115e+12  2.710e+05 -11495172   <2e-16 ***
CC           5.488e+14  1.423e+07  38563284   <2e-16 ***
WMC         -7.897e+13  2.756e+06 -28649674   <2e-16 ***
LCOM         4.530e+15  2.257e+08  20069485   <2e-16 ***
CE           2.661e+14  6.370e+06  41770646   <2e-16 ***
DCBO         6.942e+14  1.828e+07  37980863   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -1338.47757579276
================================================================================
SUCCESSABILITY Vs   ABST + WM + NOM + ABD + LOC + CC + WMC + I + CE + DCBO + OMI
+ DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept)  2.730e+16  1.342e+09  20342811   <2e-16 ***
ABST        -7.224e+13  8.882e+06  -8133102   <2e-16 ***
WM          -2.512e+13  1.752e+06 -14336071   <2e-16 ***
NOM          6.269e+13  6.958e+06   9010355   <2e-16 ***
ABD          8.982e+14  9.973e+07   9006505   <2e-16 ***
LOC         -1.548e+12  3.581e+05  -4323167   <2e-16 ***
CC           2.599e+14  1.428e+07  18191598   <2e-16 ***
WMC          1.129e+14  4.243e+06  26603780   <2e-16 ***
I           -3.129e+16  1.249e+09 -25046005   <2e-16 ***
CE           7.669e+14  1.772e+07  43268602   <2e-16 ***
DCBO        -2.145e+14  4.362e+07  -4916513   <2e-16 ***
OMI          4.389e+14  2.941e+07  14923431   <2e-16 ***
DMI         -8.935e+13  2.593e+06 -34458062   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1878.38961267511
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + WMC + LCOM + I +
CE + DCBO + DC

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -2.422e+16  1.638e+09 -14782624   <2e-16 ***
DIST         1.149e+18  3.232e+10  35539827   <2e-16 ***
ABST        -1.095e+16  3.031e+08 -36139893   <2e-16 ***
WM           1.280e+13  1.922e+06   6661053   <2e-16 ***
NOM          5.909e+13  8.206e+06   7201189   <2e-16 ***
ABD          9.833e+14  8.887e+07  11063955   <2e-16 ***
LOC         -2.322e+12  3.607e+05  -6439433   <2e-16 ***
CC           4.044e+14  1.403e+07  28824914   <2e-16 ***
WMC         -1.495e+14  4.281e+06 -34926553   <2e-16 ***
LCOM         5.401e+15  2.945e+08  18338606   <2e-16 ***
I            2.464e+16  1.569e+09  15706978   <2e-16 ***
CE           4.029e+12  1.557e+07    258834   <2e-16 ***
DCBO        -8.334e+13  4.669e+07  -1784825   <2e-16 ***
DC          -4.313e+14  5.032e+07  -8571498   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
R2 (Nagelkerke):  -28.4799919425685
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + I + CA + CE + DCBO
+ OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)    
(Intercept) -1.044e+16  1.509e+09  -6917309   <2e-16 ***
DIST        -8.371e+16  5.477e+10  -1528365   <2e-16 ***
ABST         9.211e+14  5.248e+08   1755144   <2e-16 ***
WM           3.143e+13  2.111e+06  14891525   <2e-16 ***
NOM          3.904e+13  8.875e+06   4399274   <2e-16 ***
ABD          6.325e+15  1.585e+08  39893006   <2e-16 ***
LOC         -8.022e+12  5.669e+05 -14151704   <2e-16 ***
CC          -6.824e+14  1.426e+07 -47852673   <2e-16 ***
```

```
I            6.598e+15  1.268e+09   5203380   <2e-16 ***
CA          -8.918e+14  5.906e+07 -15099585   <2e-16 ***
CE           5.980e+14  1.688e+07  35436259   <2e-16 ***
DCBO        -1.185e+15  6.419e+07 -18457390   <2e-16 ***
OMI         -1.372e+15  3.112e+07 -44083820   <2e-16 ***
DMI          9.080e+13  3.166e+06  28682126   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1878.38961267511
=============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + WMC + I + CA + CE
+ DCBO + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept)  4.094e+15  1.763e+09   2322591   <2e-16 ***
DIST         4.465e+17  5.626e+10   7935887   <2e-16 ***
ABST        -4.449e+15  5.382e+08  -8265433   <2e-16 ***
WM          -2.447e+12  2.387e+06  -1024934   <2e-16 ***
NOM          6.827e+13  9.508e+06   7180281   <2e-16 ***
ABD          9.651e+14  1.410e+08   6846496   <2e-16 ***
LOC         -5.330e+12  5.915e+05  -9012002   <2e-16 ***
CC           3.948e+14  1.429e+07  27629156   <2e-16 ***
WMC          4.462e+12  4.364e+06   1022499   <2e-16 ***
I           -6.595e+15  1.579e+09  -4175677   <2e-16 ***
CA           9.624e+14  5.700e+07  16883203   <2e-16 ***
CE           9.373e+14  1.885e+07  49732312   <2e-16 ***
DCBO        -2.656e+14  6.451e+07  -4117686   <2e-16 ***
DMI         -3.117e+13  2.667e+06 -11685695   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -32.6424632733131
=============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + WMC + LCOM + I +
CA + DCBO + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -6.513e+16  1.771e+09 -36766888   <2e-16 ***
DIST        -1.044e+18  5.185e+10 -20142999   <2e-16 ***
ABST         1.036e+16  4.961e+08  20882358   <2e-16 ***
WM           9.615e+13  2.391e+06  40207586   <2e-16 ***
NOM          3.929e+14  9.759e+06  40260084   <2e-16 ***
ABD          6.002e+15  1.463e+08  41034403   <2e-16 ***
LOC         -2.609e+13  5.829e+05 -44752668   <2e-16 ***
CC           7.990e+14  1.533e+07  52109717   <2e-16 ***
WMC         -1.651e+14  3.496e+06 -47209371   <2e-16 ***
LCOM         5.638e+15  2.654e+08  21247274   <2e-16 ***
I            5.446e+16  1.555e+09  35022037   <2e-16 ***
CA           1.575e+15  4.919e+07  32011101   <2e-16 ***
DCBO        -2.657e+15  6.566e+07 -40468801   <2e-16 ***
OMI          3.907e+14  2.843e+07  13741774   <2e-16 ***
DMI          5.989e+12  3.138e+06   1908658   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -1878.38961267511
=============================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + WMC + I + CA + CE
+ DCBO + OMI + DMI

Coefficients:
              Estimate Std. Error   z value Pr(>|z|)
(Intercept) -2.124e+16  1.783e+09 -11912025   <2e-16 ***
DIST        -1.270e+18  5.638e+10 -22519955   <2e-16 ***
ABST         1.223e+16  5.395e+08  22672972   <2e-16 ***
WM           6.167e+13  2.387e+06  25829222   <2e-16 ***
NOM          1.332e+14  9.509e+06  14002973   <2e-16 ***
```

```
ABD          4.687e+15  1.589e+08  29500630   <2e-16 ***
LOC         -1.519e+13  5.940e+05 -25565893   <2e-16 ***
CC          -1.242e+14  1.567e+07  -7924141   <2e-16 ***
WMC         -3.702e+13  4.369e+06  -8474155   <2e-16 ***
I            1.546e+16  1.590e+09   9720805   <2e-16 ***
CA          -2.255e+12  5.980e+07    -37710   <2e-16 ***
CE           4.742e+14  2.166e+07  21894039   <2e-16 ***
DCBO        -2.082e+15  6.453e+07 -32264339   <2e-16 ***
OMI         -8.054e+13  3.116e+07  -2584947   <2e-16 ***
DMI          1.097e+14  3.185e+06  34457508   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  (1 observation deleted due to missingness)
R2 (Nagelkerke):  -32.6424632733131
===============================================================================
```

Appendix F. ORM models

1. R script used for building the ORM models

```
#########
# R script to build models for the Accessibiltiy, Availalbiltiy and
# Successibility using the rms package (orm())
#########

# Read all data points from .csv file
dataset <-read.csv("D:/Experiment/Analysis/Dataset.csv")
attach(dataset)

internalmetrics.array <- c("DIST","ABST", "WM", "NOM","LCPM","ABD","LOC","CC",
                           "WMC","LCOM","I","CA","CE","DCBO","OMI","DC","DMI")

externalmetrics.array <- c("ACCESSIBILITY","AVAILABILITY","SUCCESSABILITY")

require(combinat)
require(rms)

numberOfindpVar = length(internalmetrics.array)

counter = 1

for (t in 1:numberOfindpVar) {

  # combination of numberOfindpVar independent variable at the time
  internalmetrics<- combn(internalmetrics.array, t)

  myFile <- paste("D:/Doktorarbeit/1 Controlled_Experiment/Experiment
Analysis/Output/20140719/Output_",t,".txt")
  # output directed to file (appended to existing file) and sent to terminal.
  sink(myFile,append=TRUE, split=TRUE)

  for (n in 1:length(externalmetrics.array)) {
       dependent.var <- externalmetrics.array[n]

       length1 <- (length(internalmetrics)/t)

       for (i in 1: length1 )  {
         errorOccured = FALSE
         indpVar <- ""
         if (t == length(internalmetrics.array)){
           for (k in 1: t )  {
             if (k<t)
              indpVar <- paste (indpVar,internalmetrics.array[k], "+")
          else {
            indpVar <- paste (indpVar,internalmetrics.array[k])

          }
           }
         }

      else {

         for (k in 1: t )  {
           if (k<t)
             indpVar <- paste (indpVar, internalmetrics[k,i], "+")
           else
             indpVar <- paste (indpVar, internalmetrics[k,i])
         }
      }
         formulastr <- paste ( dependent.var, "~" , indpVar)
         testdata.reg <-  tryCatch( {
             orm(as.formula(formulastr), family = logistic, maxit=24)
```

```
          }, error = function(err) {
            errorOccured = TRUE
          }, warning = function(war) {
            errorOccured = TRUE
            #print(paste("WARNING while running orm():  ",war))
          })

         # Here we are avoiding error  thrown while fitting the model
      if ( length(testdata.reg)!=1 && !errorOccured){
          model.anova<-  tryCatch( {
            anova(testdata.reg)

          }, error = function(err) {
             errorOccured = TRUE
            })

          # Check significance of the coefficients (p-value must be <= 0.05)
          p.valueLow = TRUE
          for (m in 1: t )  {
             tmpBoolean <- anova(testdata.reg)[m,3] <= 0.05
             p.valueLow = p.valueLow && tmpBoolean
          }

          if (p.valueLow ){
           cat("====================================================","\n\n")
            cat(paste(dependent.var, "Vs ",indpVar, "\n\n"))
            cat(paste("Counter: ",counter,  "\n\n"))
            capture.output(testdata.reg, file = myFile, append = TRUE)
          } else {

            for (h in 1: t )  {

            }
          }
       }
          counter = counter+1
     }
   }
   sink()
 }
```

2. ORM models built with the complete dataset

Note:
Since the number of identified significant models (366) is large and more than 13950 lines will be needed to accommodate all models in this document, we listed only three models for each combination of predictors of specific size (i.e., where possible, three models with 2 predictors, three models with 3 predictors, etc.). Otherwise, the complete set of models will require alone about 147 pages of this document.

```
================================================================================
ACCESSIBILITY Vs  WM
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                Indexes
Indexes
```

```
Obs           20    LR chi2      5.06    R2                  0.224    rho
0.422
Unique Y      16    d.f.            1    g                   0.884
Median Y    0.861   Pr(> chi2) 0.0245    gr                  2.422
max |deriv| 0.004   Score chi2   6.41    |Pr(Y>=median)-0.5| 0.158
                    Pr(> chi2) 0.0114
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  4.1130 1.2818  3.21  0.0013
y>=0.789  3.2840 1.0353  3.17  0.0015
y>=0.798  2.2302 0.7638  2.92  0.0035
y>=0.804  1.8178 0.6667  2.73  0.0064
y>=0.813  1.4969 0.6105  2.45  0.0142
y>=0.846  1.2291 0.5758  2.13  0.0328
y>=0.86   0.9929 0.5542  1.79  0.0732
y>=0.861  0.7665 0.5390  1.42  0.1550
y>=0.879  0.3092 0.5197  0.59  0.5520
y>=0.882 -0.1513 0.5245 -0.29  0.7730
y>=0.891 -0.3865 0.5395 -0.72  0.4737
y>=0.924 -0.6514 0.5622 -1.16  0.2466
y>=0.929 -1.3258 0.6574 -2.02  0.0437
y>=0.943 -1.7950 0.7705 -2.33  0.0198
y>=0.95  -2.5488 1.0436 -2.44  0.0146
WM       -0.0028 0.0013 -2.15  0.0317
================================================================================
ACCESSIBILITY Vs   LOC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                    Model Likelihood         Discrimination         Rank
Discrim.
                       Ratio Test                Indexes                Indexes
Obs           20    LR chi2      8.30    R2                  0.341    rho
0.459
Unique Y      16    d.f.            1    g                   1.230
Median Y   0.861    Pr(> chi2) 0.0040    gr                  3.422
max |deriv| 0.08    Score chi2  11.45    |Pr(Y>=median)-0.5| 0.185
                    Pr(> chi2) 0.0007
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  5.0419 1.6711  3.02  0.0026
y>=0.789  3.8638 1.2300  3.14  0.0017
y>=0.798  2.5643 0.8357  3.07  0.0022
y>=0.804  2.0828 0.7092  2.94  0.0033
y>=0.813  1.7285 0.6407  2.70  0.0070
y>=0.846  1.4420 0.5997  2.40  0.0162
y>=0.86   1.1939 0.5743  2.08  0.0376
y>=0.861  0.9566 0.5562  1.72  0.0855
y>=0.879  0.4732 0.5318  0.89  0.3736
y>=0.882 -0.0095 0.5324 -0.02  0.9858
y>=0.891 -0.2515 0.5461 -0.46  0.6452
y>=0.924 -0.5227 0.5677 -0.92  0.3571
y>=0.929 -1.2078 0.6611 -1.83  0.0677
y>=0.943 -1.6802 0.7732 -2.17  0.0298
y>=0.95  -2.4387 1.0452 -2.33  0.0196
LOC      -0.0009 0.0003 -2.68  0.0074
================================================================================
ACCESSIBILITY Vs   NOM
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                    Model Likelihood         Discrimination         Rank
Discrim.
                       Ratio Test                Indexes
Indexes
Obs           20    LR chi2      4.46    R2                  0.201    rho
0.511
Unique Y      16    d.f.            1    g                   0.744
Median Y    0.861   Pr(> chi2) 0.0347    gr                  2.105
```

```
max |deriv| 0.003    Score chi2   5.69    |Pr(Y>=median)-0.5| 0.147
                     Pr(> chi2) 0.0170
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  3.9218 1.2129  3.23  0.0012
y>=0.789  3.1659 0.9906  3.20  0.0014
y>=0.798  2.1707 0.7492  2.90  0.0038
y>=0.804  1.7783 0.6617  2.69  0.0072
y>=0.813  1.4700 0.6107  2.41  0.0161
y>=0.846  1.2104 0.5793  2.09  0.0367
y>=0.86   0.9778 0.5596  1.75  0.0806
y>=0.861  0.7518 0.5451  1.38  0.1679
y>=0.879  0.2861 0.5230  0.55  0.5844
y>=0.882 -0.1918 0.5224 -0.37  0.7134
y>=0.891 -0.4377 0.5350 -0.82  0.4133
y>=0.924 -0.7068 0.5569 -1.27  0.2044
y>=0.929 -1.3746 0.6541 -2.10  0.0356
y>=0.943 -1.8453 0.7676 -2.40  0.0162
y>=0.95  -2.6042 1.0410 -2.50  0.0124
NOM      -0.0088 0.0043 -2.03  0.0426
================================================================================
ACCESSIBILITY Vs   LOC + CC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs            20    LR chi2     13.71    R2                  0.498    rho
0.615
Unique Y       16    d.f.            2    g                   1.912
Median Y    0.861    Pr(> chi2) 0.0011    gr                  6.766
max |deriv| 0.002    Score chi2  17.85    |Pr(Y>=median)-0.5| 0.213
                     Pr(> chi2) 0.0001
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  3.3288 1.7254  1.93  0.0537
y>=0.789  2.3220 1.3971  1.66  0.0965
y>=0.798  1.0278 1.0819  0.95  0.3421
y>=0.804  0.5352 0.9929  0.54  0.5899
y>=0.813  0.1682 0.9517  0.18  0.8597
y>=0.846 -0.1268 0.9297 -0.14  0.8915
y>=0.86  -0.3903 0.9215 -0.42  0.6719
y>=0.861 -0.6587 0.9255 -0.71  0.4766
y>=0.879 -1.2236 0.9484 -1.29  0.1970
y>=0.882 -1.8122 1.0005 -1.81  0.0701
y>=0.891 -2.1396 1.0557 -2.03  0.0427
y>=0.924 -2.5203 1.1292 -2.23  0.0256
y>=0.929 -3.3741 1.2822 -2.63  0.0085
y>=0.943 -3.9299 1.3895 -2.83  0.0047
y>=0.95  -4.9223 1.6871 -2.92  0.0035
LOC      -0.0010 0.0003 -2.97  0.0030
CC        0.5662 0.2555  2.22  0.0267
================================================================================
ACCESSIBILITY Vs   WM + LOC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           20    LR chi2      19.92    R2                  0.633    rho
0.705
Unique Y      16    d.f.             2    g                   5.741
Median Y   0.861    Pr(> chi2) <0.0001    gr                311.307
max |deriv| 0.09    Score chi2   29.89    |Pr(Y>=median)-0.5| 0.308
                    Pr(> chi2) <0.0001
```

```
         Coef    S.E.    Wald Z Pr(>|Z|)
y>=0.783 13.0124 29.7270  0.44  0.6616
y>=0.789  6.0785  1.7293  3.52  0.0004
y>=0.798  4.1808  1.2823  3.26  0.0011
y>=0.804  3.4606  1.0340  3.35  0.0008
y>=0.813  3.0181  0.9328  3.24  0.0012
y>=0.846  2.6843  0.8815  3.05  0.0023
y>=0.86   2.3919  0.8486  2.82  0.0048
y>=0.861  2.0962  0.8189  2.56  0.0105
y>=0.879  1.3981  0.7284  1.92  0.0549
y>=0.882  0.6528  0.6484  1.01  0.3140
y>=0.891  0.3020  0.6404  0.47  0.6372
y>=0.924 -0.0237  0.6479 -0.04  0.9709
y>=0.929 -0.7117  0.7217 -0.99  0.3240
y>=0.943 -1.2094  0.8211 -1.47  0.1408
y>=0.95  -2.0249  1.0746 -1.88  0.0595
WM        0.0581  0.0212  2.74  0.0062
LOC      -0.0164  0.0058 -2.82  0.0048
================================================================================
SUCCESSABILITY Vs   NOM + LCPM
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    11
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs            20    LR chi2      6.81    R2                  0.301    rho
0.646
Unique Y        9    d.f.            2    g                   1.312
Median Y        1    Pr(> chi2) 0.0331    gr                  3.713
max |deriv| 0.008    Score chi2   6.94    |Pr(Y>=median)-0.5| 0.214
                     Pr(> chi2) 0.0311
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  6.5065 1.9126  3.40  0.0007
y>=0.472  5.7814 1.7853  3.24  0.0012
y>=0.844  5.3418 1.7478  3.06  0.0022
y>=0.977  4.9805 1.7187  2.90  0.0038
y>=0.985  4.2946 1.6370  2.62  0.0087
y>=0.988  3.9403 1.5720  2.51  0.0122
y>=0.994  3.5694 1.4815  2.41  0.0160
y>=1      3.2316 1.4126  2.29  0.0222
NOM      -0.0094 0.0047 -2.02  0.0438
LCPM     -0.1485 0.0696 -2.13  0.0330
================================================================================
ACCESSIBILITY Vs   DIST + ABST + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST           DMI
            0             0             0             1
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs            19    LR chi2      8.41    R2                  0.359    rho
0.593
Unique Y       16    d.f.            3    g                   1.274
Median Y    0.861    Pr(> chi2) 0.0382    gr                  3.574
max |deriv| 0.006    Score chi2   9.79    |Pr(Y>=median)-0.5| 0.199
                     Pr(> chi2) 0.0204
         Coef     S.E.     Wald Z Pr(>|Z|)
y>=0.783   4.5956   1.3576  3.39  0.0007
y>=0.789   3.8289   1.1707  3.27  0.0011
y>=0.798   2.8194   0.9794  2.88  0.0040
y>=0.804   2.3116   0.8651  2.67  0.0075
y>=0.813   1.8430   0.7501  2.46  0.0140
y>=0.846   1.4912   0.6916  2.16  0.0311
```

```
y>=0.86    1.1668   0.6501  1.79  0.0727
y>=0.861   0.8474   0.6128  1.38  0.1667
y>=0.879   0.5488   0.5864  0.94  0.3494
y>=0.882  -0.0177   0.5747 -0.03  0.9754
y>=0.891  -0.3078   0.5882 -0.52  0.6007
y>=0.924  -0.6021   0.6063 -0.99  0.3207
y>=0.929  -1.2738   0.6847 -1.86  0.0628
y>=0.943  -1.7513   0.7896 -2.22  0.0265
y>=0.95   -2.5133   1.0550 -2.38  0.0172
DIST     698.7258 289.9013  2.41  0.0159
ABST      -6.7934   2.8248 -2.40  0.0162
DMI       -0.0285   0.0114 -2.50  0.0126
================================================================================
ACCESSIBILITY Vs   WM + CC + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY            WM            CC            DMI
            0             0             0             1
                      Model Likelihood         Discrimination          Rank
Discrim.
                         Ratio Test                Indexes
Indexes
Obs            19     LR chi2      15.65    R2                  0.564    rho
0.594
Unique Y       16     d.f.             3    g                   2.265
Median Y    0.861     Pr(> chi2)  0.0013    gr                  9.636
max |deriv| 0.001     Score chi2   23.11    |Pr(Y>=median)-0.5| 0.205
                      Pr(> chi2) <0.0001
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  3.0247 2.3381  1.29  0.1958
y>=0.789  1.1679 1.4696  0.79  0.4268
y>=0.798 -0.2779 1.1850 -0.23  0.8146
y>=0.804 -0.8138 1.1278 -0.72  0.4706
y>=0.813 -1.2508 1.1187 -1.12  0.2636
y>=0.846 -1.6164 1.1250 -1.44  0.1508
y>=0.86  -1.9255 1.1349 -1.70  0.0898
y>=0.861 -2.2097 1.1482 -1.92  0.0543
y>=0.879 -2.4851 1.1625 -2.14  0.0325
y>=0.882 -3.0765 1.2230 -2.52  0.0119
y>=0.891 -3.4409 1.2952 -2.66  0.0079
y>=0.924 -3.8522 1.3788 -2.79  0.0052
y>=0.929 -4.7103 1.5297 -3.08  0.0021
y>=0.943 -5.2512 1.6281 -3.23  0.0013
y>=0.95  -6.3188 1.9656 -3.21  0.0013
WM       -0.0105 0.0039 -2.70  0.0070
CC        0.8216 0.3051  2.69  0.0071
DMI       0.0399 0.0191  2.09  0.0364
================================================================================
SUCCESSABILITY Vs   LCPM + DCBO + DC
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    11
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                Indexes
Indexes
Obs            20     LR chi2      9.11    R2                  0.381    rho
0.655
Unique Y        9     d.f.            3    g                   1.696
Median Y        1     Pr(> chi2) 0.0279    gr                  5.453
max |deriv| 6e-06     Score chi2   9.54    |Pr(Y>=median)-0.5| 0.228
                      Pr(> chi2) 0.0229
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  6.2855 1.9780  3.18  0.0015
y>=0.472  5.5388 1.8620  2.97  0.0029
y>=0.844  4.9524 1.7868  2.77  0.0056
y>=0.977  4.4022 1.7011  2.59  0.0097
```

```
y>=0.985  3.5126 1.5983  2.20  0.0280
y>=0.988  3.1186 1.5422  2.02  0.0432
y>=0.994  2.7455 1.4628  1.88  0.0605
y>=1      2.4294 1.4062  1.73  0.0841
LCPM     -0.1719 0.0765 -2.25  0.0247
DCBO     -0.7151 0.3021 -2.37  0.0179
DC        1.3317 0.6769  1.97  0.0491

================================================================================
ACCESSIBILITY Vs   DIST + ABST + CA + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST            CA           DMI
            0             0             0             0             1
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           19    LR chi2     13.82    R2                  0.519    rho
0.613
Unique Y      16    d.f.            4    g                   2.130
Median Y   0.861    Pr(> chi2) 0.0079    gr                  8.414
max |deriv| 5e-04    Score chi2  16.59    |Pr(Y>=median)-0.5| 0.279
                    Pr(> chi2) 0.0023
         Coef      S.E.     Wald Z Pr(>|Z|)
y>=0.783    6.6944   2.2387  2.99  0.0028
y>=0.789    5.0795   1.4806  3.43  0.0006
y>=0.798    3.7688   1.1561  3.26  0.0011
y>=0.804    3.2072   1.0263  3.13  0.0018
y>=0.813    2.7366   0.9216  2.97  0.0030
y>=0.846    2.3683   0.8661  2.73  0.0062
y>=0.86     1.9949   0.8169  2.44  0.0146
y>=0.861    1.5844   0.7503  2.11  0.0347
y>=0.879    1.1832   0.6863  1.72  0.0847
y>=0.882    0.5184   0.6421  0.81  0.4195
y>=0.891    0.2109   0.6490  0.32  0.7453
y>=0.924   -0.0905   0.6636 -0.14  0.8915
y>=0.929   -0.7921   0.7265 -1.09  0.2756
y>=0.943   -1.2982   0.8198 -1.58  0.1133
y>=0.95    -2.0865   1.0740 -1.94  0.0520
DIST     1190.8372 387.3928  3.07  0.0021
ABST      -11.4785   3.7378 -3.07  0.0021
CA         -0.9756   0.4633 -2.11  0.0352
DMI        -0.0454   0.0145 -3.12  0.0018
================================================================================
ACCESSIBILITY Vs   ABST + WM + LOC + CA
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes                Indexes
Obs          20    LR chi2      31.00    R2                  0.791    rho
0.859
Unique Y     16    d.f.             4    g                  11.699
Median Y  0.861    Pr(> chi2) <0.0001    gr             120477.648
max |deriv| 0.2    Score chi2   32.77    |Pr(Y>=median)-0.5| 0.385
                   Pr(> chi2) <0.0001
         Coef    S.E.    Wald Z Pr(>|Z|)
y>=0.783 17.0475 28.7542  0.59  0.5533
y>=0.789  9.9106  2.6822  3.69  0.0002
y>=0.798  7.0988  2.0348  3.49  0.0005
y>=0.804  5.8783  1.6112  3.65  0.0003
y>=0.813  5.1528  1.4335  3.59  0.0003
y>=0.846  4.7122  1.3717  3.44  0.0006
```

```
y>=0.86   4.3351  1.3316  3.26  0.0011
y>=0.861  3.8353  1.2518  3.06  0.0022
y>=0.879  2.6151  0.9782  2.67  0.0075
y>=0.882  1.5830  0.7777  2.04  0.0418
y>=0.891  1.1619  0.7473  1.55  0.1200
y>=0.924  0.7645  0.7344  1.04  0.2979
y>=0.929 -0.0730  0.7795 -0.09  0.9254
y>=0.943 -0.7064  0.8703 -0.81  0.4170
y>=0.95  -1.7049  1.1010 -1.55  0.1215
ABST     -0.2864  0.1047 -2.74  0.0062
WM        0.1406  0.0400  3.51  0.0004
LOC      -0.0378  0.0107 -3.55  0.0004
CA        0.3854  0.1327  2.90  0.0037
================================================================================
SUCCESSABILITY Vs   LCPM + CC + WMC + DC
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    11
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           20    LR chi2     13.31    R2                  0.506    rho
0.696
Unique Y       9    d.f.            4    g                   2.686
Median Y       1    Pr(> chi2) 0.0099    gr                 14.676
max |deriv| 0.001   Score chi2  11.74    |Pr(Y>=median)-0.5| 0.292
                    Pr(> chi2) 0.0194
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  4.3536 1.8939  2.30  0.0215
y>=0.472  3.4870 1.7913  1.95  0.0516
y>=0.844  2.6807 1.7925  1.50  0.1348
y>=0.977  1.9076 1.7837  1.07  0.2848
y>=0.985  0.8655 1.7755  0.49  0.6259
y>=0.988  0.4433 1.7669  0.25  0.8019
y>=0.994  0.0134 1.7181  0.01  0.9938
y>=1     -0.3482 1.6678 -0.21  0.8346
LCPM     -0.3093 0.1168 -2.65  0.0081
CC        1.2373 0.5332  2.32  0.0203
WMC      -0.0976 0.0378 -2.58  0.0099
DC        1.7227 0.8608  2.00  0.0454
================================================================================
ACCESSIBILITY Vs   CC + WMC + I + CE + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           CC           WMC             I            CE
DMI
           0             0             0             0             0
1
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           19    LR chi2     19.36    R2                  0.642    rho
0.722
Unique Y      16    d.f.            5    g                   3.001
Median Y   0.861    Pr(> chi2) 0.0016    gr                 20.115
max |deriv| 1e-04   Score chi2  24.50    |Pr(Y>=median)-0.5| 0.277
                    Pr(> chi2) 0.0002
         Coef     S.E.   Wald Z Pr(>|Z|)
y>=0.783  -5.1342 4.3967 -1.17  0.2429
y>=0.789  -7.2452 4.8393 -1.50  0.1343
y>=0.798  -8.8574 4.8775 -1.82  0.0694
y>=0.804  -9.4814 4.8630 -1.95  0.0512
y>=0.813 -10.0397 4.8934 -2.05  0.0402
y>=0.846 -10.4876 4.9220 -2.13  0.0331
y>=0.86  -10.8379 4.9265 -2.20  0.0278
```

```
y>=0.861 -11.1612 4.9387 -2.26  0.0238
y>=0.879 -11.4817 4.9661 -2.31  0.0208
y>=0.882 -12.1993 5.0402 -2.42  0.0155
y>=0.891 -12.6300 5.0960 -2.48  0.0132
y>=0.924 -13.1204 5.1684 -2.54  0.0111
y>=0.929 -14.0537 5.2754 -2.66  0.0077
y>=0.943 -14.5771 5.3201 -2.74  0.0061
y>=0.95  -15.6465 5.5243 -2.83  0.0046
CC         1.0380 0.3970  2.61  0.0089
WMC       -0.0716 0.0329 -2.18  0.0295
I          9.7903 4.7284  2.07  0.0384
CE        -0.4425 0.1515 -2.92  0.0035
DMI        0.0695 0.0271  2.56  0.0105
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + LOC + I
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
                    Model Likelihood         Discrimination          Rank
Discrim.
                       Ratio Test                Indexes                Indexes
Obs          20    LR chi2      39.04    R2                 0.862    rho
0.843
Unique Y     16    d.f.             5    g                 16.304
Median Y  0.861    Pr(> chi2) <0.0001    gr          12045346.904
max |deriv| 0.2    Score chi2   34.15    |Pr(Y>=median)-0.5| 0.357
                   Pr(> chi2) <0.0001
     Coef       S.E.     Wald Z Pr(>|Z|)
DIST -1326.8043 503.6227 -2.63  0.0084
ABST    12.1675   4.7407  2.57  0.0103
WM       0.2300   0.0605  3.80  0.0001
LOC     -0.0595   0.0154 -3.85  0.0001
I      -33.1806   9.3349 -3.55  0.0004
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + LOC + CE
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    11
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                Indexes
Indexes
Obs            20    LR chi2     12.55    R2                 0.486    rho
0.655
Unique Y        9    d.f.            5    g                  1.945
Median Y        1    Pr(> chi2) 0.0280    gr                 6.994
max |deriv| 0.002    Score chi2  15.14    |Pr(Y>=median)-0.5| 0.243
                     Pr(> chi2) 0.0098
         Coef      S.E.     Wald Z Pr(>|Z|)
y>=0.442    5.9264   1.9015  3.12  0.0018
y>=0.472    4.8060   1.5596  3.08  0.0021
y>=0.844    3.8468   1.2805  3.00  0.0027
y>=0.977    3.1400   1.1471  2.74  0.0062
y>=0.985    1.8651   0.8448  2.21  0.0273
y>=0.988    1.3697   0.7609  1.80  0.0719
y>=0.994    0.9841   0.7145  1.38  0.1684
y>=1        0.6492   0.6702  0.97  0.3328
DIST     1257.2896 471.5039  2.67  0.0077
ABST      -12.2443   4.5774 -2.67  0.0075
WM         -0.0296   0.0125 -2.36  0.0182
LOC         0.0038   0.0019  2.07  0.0385
CE          0.2410   0.1079  2.23  0.0255
================================================================================
ACCESSIBILITY Vs   WM + NOM + ABD + LOC + CC + LCOM
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     2     1     1     2
1     1     1
```

```
                    Model Likelihood         Discrimination         Rank
Discrim.
                       Ratio Test                  Indexes               Indexes
Obs          20    LR chi2      45.89    R2                  0.903    rho
0.917
Unique Y     16    d.f.             6    g                  20.491
Median Y  0.861    Pr(> chi2) <0.0001    gr          792392761.527
max |deriv| 0.4    Score chi2   42.28    |Pr(Y>=median)-0.5| 0.424
                   Pr(> chi2) <0.0001
     Coef    S.E.   Wald Z Pr(>|Z|)
WM    0.2010 0.0548  3.67  0.0002
NOM   0.1015 0.0361  2.81  0.0050
ABD   3.1469 1.0002  3.15  0.0017
LOC  -0.0636 0.0170 -3.73  0.0002
CC    1.4681 0.5068  2.90  0.0038
LCOM 24.2211 7.7755  3.12  0.0018
================================================================================
SUCCESSABILITY Vs   WM + LOC + LCOM + DCBO + DC + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    11
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY             WM            LOC           LCOM           DCBO
DC            DMI
             0              0              0              0              0
0             1
                    Model Likelihood         Discrimination         Rank
Discrim.
                       Ratio Test                  Indexes               Indexes
Obs           19    LR chi2     20.86    R2                  0.703    rho
0.833
Unique Y       8    d.f.            6    g                  35.304
Median Y       1    Pr(> chi2) 0.0019    gr           2.149825e+15
max |deriv| 0.01    Score chi2  10.19    |Pr(Y>=median)-0.5| 0.371
                    Pr(> chi2) 0.1168
         Coef     S.E.     Wald Z Pr(>|Z|)
y>=0.442   7.0669   2.8032  2.52  0.0117
y>=0.472   6.0549   2.6759  2.26  0.0237
y>=0.844   5.1694   2.5887  2.00  0.0458
y>=0.977   4.4295   2.5070  1.77  0.0773
y>=0.985   2.5655   2.2161  1.16  0.2470
y>=0.988   1.4937   1.9857  0.75  0.4519
y>=1       0.7366   1.8296  0.40  0.6873
WM         0.4707   0.1994  2.36  0.0182
LOC       -0.0871   0.0365 -2.38  0.0171
LCOM     317.5147 129.4877  2.45  0.0142
DCBO     -13.7228   5.5048 -2.49  0.0127
DC        16.8434   6.7074  2.51  0.0120
DMI       -0.9797   0.4177 -2.35  0.0190
================================================================================
SUCCESSABILITY Vs   DIST + ABST + CC + WMC + LCOM + CE
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    11
                     Model Likelihood         Discrimination         Rank
Discrim.
                        Ratio Test                  Indexes
Indexes
Obs           20    LR chi2     18.73    R2                  0.634    rho
0.732
Unique Y       9    d.f.            6    g                   4.447
Median Y       1    Pr(> chi2) 0.0046    gr                 85.385
max |deriv| 5e-04    Score chi2  15.27    |Pr(Y>=median)-0.5| 0.325
                    Pr(> chi2) 0.0183
         Coef     S.E.     Wald Z Pr(>|Z|)
y>=0.442   5.3474   2.3102  2.31  0.0206
y>=0.472   4.3468   2.1419  2.03  0.0424
y>=0.844   3.2784   2.0378  1.61  0.1077
y>=0.977   2.3199   1.9122  1.21  0.2250
y>=0.985   0.8392   1.6511  0.51  0.6113
y>=0.988   0.2315   1.5956  0.15  0.8847
```

```
y>=0.994  -0.2580   1.5825 -0.16  0.8705
y>=1      -0.7432   1.5550 -0.48  0.6327
DIST     955.6371 381.3437  2.51  0.0122
ABST      -9.2597   3.6929 -2.51  0.0122
CC         0.9615   0.4756  2.02  0.0432
WMC       -0.1933   0.0727 -2.66  0.0079
LCOM      24.1722  10.3318  2.34  0.0193
CE        -0.2176   0.0962 -2.26  0.0238
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + ABD + LCOM + CE + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    11
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY          DIST           ABST             WM            ABD
LCOM             CE            DMI
             0              0              0              0              0
0             0              1
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                   Indexes
Indexes
Obs             19    LR chi2     21.90    R2                  0.721    rho
0.802
Unique Y         8    d.f.            7    g                  12.400
Median Y         1    Pr(> chi2) 0.0026    gr             242840.357
max |deriv| 0.003    Score chi2  14.38    |Pr(Y>=median)-0.5| 0.415
                     Pr(> chi2) 0.0449
         Coef      S.E.      Wald Z Pr(>|Z|)
y>=0.442   -2.7094    3.4149 -0.79  0.4275
y>=0.472   -3.9738    3.5742 -1.11  0.2662
y>=0.844   -5.1044    3.7456 -1.36  0.1730
y>=0.977   -6.1251    3.8864 -1.58  0.1150
y>=0.985   -8.0579    4.2830 -1.88  0.0599
y>=0.988   -8.8433    4.4860 -1.97  0.0487
y>=1       -9.3601    4.5567 -2.05  0.0400
DIST     5423.8662 2292.2639  2.37  0.0180
ABST      -51.7655   21.8729 -2.37  0.0179
WM         -0.0692    0.0313 -2.21  0.0273
ABD         4.0060    2.0103  1.99  0.0463
LCOM       82.0469   37.5427  2.19  0.0289
CE          2.8252    1.2725  2.22  0.0264
DMI        -0.3959    0.1759 -2.25  0.0244
================================================================================
ACCESSIBILITY Vs   WMC + CA + CE + DCBO + OMI + DC + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          WMC            CA             CE           DCBO
OMI            DC            DMI
            0              0              0              0              0
1             0              1
                      Model Likelihood          Discrimination          Rank
Discrim.
                         Ratio Test                   Indexes
Indexes
Obs             19    LR chi2      30.03    R2                  0.798    rho
0.762
Unique Y        16    d.f.             7    g                  7.218
Median Y     0.861    Pr(> chi2) <0.0001    gr              1363.753
max |deriv| 0.009    Score chi2   35.22    |Pr(Y>=median)-0.5| 0.389
                     Pr(> chi2) <0.0001
     Coef    S.E.   Wald Z Pr(>|Z|)
WMC   0.0766 0.0362  2.12  0.0344
CA   -2.9609 1.0455 -2.83  0.0046
CE   -1.2984 0.4388 -2.96  0.0031
DCBO -3.3774 0.9812 -3.44  0.0006
OMI  -2.1628 0.7902 -2.74  0.0062
```

```
DC    6.7411 2.0114  3.35  0.0008
DMI   0.2310 0.0785  2.94  0.0032
================================================================================
ACCESSIBILITY Vs   ABST + WM + NOM + LCPM + LOC + LCOM + CA + OMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          ABST            WM           NOM          LCPM
LOC          LCOM           CA           OMI
            0             0             0             0             0
0             0             0             1
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes                Indexes
Obs          19    LR chi2      44.18    R2                  0.906    rho
0.841
Unique Y     16    d.f.             8    g                  28.472
Median Y  0.861    Pr(> chi2) <0.0001    gr      2319017889428.576
max |deriv| 0.2    Score chi2   34.92    |Pr(Y>=median)-0.5| 0.425
                   Pr(> chi2) <0.0001
     Coef    S.E.   Wald Z Pr(>|Z|)
ABST -0.6775 0.2181 -3.11  0.0019
WM    0.3222 0.0922  3.49  0.0005
NOM   0.0922 0.0433  2.13  0.0333
LCPM  0.4256 0.1678  2.54  0.0112
LOC  -0.0940 0.0274 -3.43  0.0006
LCOM 27.0214 9.1113  2.97  0.0030
CA    3.3371 1.2342  2.70  0.0069
OMI  -0.9673 0.4428 -2.18  0.0289
================================================================================
ACCESSIBILITY Vs   WM + ABD + LOC + CC + LCOM + I + CE + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY            WM           ABD           LOC            CC
LCOM             I            CE           DMI
            0             0             0             0             0
0             0             0             1
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes                Indexes
Obs          19    LR chi2      50.59    R2                  0.934    rho
0.919
Unique Y     16    d.f.             8    g                  25.975
Median Y  0.861    Pr(> chi2) <0.0001    gr       190853723401.769
max |deriv| 0.4    Score chi2   43.61    |Pr(Y>=median)-0.5| 0.493
                   Pr(> chi2) <0.0001
     Coef     S.E.    Wald Z Pr(>|Z|)
WM     0.3355  0.1113  3.01  0.0026
ABD    8.6503  3.0182  2.87  0.0042
LOC   -0.0881  0.0284 -3.10  0.0019
CC     1.7347  0.5643  3.07  0.0021
LCOM  55.3953 18.9896  2.92  0.0035
I    -25.0907 11.0928 -2.26  0.0237
CE     0.8547  0.3757  2.27  0.0229
DMI   -0.2413  0.1098 -2.20  0.0280
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + NOM + LOC + WMC + CA + OMI + DC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST            WM           NOM
LOC           WMC           CA           OMI            DC
```

```
            0             0             0             0             0
0             0             0             1             0
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                  Indexes                Indexes
Obs          19    LR chi2      59.06    R2                   0.959    rho
0.942
Unique Y     16    d.f.             9    g                   74.314
Median Y  0.861    Pr(> chi2) <0.0001    gr          1.880547e+32
max |deriv| 0.8    Score chi2   36.79    |Pr(Y>=median)-0.5| 0.451
                   Pr(> chi2) <0.0001
     Coef      S.E.      Wald Z Pr(>|Z|)
DIST 3328.9452 1124.4411  2.96  0.0031
ABST  -32.4091   10.8911 -2.98  0.0029
WM      0.6153    0.1913  3.22  0.0013
NOM     0.5832    0.1905  3.06  0.0022
LOC    -0.2184    0.0672 -3.25  0.0012
WMC     0.5518    0.1830  3.02  0.0026
CA     -3.1812    1.4050 -2.26  0.0236
OMI    -4.1409    1.6555 -2.50  0.0124
DC      8.8034    3.3010  2.67  0.0077
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + NOM + LOC + WMC + LCOM + DC + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST            WM           NOM
LOC           WMC          LCOM           DC           DMI
            0             0             0             0             0
0             0             0             0             1
                   Model Likelihood          Discrimination          Rank
Discrim.
                      Ratio Test                  Indexes                Indexes
Obs         19    LR chi2      61.83    R2                   0.966    rho
0.959
Unique Y    16    d.f.             9    g                   78.944
Median Y 0.861    Pr(> chi2) <0.0001    gr          1.927287e+34
max |deriv|  1    Score chi2   36.09    |Pr(Y>=median)-0.5| 0.460
                  Pr(> chi2) <0.0001
     Coef      S.E.     Wald Z Pr(>|Z|)
DIST 2352.3988 787.9701  2.99  0.0028
ABST  -23.1323   7.7178 -3.00  0.0027
WM      0.7625   0.2473  3.08  0.0020
NOM     0.7453   0.2533  2.94  0.0033
LOC    -0.2549   0.0821 -3.10  0.0019
WMC     0.5507   0.1983  2.78  0.0055
LCOM   20.3337   8.9703  2.27  0.0234
DC      3.8168   1.4496  2.63  0.0085
DMI    -0.3151   0.1249 -2.52  0.0116
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + LCPM + ABD + LOC + CA + OMI + DC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST            WM          LCPM
ABD           LOC            CA           OMI            DC
            0             0             0             0             0
0             0             0             1             0
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                  Indexes                Indexes
Obs          19    LR chi2      50.83    R2                   0.935    rho
0.942
Unique Y     16    d.f.             9    g                   29.075
Median Y  0.861    Pr(> chi2) <0.0001    gr      4237723429951.777
max |deriv| 0.3    Score chi2   38.45    |Pr(Y>=median)-0.5| 0.445
```

```
                   Pr(> chi2) <0.0001
     Coef      S.E.      Wald Z Pr(>|Z|)
DIST 4307.9581 1448.0541  2.97  0.0029
ABST  -42.1217   14.0626 -3.00  0.0027
WM      0.2479    0.0745  3.33  0.0009
LCPM    0.3727    0.1702  2.19  0.0286
ABD    -7.4416    2.5390 -2.93  0.0034
LOC    -0.0719    0.0213 -3.38  0.0007
CA     -4.0595    1.5444 -2.63  0.0086
OMI    -6.4933    1.9318 -3.36  0.0008
DC     14.2383    4.1548  3.43  0.0006
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + WMC + OMI + DC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     2     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY    DIST     ABST     WM    NOM     LCPM    ABD    LOC    WMC   OMI
DC
      0          0        0        0      0        0      0      0      0     1
0
                    Model Likelihood         Discrimination         Rank
Discrim.
                       Ratio Test                Indexes                 Indexes
Obs          19    LR chi2      59.38    R2                0.960    rho
0.954
Unique Y     16    d.f.            10    g                60.715
Median Y  0.861    Pr(> chi2) <0.0001    gr          2.335311e+26
max |deriv| 0.5    Score chi2   38.07    |Pr(Y>=median)-0.5| 0.419
                   Pr(> chi2) <0.0001
     Coef      S.E.      Wald Z Pr(>|Z|)
DIST 2765.6810 1096.7213  2.52  0.0117
ABST  -27.5298   10.7859 -2.55  0.0107
WM      0.5152    0.1668  3.09  0.0020
NOM     0.4722    0.1715  2.75  0.0059
LCPM    0.4932    0.2497  1.98  0.0482
ABD    -6.8837    3.1086 -2.21  0.0268
LOC    -0.1810    0.0577 -3.14  0.0017
WMC     0.4077    0.1617  2.52  0.0117
OMI    -4.0300    1.6463 -2.45  0.0144
DC      9.2993    3.5447  2.62  0.0087
================================================================================
```

3. ORM models built after removing the outlier data point 18

Note:
Since the number of identified significant models (323) is large and more than 13278 lines will be needed to accommodate all models in this document, we listed only two models for each combination of predictors of specific size (i.e., where possible, three models with 2 predictors, three models with 3 predictors, etc.). Otherwise, the complete set of models will require alone about 140 pages of this document.

```
================================================================================
ACCESSIBILITY Vs   WM
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
```

```
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           19    LR chi2      4.78    R2                  0.223    rho
0.414
Unique Y      16    d.f.            1    g                   0.892
Median Y    0.861    Pr(> chi2) 0.0288    gr                  2.441
max |deriv| 0.002    Score chi2   5.97    |Pr(Y>=median)-0.5| 0.148
                     Pr(> chi2) 0.0145
          Coef   S.E.   Wald Z Pr(>|Z|)
y>=0.783  4.0502 1.2843  3.15  0.0016
y>=0.789  3.2207 1.0387  3.10  0.0019
y>=0.798  2.1662 0.7700  2.81  0.0049
y>=0.804  1.7519 0.6742  2.60  0.0094
y>=0.813  1.4280 0.6192  2.31  0.0211
y>=0.846  1.1567 0.5861  1.97  0.0484
y>=0.86   0.9161 0.5664  1.62  0.1057
y>=0.861  0.6843 0.5532  1.24  0.2161
y>=0.879  0.2101 0.5397  0.39  0.6970
y>=0.882 -0.0326 0.5424 -0.06  0.9520
y>=0.891 -0.2778 0.5549 -0.50  0.6166
y>=0.924 -0.5518 0.5750 -0.96  0.3372
y>=0.929 -1.2424 0.6653 -1.87  0.0618
y>=0.943 -1.7175 0.7765 -2.21  0.0270
y>=0.95  -2.4764 1.0476 -2.36  0.0181
WM       -0.0027 0.0013 -2.09  0.0363
================================================================================
ACCESSIBILITY Vs   LOC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes                 Indexes
Obs           19    LR chi2      7.94    R2                  0.343    rho
0.444
Unique Y      16    d.f.            1    g                   1.250
Median Y   0.861    Pr(> chi2) 0.0048    gr                  3.491
max |deriv| 0.05    Score chi2  10.78    |Pr(Y>=median)-0.5| 0.176
                    Pr(> chi2) 0.0010
          Coef   S.E.   Wald Z Pr(>|Z|)
y>=0.783  4.9744 1.6701  2.98  0.0029
y>=0.789  3.8027 1.2324  3.09  0.0020
y>=0.798  2.5053 0.8418  2.98  0.0029
y>=0.804  2.0221 0.7166  2.82  0.0048
y>=0.813  1.6651 0.6494  2.56  0.0103
y>=0.846  1.3755 0.6100  2.26  0.0241
y>=0.86   1.1235 0.5864  1.92  0.0554
y>=0.861  0.8813 0.5705  1.54  0.1224
y>=0.879  0.3818 0.5517  0.69  0.4889
y>=0.882  0.1265 0.5521  0.23  0.8188
y>=0.891 -0.1274 0.5628 -0.23  0.8208
y>=0.924 -0.4099 0.5815 -0.70  0.4808
y>=0.929 -1.1145 0.6694 -1.66  0.0960
y>=0.943 -1.5936 0.7795 -2.04  0.0409
y>=0.95  -2.3581 1.0494 -2.25  0.0246
LOC      -0.0008 0.0003 -2.63  0.0086
================================================================================
ACCESSIBILITY Vs   LOC + CC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
```

```
Obs            19    LR chi2     12.96    R2                  0.496    rho
0.610
Unique Y       16    d.f.            2    g                   1.914
Median Y    0.861    Pr(> chi2) 0.0015    gr                  6.780
max |deriv| 3e-05    Score chi2  16.66    |Pr(Y>=median)-0.5| 0.205
                     Pr(> chi2) 0.0002
    Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.783  3.3559 1.7291  1.94  0.0523
y>=0.789  2.3434 1.3978  1.68  0.0936
y>=0.798  1.0451 1.0820  0.97  0.3341
y>=0.804  0.5491 0.9929  0.55  0.5802
y>=0.813  0.1786 0.9522  0.19  0.8512
y>=0.846 -0.1200 0.9311 -0.13  0.8974
y>=0.86  -0.3877 0.9242 -0.42  0.6749
y>=0.861 -0.6617 0.9299 -0.71  0.4767
y>=0.879 -1.2456 0.9588 -1.30  0.1939
y>=0.882 -1.5592 0.9877 -1.58  0.1144
y>=0.891 -1.9052 1.0450 -1.82  0.0683
y>=0.924 -2.3012 1.1196 -2.06  0.0398
y>=0.929 -3.1735 1.2709 -2.50  0.0125
y>=0.943 -3.7356 1.3785 -2.71  0.0067
y>=0.95  -4.7324 1.6767 -2.82  0.0048
LOC -0.0010 0.0003 -2.90  0.0037
CC   0.5408 0.2534  2.13  0.0328
================================================================================
SUCCESSABILITY Vs   LCPM + ABD
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                Indexes
Indexes
Obs            19    LR chi2      7.37    R2                  0.333    rho
0.552
Unique Y        9    d.f.            2    g                   1.577
Median Y        1    Pr(> chi2) 0.0252    gr                  4.839
max |deriv| 0.005    Score chi2   7.42    |Pr(Y>=median)-0.5| 0.228
                     Pr(> chi2) 0.0245
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  4.6651 1.6658  2.80  0.0051
y>=0.472  3.7171 1.4631  2.54  0.0111
y>=0.844  3.0520 1.3568  2.25  0.0245
y>=0.977  2.5982 1.3046  1.99  0.0464
y>=0.985  1.8667 1.2493  1.49  0.1351
y>=0.988  1.5532 1.2212  1.27  0.2034
y>=0.994  1.2319 1.1731  1.05  0.2937
y>=1      0.9145 1.1371  0.80  0.4213
LCPM     -0.2364 0.0952 -2.48  0.0130
ABD       1.8783 0.9138  2.06  0.0398

================================================================================
ACCESSIBILITY Vs   CE + DCBO + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           CE          DCBO           DMI
           0             0             0             1
                    Model Likelihood         Discrimination          Rank
Discrim.
                       Ratio Test                Indexes                 Indexes
Obs            18    LR chi2     10.14    R2                  0.432    rho
0.493
Unique Y       16    d.f.            3    g                   1.858
Median Y     0.86    Pr(> chi2) 0.0174    gr                  6.409
max |deriv| 0.08     Score chi2  11.82    |Pr(Y>=median)-0.5| 0.223
                    Pr(> chi2) 0.0080
         Coef    S.E.   Wald Z Pr(>|Z|)
```

```
y>=0.783  6.4863 2.0296  3.20  0.0014
y>=0.789  5.3337 1.7099  3.12  0.0018
y>=0.798  3.8631 1.3498  2.86  0.0042
y>=0.804  3.1977 1.1268  2.84  0.0045
y>=0.813  2.7117 1.0210  2.66  0.0079
y>=0.846  2.3407 0.9705  2.41  0.0159
y>=0.86   2.0171 0.9359  2.16  0.0311
y>=0.861  1.7188 0.9047  1.90  0.0574
y>=0.879  1.4497 0.8856  1.64  0.1017
y>=0.882  1.1896 0.8812  1.35  0.1770
y>=0.891  0.9150 0.8834  1.04  0.3003
y>=0.924  0.6305 0.8896  0.71  0.4785
y>=0.929 -0.0167 0.9421 -0.02  0.9859
y>=0.943 -0.4753 1.0202 -0.47  0.6413
y>=0.95  -1.2397 1.2311 -1.01  0.3140
CE       -0.2789 0.1047 -2.66  0.0077
DCBO     -0.5495 0.2704 -2.03  0.0422
DMI       0.0371 0.0176  2.10  0.0354
================================================================================
SUCCESSABILITY Vs   LCPM + ABD + DCBO
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           19    LR chi2     12.15    R2                  0.490    rho
0.648
Unique Y       9    d.f.            3    g                   2.417
Median Y       1    Pr(> chi2) 0.0069    gr                 11.215
max |deriv| 1e-04    Score chi2  11.08    |Pr(Y>=median)-0.5| 0.282
                     Pr(> chi2) 0.0113
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  7.3655 2.3578  3.12  0.0018
y>=0.472  6.4334 2.2061  2.92  0.0035
y>=0.844  5.6568 2.0666  2.74  0.0062
y>=0.977  5.0624 1.9524  2.59  0.0095
y>=0.985  4.1739 1.8413  2.27  0.0234
y>=0.988  3.7973 1.7958  2.11  0.0345
y>=0.994  3.3717 1.7036  1.98  0.0478
y>=1      2.9373 1.6143  1.82  0.0688
LCPM     -0.3290 0.1191 -2.76  0.0057
ABD       2.8015 1.1276  2.48  0.0130
DCBO     -0.6718 0.3119 -2.15  0.0312
================================================================================
ACCESSIBILITY Vs   CC + CA + CE + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           CC            CA            CE           DMI
            0            0             0             0             1
                     Model Likelihood         Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           18    LR chi2     14.75    R2                  0.562    rho
0.592
Unique Y      16    d.f.            4    g                   2.482
Median Y    0.86    Pr(> chi2) 0.0052    gr                 11.960
max |deriv| 6e-05    Score chi2  19.08    |Pr(Y>=median)-0.5| 0.244
                     Pr(> chi2) 0.0008
    Coef    S.E.   Wald Z Pr(>|Z|)
CC   0.6176 0.2719  2.27  0.0231
CA  -0.8492 0.4032 -2.11  0.0352
CE  -0.3149 0.1186 -2.65  0.0079
DMI  0.0415 0.0195  2.13  0.0332
================================================================================
```

```
SUCCESSABILITY Vs   DIST + CE + DCBO + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           DIST             CE           DCBO           DMI
             0              0              0              0              1
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs             18    LR chi2      7.47    R2                  0.356    rho
0.468
Unique Y         8    d.f.            4    g                   1.751
Median Y         1    Pr(> chi2) 0.1131    gr                  5.762
max |deriv| 4e-05    Score chi2   7.74    |Pr(Y>=median)-0.5| 0.242
                     Pr(> chi2) 0.1015
         Coef     S.E.   Wald Z Pr(>|Z|)
y>=0.442   6.6592 2.1225  3.14  0.0017
y>=0.472   5.8647 1.9924  2.94  0.0032
y>=0.844   5.2894 1.9181  2.76  0.0058
y>=0.977   4.7143 1.7792  2.65  0.0081
y>=0.985   3.6967 1.5041  2.46  0.0140
y>=0.988   3.3081 1.4308  2.31  0.0208
y>=1       2.9410 1.3681  2.15  0.0316
DIST     -15.2408 7.6630 -1.99  0.0467
CE        -0.2350 0.1085 -2.17  0.0304
DCBO      -0.7094 0.3476 -2.04  0.0413
DMI        0.0484 0.0232  2.09  0.0366
================================================================================
ACCESSIBILITY Vs   CC + WMC + I + CE + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY            CC           WMC              I            CE
DMI
            0             0              0              0             0
1
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs             18    LR chi2     18.29    R2                  0.641    rho
0.720
Unique Y        16    d.f.            5    g                   2.991
Median Y      0.86    Pr(> chi2) 0.0026    gr                 19.915
max |deriv| 1e-04    Score chi2  22.77    |Pr(Y>=median)-0.5| 0.286
                     Pr(> chi2) 0.0004
    Coef    S.E.   Wald Z Pr(>|Z|)
CC   0.9896 0.3906  2.53  0.0113
WMC -0.0688 0.0325 -2.12  0.0342
I    9.3728 4.6397  2.02  0.0434
CE  -0.4275 0.1480 -2.89  0.0039
DMI  0.0670 0.0265  2.53  0.0116
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + LOC + CE
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood          Discrimination          Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs             19    LR chi2     12.02    R2                  0.486    rho
0.643
Unique Y         9    d.f.            5    g                   1.972
Median Y         1    Pr(> chi2) 0.0346    gr                  7.187
max |deriv| 2e-04    Score chi2  14.31    |Pr(Y>=median)-0.5| 0.234
```

```
                     Pr(> chi2) 0.0138
         Coef      S.E.     Wald Z Pr(>|Z|)
y>=0.442    5.8206   1.8944  3.07  0.0021
y>=0.472    4.7057   1.5554  3.03  0.0025
y>=0.844    3.7481   1.2808  2.93  0.0034
y>=0.977    3.0378   1.1489  2.64  0.0082
y>=0.985    1.7566   0.8524  2.06  0.0393
y>=0.988    1.2524   0.7715  1.62  0.1045
y>=0.994    0.8593   0.7284  1.18  0.2381
y>=1        0.5181   0.6867  0.75  0.4505
DIST     1249.0447 469.7270  2.66  0.0078
ABST      -12.1600   4.5600 -2.67  0.0077
WM         -0.0295   0.0125 -2.36  0.0181
LOC         0.0038   0.0018  2.08  0.0378
CE          0.2399   0.1071  2.24  0.0251
================================================================================
ACCESSIBILITY Vs   NOM + LOC + WMC + CE + DCBO + DC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                     Model Likelihood         Discrimination         Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           19    LR chi2      21.63    R2                  0.683    rho
0.708
Unique Y      16    d.f.             6    g                   4.712
Median Y   0.861    Pr(> chi2)  0.0014    gr                111.268
max |deriv| 0.09    Score chi2   32.57    |Pr(Y>=median)-0.5| 0.317
                    Pr(> chi2) <0.0001
     Coef    S.E.   Wald Z Pr(>|Z|)
NOM   0.1140 0.0493  2.31  0.0207
LOC  -0.0070 0.0031 -2.28  0.0228
WMC   0.1638 0.0634  2.58  0.0098
CE   -0.2922 0.1432 -2.04  0.0413
DCBO -2.1477 0.7113 -3.02  0.0025
DC    2.7304 0.9260  2.95  0.0032
================================================================================
SUCCESSABILITY Vs   DIST + WM + NOM + I + CA + DCBO
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood         Discrimination         Rank
Discrim.
                        Ratio Test                 Indexes
Indexes
Obs           19    LR chi2     15.68    R2                  0.583    rho
0.755
Unique Y       9    d.f.            6    g                   4.172
Median Y       1    Pr(> chi2) 0.0156    gr                 64.814
max |deriv| 2e-04   Score chi2  10.31    |Pr(Y>=median)-0.5| 0.318
                    Pr(> chi2) 0.1122
         Coef     S.E.    Wald Z Pr(>|Z|)
y>=0.442  58.1750 20.6422  2.82  0.0048
y>=0.472  57.1822 20.4861  2.79  0.0053
y>=0.844  56.2950 20.2497  2.78  0.0054
y>=0.977  55.4792 20.0032  2.77  0.0055
y>=0.985  54.1155 19.6038  2.76  0.0058
y>=0.988  53.5939 19.4824  2.75  0.0059
y>=0.994  53.1243 19.4036  2.74  0.0062
y>=1      52.6612 19.3492  2.72  0.0065
DIST     -29.0171 10.8433 -2.68  0.0074
WM        -0.0199  0.0074 -2.69  0.0072
NOM        0.0712  0.0273  2.60  0.0092
I        -49.9612 18.7414 -2.67  0.0077
CA        -0.9237  0.3560 -2.59  0.0095
DCBO      -0.7317  0.3271 -2.24  0.0253
================================================================================
ACESSIBILITY Vs   WM + NOM + LCPM + LOC + CC + OMI + DMI
```

```
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY            WM            NOM           LCPM           LOC
CC            OMI
            0             0             0             0             0
0             1
          DMI
            1
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes                Indexes
Obs           18    LR chi2      34.64    R2                  0.858    rho
0.911
Unique Y      16    d.f.             7    g                  14.182
Median Y    0.86    Pr(> chi2) <0.0001    gr            1442547.597
max |deriv| 0.1     Score chi2   36.89    |Pr(Y>=median)-0.5| 0.373
                    Pr(> chi2) <0.0001
     Coef    S.E.   Wald Z Pr(>|Z|)
WM    0.1402 0.0437  3.21  0.0013
NOM   0.1353 0.0456  2.97  0.0030
LCPM -0.3130 0.1421 -2.20  0.0275
LOC  -0.0421 0.0126 -3.34  0.0008
CC    1.6493 0.5789  2.85  0.0044
OMI   1.8003 0.7041  2.56  0.0106
DMI  -0.1577 0.0741 -2.13  0.0333
================================================================================
SUCCESSABILITY Vs   DIST + ABST + WM + LCOM + CE + DC + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           DIST           ABST              WM            LCOM
CE             DC
             0              0              0              0              0
0              0
           DMI
             1
                    Model Likelihood          Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes                Indexes
Obs           18     LR chi2     21.00    R2                  0.722    rho
0.786
Unique Y       8     d.f.            7    g                  14.903
Median Y       1     Pr(> chi2) 0.0038    gr            2966986.746
max |deriv| 0.04     Score chi2  13.38    |Pr(Y>=median)-0.5| 0.410
                     Pr(> chi2) 0.0634
         Coef      S.E.      Wald Z Pr(>|Z|)
y>=0.442    1.5438    1.8762  0.82  0.4106
y>=0.472    0.3119    1.9020  0.16  0.8698
y>=0.844   -0.8202    1.9715 -0.42  0.6774
y>=0.977   -1.8690    2.0400 -0.92  0.3596
y>=0.985   -3.7536    2.2965 -1.63  0.1022
y>=0.988   -4.4995    2.4481 -1.84  0.0661
y>=1       -5.0159    2.5005 -2.01  0.0449
DIST     6145.1894 2659.4425  2.31  0.0208
ABST      -58.8578   25.4482 -2.31  0.0207
WM         -0.0753    0.0350 -2.15  0.0314
LCOM       87.1487   41.2932  2.11  0.0348
CE          3.1762    1.4614  2.17  0.0297
DC          2.1675    1.0563  2.05  0.0402
DMI        -0.4586    0.2075 -2.21  0.0271
================================================================================
ACCESSIBILITY Vs   ABST + WM + LOC + CC + LCOM + I + CE + DCBO
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
```

```
    1     1     2     1     1     1     1     1     2     1     1     1     2 
1     1     1 
                    Model Likelihood          Discrimination          Rank 
Discrim.    
                       Ratio Test                 Indexes                Indexes    
Obs          19    LR chi2      45.84    R2                   0.914    rho     
0.928    
Unique Y     16    d.f.             8    g                   27.921             
Median Y  0.861    Pr(> chi2) <0.0001    gr      1335834721616.729             
max |deriv| 0.1    Score chi2   37.98    |Pr(Y>=median)-0.5| 0.411             
                   Pr(> chi2) <0.0001                                          
     Coef     S.E.    Wald Z Pr(>|Z|)
ABST  -0.7046  0.2584 -2.73  0.0064  
WM     0.3139  0.0917  3.42  0.0006  
LOC   -0.0900  0.0261 -3.45  0.0006  
CC     0.8077  0.3723  2.17  0.0301  
LCOM  15.4534  7.2069  2.14  0.0320  
I    -28.3037 11.5875 -2.44  0.0146  
CE     0.5187  0.1679  3.09  0.0020  
DCBO   1.0180  0.4425  2.30  0.0214  
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + LCPM + LOC + LCOM + OMI + DC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924 
0.929 0.943  0.95 
    1     1     2     1     1     1     1     1     1     1     1     1     2 
1     1     1 
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST             WM          LCPM 
LOC          LCOM 
            0             0             0              0             0 
0             0 
          OMI            DC 
            1             0 
                    Model Likelihood          Discrimination          Rank 
Discrim.    
                       Ratio Test                 Indexes                Indexes    
Obs          18    LR chi2      60.20    R2                   0.969    rho     
0.981    
Unique Y     16    d.f.             8    g                   49.829             
Median Y   0.86    Pr(> chi2) <0.0001    gr            4.370467e+21             
max |deriv| 0.5    Score chi2   36.90    |Pr(Y>=median)-0.5| 0.465             
                   Pr(> chi2) <0.0001                                          
     Coef      S.E.      Wald Z Pr(>|Z|)
DIST 2681.2154 1017.8837  2.63  0.0084  
ABST  -26.6412    9.9937 -2.67  0.0077  
WM      0.5209    0.1490  3.50  0.0005  
LCPM    0.7474    0.2792  2.68  0.0074  
LOC    -0.1440    0.0412 -3.49  0.0005  
LCOM   54.4374   17.1576  3.17  0.0015  
OMI    -7.9124    2.3614 -3.35  0.0008  
DC     12.0016    3.5239  3.41  0.0007  
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + NOM + ABD + LOC + CC + DC + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924 
0.929 0.943  0.95 
    1     1     2     1     1     1     1     1     1     1     1     1     2 
1     1     1 
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST             WM           NOM 
ABD           LOC 
            0             0             0              0             0 
0             0 
           CC            DC           DMI 
            0             0             1 
                     Model Likelihood        Discrimination           Rank 
Discrim.    
                        Ratio Test               Indexes             Indexes    
Obs           18    LR chi2      48.54    R2             0.937       rho     0.930
Unique Y      16    d.f.             9    g             30.247                 
```

```
Median Y    0.86    Pr(> chi2) <0.0001   gr             1.368114e+13
max |deriv| 0.05    Score chi2   39.17   |Pr(Y>=median)-0.5| 0.387
                    Pr(> chi2) <0.0001
     Coef      S.E.     Wald Z Pr(>|Z|)
DIST 1778.9201 645.9127  2.75  0.0059
ABST  -17.7428   6.3638 -2.79  0.0053
WM      0.3090   0.0944  3.27  0.0011
NOM     0.2914   0.1001  2.91  0.0036
ABD   -10.5344   3.7930 -2.78  0.0055
LOC    -0.0921   0.0281 -3.27  0.0011
CC      2.4824   0.9018  2.75  0.0059
DC      8.8062   3.0886  2.85  0.0044
DMI    -0.3490   0.1250 -2.79  0.0052
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + NOM + LOC + CC + LCOM + DCBO + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY          DIST          ABST            WM           NOM
LOC            CC
            0             0             0             0             0
0             0
         LCOM          DCBO           DMI
            0             0             1
                    Model Likelihood         Discrimination         Rank
Discrim.
                       Ratio Test                Indexes                Indexes
Obs          18    LR chi2      54.26    R2                 0.955    rho
0.959
Unique Y     16    d.f.             9    g                 43.934
Median Y   0.86    Pr(> chi2) <0.0001    gr          1.203395e+19
max |deriv| 0.5    Score chi2   35.86    |Pr(Y>=median)-0.5| 0.414
                   Pr(> chi2) <0.0001
         Coef      S.E.     Wald Z Pr(>|Z|)
y>=0.783   27.5183  32.9456  0.84  0.4036
y>=0.789   17.3487   7.1887  2.41  0.0158
y>=0.798    9.6051   4.2838  2.24  0.0250
y>=0.804    7.2031   3.3064  2.18  0.0294
y>=0.813    4.4568   2.6002  1.71  0.0865
y>=0.846    2.5360   2.3413  1.08  0.2787
y>=0.86     1.6351   2.4021  0.68  0.4961
y>=0.861    0.8197   2.4297  0.34  0.7358
y>=0.879   -0.9344   2.4866 -0.38  0.7071
y>=0.882   -2.6752   2.2698 -1.18  0.2386
y>=0.891   -3.5926   2.3298 -1.54  0.1231
y>=0.924   -4.5443   2.4596 -1.85  0.0647
y>=0.929   -6.6984   2.8626 -2.34  0.0193
y>=0.943   -8.5415   3.4423 -2.48  0.0131
y>=0.95   -10.5608   3.8082 -2.77  0.0056
DIST     1572.9370 668.1664  2.35  0.0186
ABST      -15.5579   6.5176 -2.39  0.0170
WM          0.4564   0.1306  3.49  0.0005
NOM         0.2425   0.0766  3.17  0.0015
LOC        -0.1363   0.0387 -3.52  0.0004
CC          1.1665   0.4721  2.47  0.0135
LCOM       26.4750   9.0160  2.94  0.0033
DCBO        1.8533   0.6924  2.68  0.0074
DMI        -0.2044   0.0806 -2.54  0.0112
================================================================================
ACCESSIBILITY Vs   DIST + ABST + WM + NOM + LCPM + ABD + LOC + CC + DCBO + OMI +
DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
```

```
ACCESSIBILITY          DIST          ABST            WM           NOM
LCPM          ABD
            0             0             0             0             0
0             0
          LOC            CC          DCBO           OMI           DMI
            0             0             0             1             1
                    Model Likelihood         Discrimination          Rank
Discrim.
                       Ratio Test                 Indexes               Indexes
Obs          18    LR chi2      56.09    R2                  0.960    rho
0.967
Unique Y     16    d.f.            11    g                  55.252
Median Y   0.86    Pr(> chi2) <0.0001    gr           9.896941e+23
max |deriv| 0.2    Score chi2   38.79    |Pr(Y>=median)-0.5| 0.413
                   Pr(> chi2) <0.0001
     Coef      S.E.     Wald Z Pr(>|Z|)
DIST 2510.7488 942.5444  2.66  0.0077
ABST  -24.7511   9.2585 -2.67  0.0075
WM      0.6585   0.2165  3.04  0.0024
NOM     0.9148   0.3341  2.74  0.0062
LCPM   -0.6648   0.3155 -2.11  0.0351
ABD   -17.5883   7.0371 -2.50  0.0124
LOC    -0.1965   0.0632 -3.11  0.0019
CC      6.1594   2.4426  2.52  0.0117
DCBO    3.0434   1.0816  2.81  0.0049
OMI    11.3814   4.5826  2.48  0.0130
DMI    -1.2460   0.4926 -2.53  0.0114
================================================================================
```

Appendix G. Selected models

```
================================================================================
ACCESSIBILITY Vs   WM
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                     Model Likelihood          Discrimination      Rank Discrim.
                        Ratio Test                Indexes            Indexes
Obs            19    LR chi2      4.78   R2                   0.223  rho     0.414
Unique Y       16    d.f.            1   g                    0.892
Median Y    0.861    Pr(> chi2) 0.0288   gr                   2.441
max |deriv| 0.002    Score chi2   5.97  |Pr(Y>=median)-0.5| 0.148
                     Pr(> chi2) 0.0145
   Coef    S.E.   Wald Z Pr(>|Z|)
WM -0.0027 0.0013 -2.09  0.0363
================================================================================
ACCESSIBILITY Vs   LOC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                    Model Likelihood          Discrimination       Rank Discrim.
                       Ratio Test                Indexes              Indexes
Obs        19      LR chi2     7.94       R2                0.343   rho     0.444
Unique Y      16    d.f.           1      g                 1.250
Median Y   0.861    Pr(> chi2) 0.0048    gr                 3.491
max |deriv| 0.05    Score chi2  10.78    |Pr(Y>=median)-0.5| 0.176
                    Pr(> chi2) 0.0010
    Coef    S.E.   Wald Z Pr(>|Z|)
LOC -0.0008 0.0003 -2.63  0.0086
================================================================================
ACCESSIBILITY Vs   WM + CC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                    Model Likelihood        Discrimination         Rank Discrim.
                       Ratio Test               Indexes              Indexes
Obs           19    LR chi2    9.06      R2                   0.381  rho  0.586
Unique Y      16    d.f.          2      g                    1.429
Median Y   0.861    Pr(> chi2) 0.0108    gr                   4.174
max |deriv| 0.05    Score chi2  11.46    |Pr(Y>=median)-0.5| 0.170
                    Pr(> chi2) 0.0033
   Coef    S.E.   Wald Z Pr(>|Z|)
WM -0.0031 0.0014 -2.25  0.0244
CC  0.4948 0.2473  2.00  0.0454
================================================================================
ACCESSIBILITY Vs   LOC + CC
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     2     1     1     1     2
1     1     1
                    Model Likelihood       Discrimination          Rank Discrim.
                       Ratio Test                Indexes             Indexes
Obs            19    LR chi2     12.96   R2                   0.496  rho   0.610
Unique Y       16    d.f.            2   g                    1.914
Median Y    0.861    Pr(> chi2) 0.0015   gr                   6.780
max |deriv| 3e-05    Score chi2  16.66   |Pr(Y>=median)-0.5| 0.205
                     Pr(> chi2) 0.0002
    Coef    S.E.   Wald Z Pr(>|Z|)
LOC -0.0010 0.0003 -2.90  0.0037
CC   0.5408 0.2534  2.13  0.0328
================================================================================
```

```
SUCCESSABILITY Vs   LCPM + ABD
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                    Model Likelihood      Discrimination          Rank Discrim.
                       Ratio Test         Indexes                    Indexes
Obs             19  LR chi2      7.37    R2                   0.333 rho     0.552
Unique Y        9    d.f.           2    g                    1.577
Median Y        1    Pr(> chi2) 0.0252   gr                   4.839
max |deriv| 0.005    Score chi2   7.42   |Pr(Y>=median)-0.5| 0.228
                     Pr(> chi2) 0.0245
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  4.6651 1.6658  2.80  0.0051
y>=0.472  3.7171 1.4631  2.54  0.0111
y>=0.844  3.0520 1.3568  2.25  0.0245
y>=0.977  2.5982 1.3046  1.99  0.0464
y>=0.985  1.8667 1.2493  1.49  0.1351
y>=0.988  1.5532 1.2212  1.27  0.2034
y>=0.994  1.2319 1.1731  1.05  0.2937
y>=1      0.9145 1.1371  0.80  0.4213
LCPM     -0.2364 0.0952 -2.48  0.0130
ABD       1.8783 0.9138  2.06  0.0398
================================================================================
ACCESSIBILITY Vs   WM + CC + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY            WM           CC           DMI
           0             0            0             1
                    Model Likelihood      Discrimination          Rank,Discrim.
                       Ratio Test           Indexes                  Indexes
Obs            18    LR chi2      14.99   R2                  0.568 rho    0.605
Unique Y       16    d.f.            3    g                   2.303
Median Y     0.86    Pr(> chi2)  0.0018   gr                  10.003
max |deriv| 3e-05    Score chi2   21.73   |Pr(Y>=median)-0.5| 0.208
                     Pr(> chi2) <0.0001
    Coef    S.E.   Wald Z Pr(>|Z|)
WM  -0.0104 0.0039 -2.66  0.0078
CC   0.7939 0.3025  2.62  0.0087
DMI  0.0396 0.0191  2.07  0.0383
================================================================================
ACCESSIBILITY Vs   CE + DCBO + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY            CE          DCBO           DMI
           0             0            0             1
                   Model Likelihood       Discrimination          Rank Discrim.
                      Ratio Test               Indexes               Indexes
Obs           18    LR chi2     10.14    R2                   0.432 rho     0.493
Unique Y      16    d.f.            3    g                    1.858
Median Y    0.86    Pr(> chi2) 0.0174    gr                   6.409
max |deriv| 0.08    Score chi2  11.82    |Pr(Y>=median)-0.5| 0.223
                    Pr(> chi2) 0.0080
     Coef    S.E.   Wald Z Pr(>|Z|)
CE   -0.2788 0.1047 -2.66  0.0077
DCBO -0.5494 0.2704 -2.03  0.0422
DMI   0.0371 0.0176  2.10  0.0354
================================================================================

SUCCESSABILITY Vs   LCPM + ABD + DCBO
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
```

```
                     Model Likelihood      Discrimination          Rank Discrim.
                        Ratio Test            Indexes                 Indexes
Obs           19     LR chi2     12.15   R2                  0.490 rho     0.648
Unique Y       9     d.f.            3   g                   2.417
Median Y       1     Pr(> chi2) 0.0069   gr                 11.215
max |deriv| 1e-04    Score chi2  11.08   |Pr(Y>=median)-0.5| 0.282
                     Pr(> chi2) 0.0113
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  7.3655 2.3578  3.12  0.0018
y>=0.472  6.4334 2.2061  2.92  0.0035
y>=0.844  5.6568 2.0666  2.74  0.0062
y>=0.977  5.0624 1.9524  2.59  0.0095
y>=0.985  4.1739 1.8413  2.27  0.0234
y>=0.988  3.7973 1.7958  2.11  0.0345
y>=0.994  3.3717 1.7036  1.98  0.0478
y>=1      2.9373 1.6143  1.82  0.0688
LCPM     -0.3290 0.1191 -2.76  0.0057
ABD       2.8015 1.1276  2.48  0.0130
DCBO     -0.6718 0.3119 -2.15  0.0312
================================================================================
SUCCESSABILITY Vs   LCPM + DCBO + DC
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood      Discrimination          Rank Discrim.
                        Ratio Test            Indexes                Indexes
Obs           19     LR chi2      8.64   R2                  0.379 rho    0.642
Unique Y       9     d.f.            3   g                   1.707
Median Y       1     Pr(> chi2) 0.0345   gr                  5.511
max |deriv| 3e-06    Score chi2   8.92   |Pr(Y>=median)-0.5| 0.228
                     Pr(> chi2) 0.0304
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  6.0233 1.9817  3.04  0.0024
y>=0.472  5.2711 1.8680  2.82  0.0048
y>=0.844  4.6847 1.7954  2.61  0.0091
y>=0.977  4.1376 1.7123  2.42  0.0157
y>=0.985  3.2375 1.6150  2.00  0.0450
y>=0.988  2.8376 1.5623  1.82  0.0693
y>=0.994  2.4604 1.4856  1.66  0.0977
y>=1      2.1393 1.4312  1.49  0.1350
LCPM     -0.1672 0.0757 -2.21  0.0273
DCBO     -0.6876 0.3020 -2.28  0.0228
DC        1.3515 0.6782  1.99  0.0463
================================================================================
ACCESSIBILITY Vs   NOM + ABD + OMI + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           NOM           ABD           OMI           DMI
            0             0             0             1             1
                     Model Likelihood      Discrimination          Rank Discrim.
                        Ratio Test            Indexes                Indexes
Obs           18     LR chi2     17.56   R2                  0.626 rho     0.659
Unique Y      16     d.f.            4   g                   3.018
Median Y    0.86     Pr(> chi2) 0.0015   gr                 20.441
max |deriv| 0.009    Score chi2  22.27   |Pr(Y>=median)-0.5| 0.301
                     Pr(> chi2) 0.0002
    Coef    S.E.   Wald Z Pr(>|Z|)
NOM -0.0797 0.0271 -2.95  0.0032
ABD  3.2133 1.1480  2.80  0.0051
OMI -1.3869 0.5382 -2.58  0.0100
DMI  0.1256 0.0447  2.81  0.0049
================================================================================
ACCESSIBILITY Vs   ABD + CE + DCBO + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
```

```
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           ABD           CE          DCBO          DMI
          0             0             0             0             1
                    Model Likelihood     Discrimination         Rank Discrim.
                       Ratio Test               Indexes            Indexes
Obs            18    LR chi2     15.75    R2                  0.586  rho     0.719
Unique Y       16    d.f.            4    g                   2.739
Median Y     0.86    Pr(> chi2) 0.0034    gr                 15.478
max |deriv| 0.01     Score chi2  16.41    |Pr(Y>=median)-0.5| 0.334
                     Pr(> chi2) 0.0025
     Coef    S.E.   Wald Z Pr(>|Z|)
ABD   1.5311 0.6762  2.26  0.0236
CE   -0.3672 0.1200 -3.06  0.0022
DCBO -0.9072 0.3307 -2.74  0.0061
DMI   0.0586 0.0211  2.78  0.0054
================================================================================
ACCESSIBILITY Vs   CC + I + CE + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           CC            I             CE            DMI
          0             0             0             0             1
                     Model Likelihood     Discrimination         Rank Discrim.
                        Ratio Test            Indexes               Indexes
Obs             18    LR chi2     13.96    R2                  0.542 rho     0.589
Unique Y        16    d.f.            4    g                   2.468
Median Y      0.86    Pr(> chi2) 0.0074    gr                 11.793
max |deriv| 5e-05    Score chi2  16.04    |Pr(Y>=median)-0.5| 0.283
                     Pr(> chi2) 0.0030
    Coef    S.E.   Wald Z Pr(>|Z|)
CC   0.5805 0.2588  2.24  0.0249
I    9.2723 4.4782  2.07  0.0384
CE  -0.3675 0.1332 -2.76  0.0058
DMI  0.0521 0.0227  2.29  0.0219
================================================================================
ACCESSIBILITY Vs   CC + CA + CE + DMI
Frequencies of Responses
0.121 0.783 0.789 0.798 0.804 0.813 0.846  0.86 0.861 0.879 0.882 0.891 0.924
0.929 0.943  0.95
    1     1     2     1     1     1     1     1     1     1     1     1     2
1     1     1
Frequencies of Missing Values Due to Each Variable
ACCESSIBILITY           CC            CA            CE            DMI
          0             0             0             0             1
                     Model Likelihood     Discrimination         Rank Discrim.
                        Ratio Test            Indexes               Indexes
Obs             18    LR chi2     14.75    R2                  0.562 rho     0.592
Unique Y        16    d.f.            4    g                   2.482
Median Y      0.86    Pr(> chi2) 0.0052    gr                 11.960
max |deriv| 6e-05    Score chi2  19.08    |Pr(Y>=median)-0.5| 0.244
                     Pr(> chi2) 0.0008
    Coef    S.E.   Wald Z Pr(>|Z|)
CC   0.6176 0.2719  2.27  0.0231
CA  -0.8492 0.4032 -2.11  0.0352
CE  -0.3149 0.1186 -2.65  0.0079
DMI  0.0415 0.0195  2.13  0.0332
================================================================================
SUCCESSABILITY Vs   DIST + CE + DCBO + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           DIST             CE           DCBO            DMI
           0              0              0              0              1
                     Model Likelihood     Discrimination         Rank Discrim.
```

```
                    Ratio Test           Indexes                 Indexes
Obs           18    LR chi2      7.47   R2                  0.356 rho     0.468
Unique Y       8    d.f.            4   g                   1.751
Median Y       1    Pr(> chi2) 0.1131   gr                  5.762
max |deriv| 4e-05   Score chi2   7.74   |Pr(Y>=median)-0.5| 0.242
                    Pr(> chi2) 0.1015
         Coef     S.E.   Wald Z Pr(>|Z|)
y>=0.442   6.6592 2.1225  3.14  0.0017
y>=0.472   5.8647 1.9924  2.94  0.0032
y>=0.844   5.2894 1.9181  2.76  0.0058
y>=0.977   4.7143 1.7792  2.65  0.0081
y>=0.985   3.6967 1.5041  2.46  0.0140
y>=0.988   3.3081 1.4308  2.31  0.0208
y>=1       2.9410 1.3681  2.15  0.0316
DIST     -15.2408 7.6630 -1.99  0.0467
CE        -0.2350 0.1085 -2.17  0.0304
DCBO      -0.7094 0.3476 -2.04  0.0413
DMI        0.0484 0.0232  2.09  0.0366
================================================================================
SUCCESSABILITY Vs   ABST + CE + DCBO + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           ABST              CE           DCBO            DMI
             0              0               0              0              1
                    Model Likelihood      Discrimination          Rank Discrim.
                       Ratio Test           Indexes                 Indexes
Obs           18    LR chi2      7.54   R2                  0.359 rho     0.468
Unique Y       8    d.f.            4   g                   1.763
Median Y       1    Pr(> chi2) 0.1099   gr                  5.829
max |deriv| 4e-05   Score chi2   7.83   |Pr(Y>=median)-0.5| 0.243
                    Pr(> chi2) 0.0982
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  6.6883 2.1327  3.14  0.0017
y>=0.472  5.8892 2.0016  2.94  0.0033
y>=0.844  5.3079 1.9253  2.76  0.0058
y>=0.977  4.7275 1.7839  2.65  0.0080
y>=0.985  3.7031 1.5050  2.46  0.0139
y>=0.988  3.3129 1.4310  2.32  0.0206
y>=1      2.9450 1.3682  2.15  0.0314
ABST     -0.1490 0.0741 -2.01  0.0445
CE       -0.2328 0.1075 -2.17  0.0304
DCBO     -0.7087 0.3473 -2.04  0.0413
DMI       0.0477 0.0228  2.09  0.0363
================================================================================
SUCCESSABILITY Vs   WM + LCPM + DCBO + OMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY             WM          LCPM           DCBO            OMI
             0              0             0              0              1
                    Model Likelihood      Discrimination          Rank Discrim.
                       Ratio Test           Indexes                 Indexes
Obs           18    LR chi2     11.35   R2                  0.491 rho     0.684
Unique Y       8    d.f.            4   g                   2.377
Median Y       1    Pr(> chi2) 0.0229   gr                 10.773
max |deriv| 0.005   Score chi2  10.42   |Pr(Y>=median)-0.5| 0.294
                    Pr(> chi2) 0.0339
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  8.6440 2.8535  3.03  0.0025
y>=0.472  7.9244 2.7800  2.85  0.0044
y>=0.844  7.4150 2.7479  2.70  0.0070
y>=0.977  6.8602 2.6668  2.57  0.0101
y>=0.985  5.7056 2.4632  2.32  0.0205
y>=0.988  5.1481 2.3466  2.19  0.0282
y>=1      4.6424 2.2118  2.10  0.0358
WM       -0.0029 0.0015 -2.00  0.0459
LCPM     -0.2316 0.0986 -2.35  0.0188
```

```
DCBO     -0.6275 0.3071 -2.04  0.0410
OMI       0.6955 0.3473  2.00  0.0453
==============================================================================
SUCCESSABILITY Vs   NOM + LCPM + DCBO + OMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           NOM           LCPM           DCBO           OMI
             0             0              0              0             1
                    Model Likelihood     Discrimination         Rank Discrim.
                       Ratio Test           Indexes                Indexes
Obs           18    LR chi2     11.23    R2                  0.487  rho     0.663
Unique Y       8    d.f.            4    g                   2.395
Median Y       1    Pr(> chi2) 0.0241    gr                 10.968
max |deriv| 0.001   Score chi2  10.10    |Pr(Y>=median)-0.5| 0.313
                    Pr(> chi2) 0.0387
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  8.9659 2.9480  3.04  0.0024
y>=0.472  8.2419 2.8784  2.86  0.0042
y>=0.844  7.7257 2.8479  2.71  0.0067
y>=0.977  7.2028 2.7868  2.58  0.0097
y>=0.985  6.1222 2.6226  2.33  0.0196
y>=0.988  5.5318 2.4762  2.23  0.0255
y>=1      5.0070 2.3225  2.16  0.0311
NOM      -0.0114 0.0056 -2.02  0.0432
LCPM     -0.2615 0.1074 -2.44  0.0148
DCBO     -0.6099 0.3030 -2.01  0.0441
OMI       0.7113 0.3569  1.99  0.0463
==============================================================================
SUCCESSABILITY Vs   LCPM + ABD + CC + WMC
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                    Model Likelihood      Discrimination          Rank Discrim.
                       Ratio Test            Indexes                 Indexes
Obs           19    LR chi2     13.86    R2                  0.537  rho     0.744
Unique Y       9    d.f.            4    g                   2.660
Median Y       1    Pr(> chi2) 0.0078    gr                 14.300
max |deriv| 0.001   Score chi2  12.49    |Pr(Y>=median)-0.5| 0.282
                    Pr(> chi2) 0.0141
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  5.3928 1.9552  2.76  0.0058
y>=0.472  4.3363 1.7945  2.42  0.0157
y>=0.844  3.3733 1.7141  1.97  0.0491
y>=0.977  2.6689 1.6346  1.63  0.1025
y>=0.985  1.7524 1.5495  1.13  0.2581
y>=0.988  1.3839 1.5206  0.91  0.3628
y>=0.994  0.9366 1.4527  0.64  0.5191
y>=1      0.4705 1.3894  0.34  0.7349
LCPM     -0.3700 0.1279 -2.89  0.0038
ABD       2.4575 1.0815  2.27  0.0231
CC        0.9272 0.4535  2.04  0.0409
WMC      -0.0746 0.0340 -2.20  0.0281
==============================================================================
SUCCESSABILITY Vs   LCPM + CC + WMC + OMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           LCPM            CC             WMC           OMI
             0             0              0              0             1
                    Model Likelihood      Discrimination         Rank Discrim.
                       Ratio Test            Indexes                Indexes
Obs           18    LR chi2     12.10    R2                  0.513  rho     0.718
Unique Y       8    d.f.            4    g                   2.451
Median Y       1    Pr(> chi2) 0.0166    gr                 11.601
max |deriv| 4e-04   Score chi2  11.49    |Pr(Y>=median)-0.5| 0.315
                    Pr(> chi2) 0.0216
         Coef    S.E.   Wald Z Pr(>|Z|)
```

```
y>=0.442  5.6119 2.1259  2.64  0.0083
y>=0.472  4.7921 2.0275  2.36  0.0181
y>=0.844  4.0392 1.9959  2.02  0.0430
y>=0.977  3.2730 1.9401  1.69  0.0916
y>=0.985  2.1841 1.8599  1.17  0.2403
y>=0.988  1.7282 1.8225  0.95  0.3430
y>=1      1.2763 1.7508  0.73  0.4660
LCPM     -0.2919 0.1128 -2.59  0.0097
CC        0.9472 0.4396  2.15  0.0312
WMC      -0.0878 0.0350 -2.51  0.0121
OMI       0.7593 0.3724  2.04  0.0415
================================================================================
SUCCESSABILITY Vs   LCPM + CC + WMC + DC
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood      Discrimination          Rank Discrim.
                        Ratio Test            Indexes                 Indexes
Obs            19    LR chi2     13.20   R2                  0.520 rho     0.704
Unique Y        9    d.f.            4   g                   2.772
Median Y        1    Pr(> chi2) 0.0103   gr                 15.997
max |deriv| 0.001    Score chi2  11.54   |Pr(Y>=median)-0.5| 0.297
                     Pr(> chi2) 0.0211
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  4.0672 1.8992  2.14  0.0322
y>=0.472  3.1811 1.8032  1.76  0.0777
y>=0.844  2.3539 1.8123  1.30  0.1940
y>=0.977  1.5701 1.8080  0.87  0.3852
y>=0.985  0.4944 1.8141  0.27  0.7852
y>=0.988  0.0544 1.8130  0.03  0.9761
y>=0.994 -0.3898 1.7689 -0.22  0.8256
y>=1     -0.7622 1.7223 -0.44  0.6581
LCPM     -0.3067 0.1148 -2.67  0.0076
CC        1.2405 0.5283  2.35  0.0189
WMC      -0.0955 0.0376 -2.54  0.0111
DC        1.8091 0.8634  2.10  0.0361
================================================================================
SUCCESSABILITY Vs   LCPM + CE + DCBO + OMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           LCPM             CE           DCBO            OMI
             0              0              0              0              1
                     Model Likelihood      Discrimination          Rank Discrim.
                        Ratio Test           Indexes                Indexes
Obs            18    LR chi2     11.63   R2                  0.499 rho     0.703
Unique Y        8    d.f.            4   g                   2.416
Median Y        1    Pr(> chi2) 0.0203   gr                 11.205
max |deriv| 8e-04    Score chi2  10.53   |Pr(Y>=median)-0.5| 0.326
                     Pr(> chi2) 0.0324
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  9.3244 3.0202  3.09  0.0020
y>=0.472  8.5990 2.9517  2.91  0.0036
y>=0.844  8.0748 2.9207  2.76  0.0057
y>=0.977  7.5393 2.8576  2.64  0.0083
y>=0.985  6.4049 2.6757  2.39  0.0167
y>=0.988  5.7638 2.4993  2.31  0.0211
y>=1      5.2008 2.3174  2.24  0.0248
LCPM     -0.2551 0.1031 -2.47  0.0134
CE       -0.0978 0.0465 -2.10  0.0357
DCBO     -0.7517 0.3319 -2.26  0.0235
OMI       0.7503 0.3627  2.07  0.0386
================================================================================
SUCCESSABILITY Vs   LCPM + CE + DCBO + DC
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988 0.994     1
    1     1     1     1     2     1     1     1    10
                     Model Likelihood      Discrimination          Rank Discrim.
                        Ratio Test           Indexes                Indexes
```

```
Obs           19    LR chi2     13.91   R2                 0.539 rho     0.721
Unique Y       9    d.f.            4   g                  2.722
Median Y       1    Pr(> chi2) 0.0076   gr                15.206
max |deriv| 0.002   Score chi2  12.30   |Pr(Y>=median)-0.5| 0.321
                    Pr(> chi2) 0.0153
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442  9.6005 3.0100  3.19  0.0014
y>=0.472  8.8817 2.9405  3.02  0.0025
y>=0.844  8.3585 2.9098  2.87  0.0041
y>=0.977  7.8197 2.8518  2.74  0.0061
y>=0.985  6.6241 2.6630  2.49  0.0129
y>=0.988  5.9463 2.4790  2.40  0.0165
y>=0.994  5.3341 2.2707  2.35  0.0188
y>=1      4.8408 2.1389  2.26  0.0236
LCPM     -0.2728 0.1022 -2.67  0.0076
CE       -0.0954 0.0448 -2.13  0.0332
DCBO     -0.9522 0.3761 -2.53  0.0113
DC        1.7067 0.8019  2.13  0.0333
================================================================================
SUCCESSABILITY Vs   LCPM + DCBO + OMI + DMI
Frequencies of Responses
0.413 0.442 0.472 0.844 0.977 0.985 0.988     1
    1     1     1     1     2     1     1    10
Frequencies of Missing Values Due to Each Variable
SUCCESSABILITY           LCPM           DCBO            OMI            DMI
             0              0              0              1              1
                    Model Likelihood     Discrimination          Rank Discrim.
                       Ratio Test           Indexes                 Indexes
Obs           18    LR chi2     12.29   R2                 0.519 rho     0.684
Unique Y       8    d.f.            4   g                  2.927
Median Y       1    Pr(> chi2) 0.0153   gr                18.681
max |deriv| 3e-05   Score chi2  10.22  |Pr(Y>=median)-0.5| 0.336
                    Pr(> chi2) 0.0368
         Coef    S.E.   Wald Z Pr(>|Z|)
y>=0.442 10.3728 3.7464  2.77  0.0056
y>=0.472  9.6318 3.6931  2.61  0.0091
y>=0.844  9.0887 3.6659  2.48  0.0132
y>=0.977  8.5948 3.6309  2.37  0.0179
y>=0.985  7.5861 3.5112  2.16  0.0307
y>=0.988  6.9848 3.3556  2.08  0.0374
y>=1      6.4278 3.1911  2.01  0.0440
LCPM     -0.3593 0.1591 -2.26  0.0239
DCBO     -0.7142 0.3420 -2.09  0.0367
OMI       1.0726 0.4875  2.20  0.0278
DMI      -0.0246 0.0123 -2.00  0.0457
================================================================================
```

Appendix H. Model validation results

```
ORM Model: Accessibility ~ WM

      index.orig training   test optimism index.corrected   n
R2        0.2235    0.2414 0.2235  0.0180          0.2055 100
Slope     1.0000    1.0000 1.0000  0.0000          1.0000 100
================================================================================
ORM Model: Accessibility ~ LOC

      index.orig training   test optimism index.corrected   n
R2        0.3431   0.3424 0.3431  -0.0007          0.3439 100
Slope     1.0000   1.0000 0.9031   0.0969          0.9031 100
================================================================================
ORM Model: Accessibility ~ WM + CC
      index.orig training   test optimism index.corrected   n
R2      0.3809  0.4541 0.3169  0.1372              0.2437 100
Slope   1.0000  1.0000 0.6804  0.3196              0.6804 100
=======================================================================
ORM Model: Accessibility ~ LOC + CC
      index.orig training   test optimism index.corrected   n
R2        0.4965   0.5258 0.4497   0.0760          0.4204 100
Slope     1.0000   1.0000 0.7475   0.2525          0.7475 100
================================================================================
ORM Model: Successability ~ LCPM + ABD

      index.orig  training   test optimism index.corrected   n
R2        0.3334    0.3673 0.2929   0.0743          0.2591 100
Slope     1.0000    1.0000 0.8944   0.1056          0.8944 100
================================================================================
ORM Model: ACCESSIBILITY ~ WM + CC + DMI

      index.orig training   test optimism index.corrected   n
R2        0.5676   0.6031 0.4600   0.1432          0.4244 100
Slope     1.0000   1.0000 0.5817   0.4183          0.5817 100
================================================================================
ORM Model: Accessibility ~ CE + DCBO + DMI

      index.orig   training    test   optimism   index.corrected  n
R2        0.4324    0.5132    0.3182   0.1950         0.2374     100
Slope     1.0000    1.0000    0.4861   0.5139         0.4861     100
================================================================================
ORM Model: Successability ~ LCPM + ABD + DCBO

      index.orig training   test optimism index.corrected   n
R2        0.4903   0.6181 0.3956   0.2226          0.2677 100
Slope     1.0000   1.0000 0.5832   0.4168          0.5832 100
================================================================================
ORM Model: Successability ~ LCPM + DCBO + DC

      index.orig training   test optimism index.corrected   n
R2        0.3792   0.4991 0.2960   0.2031          0.1761 100
Slope     1.0000   1.0000 0.5843   0.4157          0.5843 100
================================================================================
ORM Model: Accessibility ~ NOM + ABD + OMI + DMI

      index.orig training   test optimism index.corrected   n
R2        0.6255   0.6633 0.4591   0.2043          0.4213 100
Slope     1.0000   1.0000 0.4832   0.5168          0.4832 100
================================================================================
ORM Model: Accessibility ~ ABD + CE + DCBO + DMI

      index.orig training   test optimism index.corrected   n
R2        0.5857   0.6184 0.4404   0.1780          0.4077 100
Slope     1.0000   1.0000 0.5534   0.4466          0.5534 100
================================================================================
ORM Model: Accessibility ~ CC + I + CE + DMI
      index.orig training   test optimism index.corrected   n
```

```
R2        0.5419   0.6405 0.3138   0.3267          0.2152 100
Slope     1.0000   1.0000 0.4002   0.5998          0.4002 100
================================================================================
ORM Model: Accessibility ~ CC + CA + CE + DMI

      index.orig training   test optimism index.corrected   n
R2        0.5618   0.6547 0.3857   0.2690          0.2928 100
Slope     1.0000   1.0000 0.4620   0.5380          0.4620 100
================================================================================
ORM Model: Successability ~ DIST + CE + DCBO + DMI

      index.orig   training    test   optimism index.corrected   n
R2        0.3562    0.5182    0.1816   0.3366          0.0196 100
Slope     1.0000    1.0000    0.4512   0.5488          0.4512 100
================================================================================
ORM Model: Successability ~ ABST + CE + DCBO + DMI

      index.orig training   test optimism index.corrected   n
R2        0.3590   0.5336 0.1739   0.3598         -0.0008 100
Slope     1.0000   1.0000 0.3316   0.6684          0.3316 100
================================================================================
ORM Model: Successability ~ WM + LCPM + DCBO + OMI

      index.orig training   test optimism index.corrected   n
R2        0.4906   0.6578 0.3600   0.2978          0.1928 100
Slope     1.0000   1.0000 0.4795   0.5205          0.4795 100
================================================================================
ORM Model: Successability ~ NOM + LCPM + DCBO + OMI

      index.orig training   test optimism index.corrected   n
R2        0.4868   0.6401 0.3146   0.3256          0.1612 100
Slope     1.0000   1.0000 0.4155   0.5845          0.4155 100
================================================================================
ORM Model: Successability ~ LCPM + ABD + CC + WMC

      index.orig training   test optimism index.corrected   n
R2        0.5372   0.7187 0.3667   0.3520          0.1852 100
Slope     1.0000   1.0000 0.3843   0.6157          0.3843 100
================================================================================
ORM Model: Successability ~ LCPM + CC + WMC + OMI

      index.orig training   test optimism index.corrected   n
R2        0.5132   0.6517 0.3727   0.2790          0.2342 100
Slope     1.0000   1.0000 0.4757   0.5243          0.4757 100
================================================================================
ORM Model: Successability ~ LCPM + CC + WMC + DC

      index.orig training   test optimism index.corrected   n
R2        0.5196   0.6336 0.3633   0.2703          0.2493 100
Slope     1.0000   1.0000 0.4963   0.5037          0.4963 100
================================================================================
ORM Model: Successability ~ LCPM + CE + DCBO + OMI

      index.orig training   test optimism index.corrected   n
R2        0.4992   0.6317 0.3241   0.3076          0.1916 100
Slope     1.0000   1.0000 0.4755   0.5245          0.4755 100
================================================================================
ORM Model: Successability ~ LCPM + CE + DCBO + DC

      index.orig training   test optimism index.corrected   n
R2        0.5386   0.6762 0.4264   0.2498          0.2888 100
Slope     1.0000   1.0000 0.5539   0.4461          0.5539 100
================================================================================
ORM Model: Successability ~ LCPM + DCBO + OMI + DMI

      index.orig training   test optimism index.corrected   n
R2        0.5190   0.6513 0.3336   0.3176          0.2014 100
Slope     1.0000   1.0000 0.4241   0.5759          0.4241 100
===============================================================================
```