Usability of Modelling Languages for Model Interpretation: An Empirical Research Report

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ABSTRACT
Models offer visual support for analyzing complex domains such as business processes and information systems. In both cases, models are developed using graphical modelling languages. In our study we focus on usability evaluation of modelling languages for the model interpretation scenario. The study is based on a causal model of hypotheses, which was developed under consideration of psychological cognitive theories and usability theory. Survey data is collected and the causal relations hypotheses are assessed using a structure equation modelling approach. Our study shows important findings for practical and theoretical issues of how differing modelling languages are influencing usability attributes on causal stages in model interpretation.

Keywords
Modelling Languages, Usability, Perceptibility

1. INTRODUCTION
In organizations models are important for documenting business processes and specifying information system requirements under development. Models are represented by using graphical modelling languages such as BPMN, EPC and UML providing a set of elements, relations and rules for combining them. In general, graphical modelling languages aim to support the expression of relevant aspects of real world domains such as business processes or application system structures [1]. For accurate human interpretation it is important that a model reproduces the knowledge contained in a clearly arranged and well-structured manner. When evaluating the usability of modelling languages it is necessary to distinguish between model interpretation and model development scenarios [2]. A model developer needs (1) to learn a modelling language, (2) to remember the language's elements and syntax to ensure correct models, (3) to reach a fast and correct task accomplishment and (4) to be satisfied with the modelling language.

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A model interpreter needs to recognize the meaning of a model. Due to this fact a model interpreter requires an intuitive and well-defined knowledge regarding shapes, model structure and syntax [3].

This summary research report focuses on empirical usability evaluation of graphical modelling languages in model interpretation. We define underlying background theories connected with our research. Based on this we are theoretically deriving a causal model of hypotheses, which is validated with empirical data collected in a follow-up experimental data collection. Finally, we conclude and interpret the survey results and consequently derive theoretical and practical implications.

2. BACKGROUND THEORIES
In general, usability theory has its roots in cognitive psychology and is a relatively young branch of computer science. While some of the principles of usability theory are gradually making their way to the mainstream software applications the underlying research is less known [4]. However, our research model integrating usability determinants in the field of business modelling is based on two centre theories adopted by usability research. First we underlie cognitive theory, which generally defines the external impact of human learning and acting. The theoretical constructs of cognitive psychology have direct analogies in model interpretation scenarios. From the traditional cognitive point of view, the usability system in our study is composed of three basic information generating and processing units, (1) the human being such as model interpreter, (2) the model, which contains the information interpreted and (3) particular language the graphical model is based on [5].

Secondly we underlie a development of cognitive theory called cognitive load theory [6]. This theory is focusing on the impact of memory load to human learning and knowledge acquisition. Figl et al. (2010) mapped cognitive theory to the context of modelling languages [7]. Cognitive theory differs between three types of cognitive load. The extraneous cognitive load is influenced by the way the information is represented. The intrinsic cognitive load is determined by information complexity. Finally germane cognitive load is strongly connected with learning processes and especially the load expended for learning [8]. As a result, the cognitive load referring to learning and understanding should be expanded. Extraneous cognitive load should be held low by minimizing irrelevant information. Transferring this to our approach, we conclude that language specific properties categorized in three loads are influencing the usability in model interpretation.

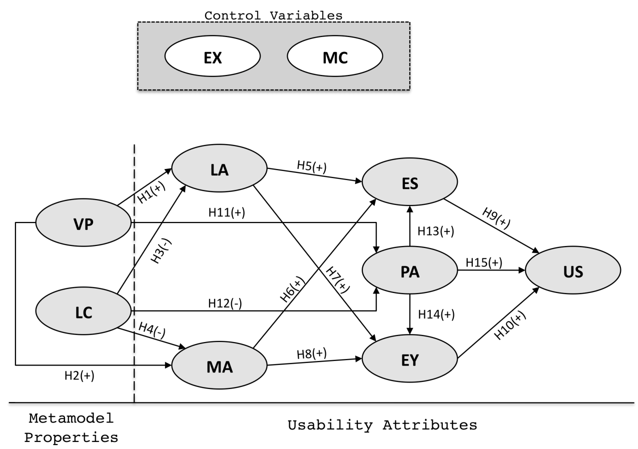
The variety of definitions and measurement models of usability complicates the extraction of capable attributes for assessing the usability of modelling languages. A usability study would be of limited value if it would not be based on a standard definition and operationalization of usability [9]. The International Organization for Standardization (ISO) defines usability as the capacity of the software product to be understood, learned and attractive to the user, when it is used under specified conditions [10]. Additionally, the ISO defined another standard which describes usability as the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use [11]. The Institute of Electrical and Electronics Engineers (IEEE) established a standard, which describes usability as the ease a user can learn how to operate, prepare inputs for, understand and interpret the outputs of a system or component [12]. Dumas and Redish (1999) define that usability means quickness and simplicity regarding a user's task accomplishment. This definition is based on four assumptions [13]: 1. Usability means focusing on users, 2. Usability includes productivity, 3. Usability means ease of use, 4. Usability means efficient task accomplishment. Shackel (1991) associates five attributes for defining usability: speed, time to learn, retention, errors and the user specific attitude [14]. Preece et al. (1994) combined effectiveness and efficiency to throughput [15]. Constantine and Lockwood (1999) and Nielsen (2006) collected the attributes defining usability and developed an overall definition of usability attributes consisting of learnability, memorability, effectiveness, efficiency and user satisfaction [16], [17]. The variety of definitions concerning usability attributes led to the use of different terms and labels for the same usability characteristics, or different terms for similar characteristics, without full consistency across these standards; in general, the situation in the literature is similar. For example, learnability is defined in ISO 9241-11 as a simple attribute, "time of learning", whereas ISO 9126 defines it as including several attributes such as "comprehensible input and output, instructions readiness, messages readiness […]" [18], [19], [11]. As a basis for our following up research we are underlying usability definition for modelling languages in model interpretation scenario including attributes as follows: The usability of modelling languages is specified by learnability, memorability, effectiveness, efficiency, user satisfaction and perceptibility. The learnability of modelling languages describes the capability of a modelling language to enable the user to learn interpreting models based on particular language. The modelling language and its semantics, syntax and elements should be easy to remember, so that a user is able to return to the language after some period of non-use without having to learn the language and especially the interpretation of models developed with specific language again. Effective model interpretation should be supported by particular language for reaching a successful task accomplishment. Modelling languages should be efficient to use, so that a high level of working productivity is possible. Users have to be satisfied when using the language. The language should offer a convenient perceptibility regarding structure, overview, elements and shapes so that an interpreter is able to search, extract and process available model information in an easy way [2, 20].

3. THEORY DEVELOPMENT

The usability concept in our research is specified by learnability, memorability, effectiveness, efficiency, user satisfaction and perceptibility. We state that these attributes and especially their causal interaction influence usability of model interpetation based on different modelling languages.

3.1 Structural Model

Usability literature and transferred theories only set the different attributes on one causal level. For example, Nielsen (2006) and Abran et al. (2003) state that usability is affected by attributes with same weightings [17, 18]. We argue that the usability of modelling languages is defined by chosen attributes on different stages. Furthermore we state a causal connection between usability attributes, which is examined in our empirical research. Adopting the background theories we propose our research model in figure 1. The research model includes two basic parts, the metamodel properties and the attributes defining usability. Metamodel properties are set in language's metamodel. They are language specific attributes, which affect the usability attributes on different stages.



VP	=	Visual Properties	PA	=	Perceptibility
LC	=	Language Complexity	EY	=	Efficiency
LA	=	Learnability	US	=	User Satisfaction
MA	=	Memorability	EX	=	User Experience
ES	=	Effectiveness	MC	=	Model Complexity

Figure 1 Research Model

HYPOTHESIS 1. *The range of different element colours and geometrics set in the language's metamodel (VP) are positively influencing user's ability to learn the application of the modelling language (LA)*

With considering perceptive factors affecting modelling languages' usability visual based metrics such as the number of different element shapes and the number of different element colours were defined [21]. Hall and Hanna (2004) analyzed the impact of colour on web usability attributes in an empirical survey. They concluded that the application of different colours results in a higher grade of website structuredness, which leads to more efficient information processing in the user's brain [22]. Transferring that, we can assume that more element colours set in the language's metamodel are leading to more information structuredness, which is influencing the learnability of modelling languages connected with model interpretation in a positive way. Furthermore we assume that the variance of different geometric shapes depicting different element types is positively influencing language learnability. The theoretic basis for this assumption is initially given by Comber et al. (1997). They concluded that screen complexity including the application of various geometric shapes is a positive influencing variable of usability and especially learnability. However, they additionally underlay a positive trade-off between screen complexity and learnability [23].

HYPOTHESIS 2. *The range of different element colours and geometrics set in the language's metamodel (VP) are positively influencing user's ability to remember the elements and syntax of the modelling language (MA)*

Hall and Hanna (2004) analyzed a strong impact of visual properties on website structuredness [22]. Furthermore Nembhard and Napassavong (2002) found a positive correlation between structured information and information storage in human's brain [24]. Deducing this to our model we state that visual variability of modelling languages is positively influencing the user's ability to remember elements and syntax of modelling languages.

HYPOTHESIS 3. *The complexity of a modelling language (LC) affects negatively the proband's ability to learn this language (LA)*

Referring to Rossi and Brinkkemper (1996) elements, relations and properties can be abstracted and defined as modelling language complexity. The language complexity influences the usability attributes [25]. For analyzing the language's complexity Welke (1992) and additionally Rossi and Brinkkemper (1996) developed metrics based on the OPRR data model [26], [27]. Transferring this to our approach metrics such as the number of object types (i.e. class), number of relationship types (i.e. association) and the number of property types (i.e. class name) are relevant for analyzing the complexity of a modelling language. The more elements, relations and properties a modelling language consists of, the more difficult a user can learn the application due to high semantically and syntactical power. We suppose, for example, that a high range of BPMN-elements is negatively influencing the user's ability of learning the interpretation of BPMN-models.

HYPOTHESIS 4. *Language complexity (LC) affects negatively the user's ability to remember elements, relations and syntax within a period of non use/training (MA)*

According to Kintsch 1998 cognitive processes underlie comprehension of a specific domain [28]. Nembhard and Napassavong (2002) found out that the complexity of a special domain influences memorability negatively [24]. According to our approach we assume that metamodel complexity is negatively related to memorability of modelling languages. A high semantically and syntactical complexity of language's metamodel is complicating model interpretation due to hindered ability of remembering elements, relations and their specific way of interpreting them.

HYPOTHESIS 5. *The gradient of a language's learning curve (LA) is positively related to the ability of completing a task with minimal errors and maximal completeness (ES)*

The ability of learning a modelling language in an easy or difficult way influences language's effectiveness in model interpretation when the language is applied. On the one hand we imply that low learnability values of a modelling language result in rising error rates and decreasing task completion rates. On the other hand we assume that an easy to learn modelling language support task completion rates and lowers error rates. In cognitive psychology low gradients of learning curves causes ineffective application of a construct in a specific domain [29]. Therefore our underlying assumption is that modelling languages, which are difficult to learn, are offering a limited user individual application. This fact influences task completion rates and task error rates, which are manifest variables for measuring the latent construct effectiveness.

HYPOTHESIS 6. *The user's ability to remember the range of elements, relations and syntactic regulations (MA) is positively related to the user's ability of performing tasks with minimal errors and maximal completeness (ES)*

Memorability describes the "remembering rate" of a modelling language. Overall it describes the fact that a modelling language should be easy to remember regarding its elements, syntax and semantics [30], [31]. Memorability is a very important attribute for measuring the usability of modelling languages considering that users may not be using a modelling language all the time [17]. Hence, we hypothesize that an easy to remember modelling language results in less errors and higher completion rates regarding model interpretation tasks.

HYPOTHESIS 7. *The gradient of a language's learning curve (LA) is positively related to the efficiency (EY) that is offered by modelling languages during applying them.*

Learnability is probably the most important attribute of usability, preferably a modelling language is easy to learn. Learning to use a modelling language in interpretation scenario seems to be the first experience most users are confronted with when using a new modelling language [25], [30]. Easy to learn languages offer a higher user-individual learning growth and consequently higher curve gradients based on task completion time values than difficult to learn modelling languages [32]. We state that this effect is supporting efficiency in interpreting models.

HYPOTHESIS 8. *The user's ability to remember the range of elements, relations and syntactic regulations (MA) is positively related to efficient task accomplishment (EY) offered by the modelling language*

Usability research shows that memorability is an initial basis for applying a system or a website [17]. Transferring this we state that some modelling languages are easier to remember than other. For example, it seems that BPMN elements are not easy to remember because of its high range of different element types. From this fact can be deduced that an efficient use and consequently a fast task completion is influenced by the memorability of the different metamodel properties a language consists of.

HYPOTHESIS 9. *The ability to perform a task with minimal errors and maximal completeness (ES) is positively related to user's individual satisfaction (US) with a modelling language*

Effectiveness characterises the fact, that it should be possible to reach a successful task accomplishment. In this regard, a user should be able to develop and comprehend models with low error rates and high task completion rates [33], [34]. Regarding the usability of modelling languages we imply that languages offering high effectiveness result in higher satisfaction values. In contrast we state that languages offering low effectiveness values are affecting user's individual satisfaction negatively.

HYPOTHESIS 10. *The Efficiency of task completion (EY) is positively related to user's individual satisfaction (US) of modelling languages*

A modelling language is efficient to use when the users are able to develop or comprehend a model relatively quickly and correctly regarding the regulations of the modelling language. Once a user has learned a modelling language it should be possible to reach a high level productivity regarding task completion time [35], [34]. Hence we hypothesize, that languages which afford an efficient interpretation completion result in higher values concerning user satisfaction.

HYPOTHESIS 11. *The variance of visual language properties (VP) set in the metamodel of the modelling language is positively influencing language's perceptibility (PA)*

Many researchers analyzed the influence of visual differentiation caused by varying geometric shapes and colours in usability and primarily neurophysical research. For example, Westphal and Würtz (2009) investigated that visual differentiation is supporting object recognition and consequently information search and information extraction [36]. However, in our research model language's perceptibility is measured by values indicating cognitive processes e.g. information search and information extraction [37]. Furthermore, Underwood (2009) corroborates the hypothesis that visual characteristics of an image are influencing eye movements [38]. From this we can deduce, that visual language properties, i.e. colours, geometric shapes, are positively influencing language's perceptibility due to stronger visual differentiation in model diagrams.

HYPOTHESIS 12. *The complexity of modelling languages (LC) is negatively influencing visual perceptibility (PA)*

The complexity of modelling languages, which is set in the language's metamodel, is strongly connected with syntactical and semantical complexity. For example, UML-class-diagrams contain a high range of syntactically different relations (e.g. association, aggregation etc.), which can be expanded by cardinalities. Furthermore, a class diagram generally includes two different class types: standard and abstract classes. Pan et al. (2004) analyze the viewing behaviour of web pages by using an eye-tracker [39]. They come to the conclusion that visual complexity negatively contributes to eye-movement behaviour due to difficulty of information search and information extraction. In our research model we state, that syntactic and semantic language properties are negatively influencing the perceptibility of a diagram developed by the application of specific modelling languages.

HYPOTHESIS 13. *The visual perceptibility (PA) of modelling languages is positively contributing to effective model interpretation (ES)*

With analyzing visual perceptibility we aim to measure processes of information search, information extraction and information processing in user's brain during model interpretation. For example, a low visual perceptibility of a model results in difficult information search and information extraction. Consequently we deduce that this fact is especially influencing task completion rate and subsequently effectiveness of model interpretation. Finally we hypothesize that visual perceptibility is influencing user's ability of ending an interpretation task with minimal errors and maximal completeness.

HYPOTHESIS 14. *The visual perceptibility of modelling languages (PA) is positively contributing to efficient model interpretation (EY)*

Goldberg and Kotval (1999) concluded that the number of overall fixations is negatively correlating with search efficiency. We state that this effect is influencing interpretation time and consequently interpretation efficiency [40]. Furthermore, high fixation durations implicate participant's difficulty of extracting information from a model [41]. Accordingly, this effect leads to increasing interpretation times and consequently lower efficiency.

HYPOTHESIS 15. *The visual perceptibility (PA) of models developed by the application of modelling languages affects positively the user's satisfaction (US) of specific modelling languages*

Many researchers concluded a strong impact of design (screen, website etc.) and especially layout and order of elements on target individual's satisfaction [42], [43]. Lindgaard 2007 states a positive link between user satisfaction and visual screen design [44]. Subsequently, in our research model we assume that a high language's visual perceptibility results in higher user satisfaction.

Furthermore we include additional variables as controls recognizing their effects on key constructs in our research model. The users of modelling languages differ regarding modelling experience. This fact influences the task accomplishment and consequently the usability and has to be considered in our research model [17]. Hence, the user and his/her individual modelling experience must be treated as control variable. The level of difficulty and complexity of a particular model affects understandability and consequently the usability of the applied modelling language [45]. When conducting a survey on usability evaluation of modelling languages, the complexity of a particular model applied in an experiment i.e. task complexity must be controlled for minimizing its influence on the outcome.

3.2 Measurement Model

In this section we theoretically underlie chosen manifest variables working as indicators for latent constructs in our research model. Evaluating **effectiveness** requires analysis of task output with measuring quantity and quality of goal achievement [46]. Quantity is defined as the proportion of task goals represented in the output of a task. Quality is the degree to which the task goals represented in the output have been achieved [47]. Bevan (1995) defined effectiveness as a product of quantity and quality [48]. Transferring this to our model, indicating manifest variables for measuring effectiveness are the grade of completeness and the grade of correctness of a model interpretation task.

The **efficiency** is the amount of human, economical and temporal resources. Measures of efficiency relate to the level of effectiveness achieved to the expenditure of resources [47]. Measure values of efficiency include time taken to complete tasks, i.e. duration time for performing a model interpretation task [49]. **Learnability** describes the ease of learning the application (i.e. interpretation) of modelling languages. For this characteristic, the standard measure values are based on task completion rates and the task accuracy [50]. In general, learnability is a development and can be graphically described by learning curves [32]. Hence, learnability can be measured by the rate of difference when the user repeats evaluation sessions [48]. Nielsen 2006 insists that highly learnable systems could be categorized as "allowing users to reach a reasonable level of usage proficiency (…)"[17].

Furthermore, Nielsen (2006) proposes measuring proficiency by quantity and quality and of task fulfillment [17]. Thus, we chose grade of completeness and grade of correctness as basic variables for measuring learnability. With conducting two measuring points mp and mp+1, it is possible to analyze the relative difference between mp and mp+1 for indicating Δ learnability, i.e. individual learning progress in percent [24], [51].

The **visual perceptibility** is measured by using the method of eye-tracking with analyzing the user's visual attention [52]. In our research we aim to include eye-tracking for measuring user's cognitive processes i.e. information search and information extraction during model interpretation process. The pioneering work regarding the use of eye-tracking was first carried out by Fitts et al. (1950) [41]. They proposed that fixation length is a measure of difficulty of information extraction and interpretation. Fixations are eye movements that stabilize the gaze over an object of interest. During this, the brain starts to process the visual information received from the eyes [53]. The number of fixations overall is thought to be negatively correlated with search efficiency [40]. Consequently, a larger number of fixations indicates less efficient search in a model. Concerning an eye-tracking experiment for evaluating the visual perceptibility of modelling languages a large number of fixations implies an intensive search to explore the model's diagram structure. This fact complicates the interpretation of a model. Furthermore, we aim to analyze the difficulty of information extraction in a model. Byrne et al. 1999 [54] propose tracking fixation duration time as a measure for information extraction. From this follows that longer fixations times during an interpretation process are indicating a participant's difficulty extracting information from a model. Compared to the other latent variables in our research model, the **individual satisfaction of a user** while interpreting a model is a user subjective criterion that can be measured best by using standardized questionnaires [49]. Currently no standardized method for measuring user satisfaction in the modelling domain exist. Therefore, we mapped questionnaires focusing on system and website usability [55], [56]. For evaluating user satisfaction we developed a questionnaire, which consists of thirty items structured in 1) General impression, 2) Recommendation rate and 3) Language application. We measured the constructs with 5-point Likert-scales. The development of this questionnaire is generally contributing to the Questionnaire for User Interaction Satisfaction (QUIS) and additionally the Software Usability Measurement Inventory (SUMI) [57] [55].

Memorability is best measured as proficiency after a period of non-use provided a user has already learned a language [58]. The non-use period can be minutes for simple element meanings, hours for simple syntactic regulations and days or weeks for measuring a complete modelling language [50]. Accordingly, the measure values for memorability are neglect curves and time-delayed knowledge tests [59]. Concerning the usability of modelling languages, the user must remember the different elements and its intended meaning (semantics), the syntax and the application. In due consideration of Nielsen 2006, the measuring points interval should be several weeks regarding memorability [17]. Thus, for measuring memorability we decided to use a knowledge test consisting of items focusing on 1) elements and relations, 2) syntax and 3) application of particular language. For measuring exogenous variable language complexity we track number of elements, number of relations and number of properties (LC) under consideration of Rossi and Brinkkemper's (1996) OPRR-model and particular expansions by Recker et al. (2009) and Indulska et al. (2009) [27, 60, 61]. Furthemore, for indicating visual properties we are analyzing different colours and different geometric shapes set in language's metamodel.

For measuring model experience we track participant's **individual experience** in 1) general modelling experience and 2) language experience on a 5-point Likert-scale. Finally, we operationalized **model complexity** by three indicator-variables: number of elements and relations (size), connectivity degree and semantic spread. With running causal analysis we include controls as moderator effects.

4. RESEARCH METHODOLOGY AND DATA COLLECTION

This study uses a various data collection methods for measuring manifest variables of latent usability attributes. Furthermore, we introduced an experimental design consisting of two data collection sessions per modelling language. The experiment focused on model interpretation tasks. Within these experiments we collected error rates, grade of completeness and task finishing time values for measuring efficiency, effectiveness and learnability, which is the relative learning growth between two data collection sessions. Additionally, we introduced the method of eye-tracking for analyzing visual perceptibility of modelling languages. The instruments were either adapted from traditional usability research or we developed new measuring instruments on modelling languages. A pretest was conducted prior collecting data for the field test. The research instruments were tested for reliability, content validity and construct validity. Necessary changes were made to improve measuring instruments. All pilot test participants were excluded from the analysis sample.

4.1 Measurement Scales

Multiple indicators measured all but one construct. The exception was EY, which represents a discrete value and therefore can be appropriately measured with a single item focusing on task completion time. We conceptualized and measured Language Complexity, Memorability, Learnability and Effectiveness as aggregations of different manifestations; thus the direction of causality is from indicator to construct (i.e. formative). The other constructs were operationalized as reflective indicators.

4.2 Data Collection

The sample includes third year students of business informatics. The experimental data collection, the questionnaire and the knowledge test were conducted with these students. The overall sample size amounts 57 students, 47% female and 53% male. The data collection was based on two different modelling concepts and connected languages. On the one hand process based languages, Event driven Process Chains (EPC), UML Activity Diagrams and on the other hand structure based modelling languages, UML Use Case and UML Class Diagrams were included in our survey. For developing variables measuring the latent construct learnability we introduce a second measuring point. In the session the students are confronted with one experimental task: the interpretation of given models. The interpretation scenario is structured in two parts. The first part is focusing on general observation while the second part includes verbal interpretation of given model. However, the interpretation task generates time, error, completeness and additionally eye-tracking values for measuring ES, EY, LA and PA. At the beginning of second collection phase we distributed the knowledge tests for measuring the ability of remembering specific metalevel properties *(MA)*. Subsequently, the user satisfaction *(US)* questionnaire was administered to the participants.

5. DATA ANALYSIS AND RESULTS

To test the proposed research model, data analyses for both the measurement model and the structural model were performed using partial leased squares (PLS), bootstrapping and the blindfolding method [62]. For calculating we took SmartPLS version 2.0 M3. Chin et al. (2003) defined various strengths of the PLS-approach. Partial Least Squares (PLS) gives reliable results and should being preferred to competing LISREL approach if 1) phenomena explored are new without existing construct and measuring theories, 2) structural model includes a large number of indicating variables, 3) relative small sample size and 4) detection of causal paths and predictions is focused on [63]. PLS is a powerful method of analysis because of the minimal demands on measurement scales, sample size, and residual distributions [64]. Although PLS can be used for theory confirmation, it can also be used to suggest where relationships might or might not exist and to suggest propositions for later testing [65].

5.1 Validity and Reliability

We conducted an exploratory factor analysis in SPSS for each construct of our models including all defined items using a Promax rotation. In all cases the Bartlett-test of sphericity indicating independency of construct items among was accepted. Consequently we analyzed different factors and assigned variables to specific factors considering Kaiser's criterion [66]. Indicating acceptable validity items with loadings smaller than 0.5 were excluded from our model. By doing so we assure that our models include construct items, which are loading sufficiently on specific factors.

5.2 Testing the Measuring Model

Internal consistency reliability was evaluated using Cronbach's Alpha, corrected item total correlation and average variance extracted (AVE) [67]. Cronbach's Alpha coefficients were all but one higher than the proposed minimum cutoff score of 0.70 [68]. The alpha value for experience is 0.68. Barker et al. (1994) conclude that values between 0.60 and 0.70 are marginal and can be accepted as well [69]. Values for composite reliability are all higher than desired threshold of 0.60 [70]. Furthermore all reflective constructs had an minimum AVE (Average Extracted Variance) of 0.5, indicating adequate internal consistency of our model [67]. For testing reliability of formative constructs we analyzed R2-value proposed by Chin (1998) with a minimum cutoff of 0.19 [65]. Furthermore, Diamantopoulos and Winklhofer (2001) concluded that sufficient significant regression weights between formative constructs and other constructs in the path model are indicating formal construct validity [71]. As shown in the following section all relevant path regression weights are at least significant at 0.05-level. According to Fornell and Larcker (1981), constructs have adequate discriminant validity if the square root of AVE is higher than variance shared between construct and other constructs in the model [67]. In all cases the correlations between each pair of constructs were lower than the square root of the AVE for specific construct. In conclusion, these results as well as the factor analysis confirm that all constructs in our model are empirically distinct. Table 1 shows detailed values for each construct of our research model.

Table 1 Reliability and Validity of our Research Model

	Measuring Model quality metrics			**Structural Model quality metrics**		
	Type	Alpha	Composite Reliability	AVE	R^2	Q^2
Threshold		≥ 0.6	≥ 0.6	≥ 0.5	≥ 0.19	≥ 0.0
Visual Properties (VP)	R	0.96	0.98	0.97	NA*	0.78
Language Complexity (LC)	F	NA	NA	NA	NA*	0.58
Memorability (MA)	F	NA	NA	NA	0.47	0.24
Learnability (LA)	F	NA	NA	NA	0.20	0.10
Efficiency (EY)	R	0.72	0.75	0.60	0.19	0.08
Effectiveness (ES)	F	NA	NA	NA	0.42	0.16
User Satisfaction (US)	R	0.89	0.90	0.68	0.19	0.07
Perceptibility (PA)	R	0.78	0.88	0.88	0.20	0.09
Task Complexity (TC)	R	0.70	0.83	0.63	NA*	0.31
Experience (EX)	R	0.68	0.62	0.52	NA*	0.66

Notes. R: reflective, F: formative; n=114 for all constructs; NA: not applicable: because formative measures need not covary, the internal consistency of formative items is not applicable [65]. NA*: not applicable: because R2 value is only relevant for assessing endogenous latent variables in the inner structural model [65].

5.3 Testing the structural model

Figure 2 presents the results of structural model testing including regression weights and significance of the paths. According to Lohmöller (1989) path regression weights should be at least 0.10 in order to be considered meaningful for discussion [72]. Our results confirmed the general assumption that language's metamodel properties are influencing usability attributes on different stages. According to Chin (1998) and for ensuring complete model assessment we additionally show effect size f^2, which is indicating whether a path's latent exogenous variable has a significant influence (effect) on latent endogenous variable or not. Thresholds for f^2 are 0.02 (weak), 0.15 (medium) and 0.35 (strong) [65].

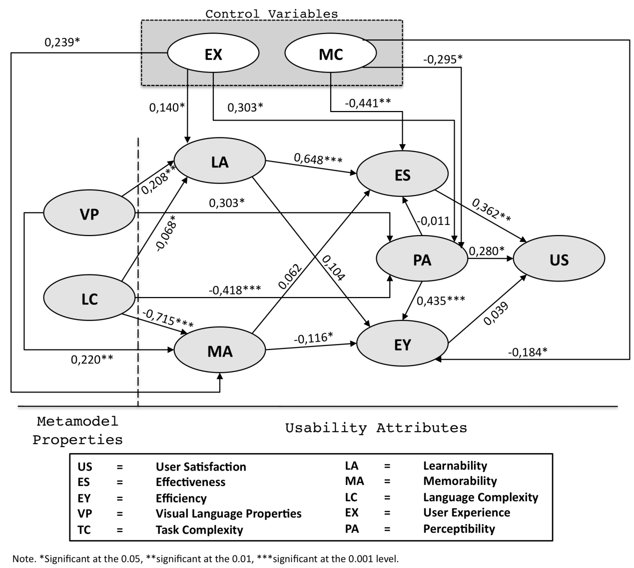


Figure 2 Structural Model Results

LC has a strong negative and highly significant influence on MA (beta=-0.715, f^2=0,80, p<0,001). This empirical result supports our hypothesis H4. LC has also a strong significant negative impact on PA underlining H12 (beta=-0.418, f^2=0.16, p<0.001). Furthermore, LC has a negative significant relation to LA contributing to H3 (beta=-0.068, f^2=0.02, p<0.05). However, this path disposes not to Lohmöller's (1989) proposed threshold for path weighting of 0.1. VP are positively influencing LA of applying modelling languages concerning to model interpretation (beta=0.208, f^2=0.02, p<0,01). In addition to that VP is positively influencing PA (beta=0.303, f^2=0.03, p<0.05). Considering this, all hypotheses in our research model connected with VP are accepted. Additionally, LA is strongly positively related to ES on a high significance level (beta=0.648, f^2=0.72, p<0.001), which is contributing to H5. Furthermore, LA is positively affecting time based latent construct EY, also, MA is positively correlating with ES. These path regression weights are not significant (p>0.05). Deducing from that, we cannot reject null hypothesis with probability level of 0.05. Consequently, we assume that these paths are not empirically explaining our research model. H6 and H7 are not empirically supported. MA has a weak negative impact on EY (beta=-0.116, f^2=0.01, p<0.05). This relation is not contributing to H8. As a consequence we state, that in modelling domain MA is negatively influencing the time used for model interpretation. PA is positively influencing EY (beta=0.435, f^2=0.24, p<0.001) and US (beta=0.280, f^2=0.075, p<0.05). Users ability of complete and correct model interpretation is positively influencing US (beta=0.362, f^2=0.11) p<0.01). From this, we can deduce that H9 is accepted. Turning to model fit, the R-square values for MA, LA, EY, ES, US and PA were 0.473, 0.202, 0.194, 0.420, 0.192 and 0.196 respectively, indicating that the model explains substantial variation in these variables. For example, the R-square value for MA implies that the causes specified in this model, VP and LC, jointly explain 47% of the total variance in MA.

In summary, the results show that most hypotheses in our research model are fully supported. However, H8 is not supported by our results. Furthermore, H6, H7 and H13 could not be confirmed by significant results. As a consequence, particular hypotheses are not confirmed for further comparable samples. The resulting regression weights of H6, H7 and H13 are valid for our specific sample and should be proved in further surveys based on our research model.

6. DISCUSSION

This study provides several important findings supporting the understanding of usability attributes. We focus on the model interpretation scenario. The two major influencing areas are (1) complexity of a language and (2) causal impact of visual properties.

Firstly, our results show that the complexity of language's metamodel, i.e. variability in elements, relations and properties, is strongly influencing user's ability to remember them. Usability research shows that memorability is an initial basis for applying a system or a website effectively [17]. However, with our results we cannot confirm those theses for model interpretation scenario. Additionally, memorability is weakly influencing effectiveness of model interpretation. Furthermore, we find that memorability is weakly influencing effectiveness and that memorability weakly impacts interpretation time negatively. Our research findings for the causal path between memorability and efficiency of model interpretation are inconclusive. Concerning this, further research into this area will be required and may lead to more conclusive findings. However, it seems that memorability plays a secondary role in model interpretation scenario.

Metamodel complexity is strongly influencing language's visual perceptibility. This result provides evidence that languages based on complex metamodels are not supporting user's ability of easy information search and extraction when interpreting a model. Additionally the visual perceptibility of modelling languages is strongly connected with duration time of information search and extraction. Concerning this, we deduce that languages offering a good perceptibility afford fast information search and information extraction times leading to an efficient model interpretation process. Considering model complexity as control variable, a process model developed with BPMN including a high range of different elements offers lower visual perceptibility and accordingly results in higher time values for information search and extraction compared to an EPC-model. Moreover, the visual perceptibility of a modelling language is positively supporting user's individual language satisfaction. From this result we infer, that visual perceptibility is one important base of user satisfaction. User acceptance is strongly connected with user satisfaction [17]. This relationship underlines the fact that visual perceptibility concerning particular languages is obviously a basic result of user satisfaction and consequently user acceptance. In other words, visual perceptibility may decide whether a modelling language is accepted or not by users concerning model interpretation.

Obviously, the positive impact of interpretation time on user satisfaction is not as much as expected. This might be underlining former findings of Walker (1998). In their studies they found out that users have demonstrated preferences for systems with which they performed less efficiently [73]. It shows that the ability for finishing interpretation tasks completely and correctly and the ability for convenient information search and information extraction out of a model are more important to satisfy users than the commonly assumed performance factors of efficiency.

Secondly, an important result of our survey is the causal impact of visual language properties, i.e. variability in shape geometrics and shape colours, in the field of model interpretation. The output of our study shows that visual language properties are positively influencing the visual perceptibility of modelling languages. This result underlines the finding that visual differentiation supports object information search and information extraction [36]. As a consequence, the application of different colours and geometrics in a model supports interpreting users in searching and extracting information. Furthermore, the variability in shape colour and geometrics is positively influencing learnability of model interpretation and memorability of language's elements and relations. Consequently, languages offering higher variability in geometrics and colours are easier to learn concerning model interpretation.

The learnability of interpreting a model based on a certain language is strongly impacting the ability of performing an interpretation task completely and correctly. For example, in industry and education it is important that users can interpret developed models with a high level of completeness and correctness [74]. With our study we found out that learnability, which is positively influenced by visual language properties acts as a basic independent variable strongly impacting on user's ability of complete and correct model interpretation. Furthermore, learnability is positively influencing efficiency of model interpretation. We conclude that learnability is a basic construct in model interpretation scenario. A theoretical basis might be cognitive load theory and especially intrinsic cognitive load [8]. The intrinsic cognititve load is determined by information complexity. The interdependency of information to be learned is positively impacting cognititve load and consequently the more important learnability appears in a causal system. Concerning modelling languages and model interpretation, the cognitive load is high because of strong information interdependency occurring in models. Considering our results and cognitive load theory the importance of learnability in model interpretation is emphasized. In due consideration of our results it consequently becomes clear that learnability is positively impacted by visual language properties. From this follows that languages offering high visual variability are easier to learn than other. As a consequence languages containing high visual variability allow higher task completion and accuracy rates in model interpretation. In conclusion, if a language should support effectiveness of model interpretation, the metamodel should offer high visual variability in elements and relations.

7. CONCLUSION

In this paper we propose a study of usability assessment of modelling languages using a structural equation modelling approach. The study focuses on model interpretation scenario. Our causal path shows that in model interpretation memorability of language's elements and relations plays a secondary role. It becomes clear that visual perceptibility and effectiveness are fundamental attributes for reaching high values in user satisfaction. Furthermore, the model supports our idea that language's metamodel properties are influencing usability attributes on different causal stages. In the following, we derive concluding implications for both theoretical and practical needs.

7.1 Implications for Theory

First, our results confirm most of our hypotheses deduced from theory. In usability research, a theoretical embedment of usability attributes in a causal model is missing up to now. In our study we show interesting causal relations between usability attributes. Thus, there might be important results for usability research concerning the causal impact of different usability attributes. Further studies are required for testing our structural model in other usability domains (e.g. website usability etc.).

7.2 Implications for Practice

Our structural model delivers important results showing how modelling languages affect usability attributes on different causal stages in the model interpretation scenario. We structure practical implications in two parts focusing on 1) industry and 2) language specification/development organizations.

In companies the importance of business process and application system modelling has steadily risen. Consequently, the interpretation of models becomes an issue of organizational concerns. How efficiently can an employee extract information out of a model? Does he/she understand the information, i.e. does he/she interpret the model accurately? These might be basic questions connected with decision-making for or against the use of particular modelling languages in organizations. With considering our first results, the structural model can support the process of decision-making focusing on language usability in model interpretation. Thus, companies aiming for fast, complete and correct model interpretation, e.g. business process consulting companies, should apply modelling languages with high variability in visual properties.

Our second practical implication deduced from our results is focusing on modelling language specification and development organizations. For example, an important finding in our study is that visual variability of elements and relations is supporting accuracy, completeness and speed in model interpretation processes. In this regard, we conclude that UML activity diagrams (i.e. low visual variability) are not as usable as EPCs (i.e. high visual variability) in model interpretation. For optimizing UML activity diagram's usability in the model interpretation scenario it might be worth increasing visual variability in the meta-model by adding colours and various geometric shapes. Furthermore, to improve user satisfaction values in the model interpretation scenario it is necessary to decrease language complexity (e.g. by reducing number of different elements and relations) and increase visual variability. We are aware that complexity reduction possibly may impact the expense of explanatory power offered by particular language. The results in this paper provide a starting point for further empirical based discussions on usability of graphical modelling languages.

7.3 Limitations and Future Directions

The study is limited to the model interpretation scenario. Henceforth, we are expanding our study to model development cases. A comparison of results for interpretation and development scenarios may lead to a greater understanding for usability and particular attributes in the domain of modelling languages.

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