Using Techniques from Neuroscience in Information Systems Modelling Research: A Systematic Mapping Study

John Krogstie
Norwegian University of Science and Technology (NTNU) {John.Krogstie@ntnu.no}

Abstract A lot of research has been done on the use of conceptual models in information systems development. In other areas working with knowledge representations, such as linguistics and software engineering one has applied techniques from neuroscience to study the physiological and neurological processes when working with textual knowledge structures in tasks such as program code debugging. The use of such techniques has only to a limited degree been used when it comes to our understanding of visual conceptual models so far. We will argue for the utility of using such techniques also in information systems modelling research and present a systematic mapping study on the use of techniques from neuroscience to investigate how we work with visual conceptual models. The main approach is based on techniques used in multi-modal learning analytics, which investigates how performance on learning tasks is correlated with biometric data, collecting data in parallel from EEG, eye-tracking (ET), wristbands, and facial expression (through cameras). Through this study, we also identify gaps in our knowledge on information systems modelling, which can be filled with extending the use of collecting and analysing biometric data under modelling activities.

Keywords: Information systems and business modelling, Systematic mapping study, Biometrics

1 Introduction

Whereas in most areas of human conduct, models in one-dimensional natural language are used to express and share knowledge, we see the use of two and many-dimensional representational forms to become more important [48,53]. One such representational form is *conceptual models.* A *conceptual model* is traditionally defined as a description of the phenomena in a domain at some level of abstraction, which is expressed using a semi-formal or formal (usually two-dimensional) visual modelling language [31]. Over the last 50 years, researchers have developed our understanding of the use of such models for representing different aspects of information systems, but mainly by studying the externally visible behaviour of modellers and model users [37]. Modeling involves the construction of abstract visual representation that capture the structure, behaviour, and relationships of real-world entities or phenomena, and the two-dimensional layout allows to play with both the primary and secondary notation [54] to create knowledge and convey meaning. Using techniques from multi-modal learning analytics (MMLA) in conceptual modelling opens new opportunities for understanding how we process and represents complex information, which can, in turn, inform and enhance the development of more effective modelling approaches, support modelling and make it more probable that modelling is used in the most appropriate way.

We will in this paper present parts of the results from a systematic mapping study of the use of techniques from neuro-science and biometrics used in MMLA in conceptual modelling research and point to further work to be done in providing results from biometrics and neuro-science to support the application of conceptual models, including data models, business process models and enterprise models.

In Section 2, we present further background on conceptual modelling and use of biometrics in other areas of information systems and software engineering, in addition to learning analytics. Section 3 present the methodology used for the study, whereas selected results are presented in section 4. A number of knowledge gaps are identified in section 5 for further research opportunities in this area which we have termed neuro-conceptualization.

2 Background

There are five primary tasks in the use of conceptual models [31]: *Modelling* of an existing or envisioned domain, *model comprehension*, *model validation* (are the models correct?), *model integration* and *model activation* (implementing the model in an organizational or societal setting so that it influences other people and their behaviour). Secondary tasks are the development of the approaches and tools for knowledge representation (including the modelling languages, so-called meta-modelling [22]), supporting the modelling activities using these modelling languages (for modelling, model comprehension and validation) and develop tools for model activation. Modeling and meta-modelling are normally done as separate processes [26]. Modeling is done *individually* or *collaboratively*, often in a facilitated fashion (e.g. for participatory modelling to include a wider set of stakeholders than modelling experts [25]).

These activities are done to achieve various *goals* [33], including 1) sense-making, 2) supporting communication 3) to identify possible improvements, 4) quality assurance, 5) development of new IT-solutions or business processes either directly or through model activation 6) to give the context for conventional IT-development and 7) model implementation, having new solutions based on models being taken into use in practice.

In [42], the authors describe how different modeling approaches emerged and what characterizes them with a discussion of the potential modeling future. Important areas is highlighted to be Artificial Intelligence (AI) (how to use AI in modeling, but also how to combine AI (ML) techniques and more traditonal symbolic modeling techniques), conceptual modeling, and Domain Specific Languages (DSLs) based on meta-modelling [29]. Topics such as Flexible Modeling and Model Integration, which allow for combining different tools and languages, are also mentioned frequently. Most mentioned topics with a need for action was modeling tools, AI and human aspects of modelling. Most important aspect of the vision of the future of modelling was that modelling should be easier and become more usable also for practitioners, not only modelling experts.

Many of the modeling tasks include *model comprehension* and learning, necessitating *pragmatic quality* meaning that the models need to be understood by other people than those making the models in the first place, either for *model validation*, for learning, for process improvements, or for changing behavior to be compliant to mandated organizational practices represented in the models. Much has been done on understanding different aspects of in particular business process model (BPM) *comprehension*, as summarized in [37].

For visual processing, gestalt knowledge [62] is used. Models are mostly static, but model simulations can be used to support comprehenison, exploiting that the magnocellular pathway transfer visual movement stimuli in the brain faster than the parvocellular pathway transfering information about form [13]. Natural language and domain knowledge is used for verbal processing of the natural language text e.g. in labels and comments in the model. Modeling language knowledge and domain knowledge is used in the interpretation of the meaning of the model, and knowledge of the *goal* of modeling is used for task processing. Some future research directions highlighted in [37] include "Visual processing is potentially subject to affects, heuristics, and biases. Dual-process theories can help for designing future experiments. Verbal processing has generally received little attention". It is an interesting question how and to what extent prior theories on reading from neuro-linguistics on verbal processing [16] can be integrated with studies on visual models. "Semantic processing has largely focused on the diagram and not the text as an information source. Theories of sense-making [61] could help to explain how information from the diagram is integrated with prior domain knowledge. Finally, research on task processing has suffered from the lack of a suitable task taxonomy. Theories on external cognition might be useful for investigating different types of tasks systematically".

MMLA combines a number of theoretical frameworks [20]. Two of the main ones are Cognitive Load Theory (CLT) [45] and the Affective Learning Framework (ALF) [10], and one can look at these in concert to understand comprehension, learning and other processes in conceptual modelling [32, 37]. CLT considers the cognitive processes of comprehension and learning. The working principle of CLT is that humans have a limited information processing capacity when they engage with a learning task. CLT defines three types of cognitive loads: intrinsic (inherent difficulty associated with the topic), extraneous (generated by information presented to learners), and germane (generated by processing, tapping into existing gestalt knowledge, natural language knowledge, domain knowledge, modelling knowledge, and means-end knowledge). To model the learner behaviour using the principles of CLT, one can use EEG and Eye-tracking (ET) data streams.

The second theoretical framework is the Affective Learning Framework (ALF). ALF is mostly concerned with "how learners feel while they are processing the information presented" To incorporate ALF in the methodology, one can use facial and physiological (Heart rate variability (HRV), electrodermal activity (EDA), blood volume pulse (BVP), temperature (TMP)) data. Using facial data, one can capture several sets of emotions. Using physiological data (i.e., HRV, BVP, EDA, TMP) one can also detect the emotional states of the learners as well as their stress and arousal levels. Recently, with the advent in the wearable technology, researchers have employed smartwatch-like devices to leverage the notion of "quantified-self" and to compute physiological arousal and stress in various settings [9,18].

Individually, both CLT and ALF provide two different, separate and important views of the same process. All the individual data streams (eye-tracking, electroencephalography, facial videos, HRV, BVP, EDA, TMP), provides each one of these data streams to have individual unique point-of-view about the learners' cognitive processes, affective mechanisms and outcomes. One main limitation of using these individual data streams alone is the lack of overall understanding. These data streams provide knowledge about a few aspects of learners' learning processes and/or outcomes, but to gain a holistic understanding one needs to combine the information emerging from a multitude of data streams (i.e., MMD, [5,19]). One of the prime advantages of using the MMD is for the design of new learning systems. For example, two modalities could be used to assess the current state of the learner, while others could be used to provide feedback on the current state, thus, increasing the internal validity of the modelling systems.

NeuroIS (Information System) [50] is a research field in which neuroscience theories and tools including MMLA are used to better understand information systems phenomena. [67] have analysed 78 empirical articles and put forward a framework for understanding what existing NeuroIS research focuses on. The framework is built upon stimulus–organism–response theory, which explains that stimulus factors can affect users' psychological processes, which further lead to their responses. Existing subjects, and techniques used are listed below.

• IS use efficiency	fMRI, EEG, ECG, Eye-tracking.
• Attractiveness of IS feature	EEG, Eye-tracking.
• IS Security	fMRI, EEG, Eye tracking, HRV
• User experience in IS	fMRI, EEG, ECG, SC, Eye-tracking.
• IS adoption	EEG, Hormones
• Technostress in IS	Hormones
• IS use consequences	Hormones, HRV, BPV
• Trust in IS	EEG, fMRI.

A major trend is multi-modal data collection as we outline above on MMLA. Most of the work in NeuroIS is studying IS in use, and not the processes in *developing* the IS. This is an area that is of focus in NeuroSE (SE - software engineering). In the past decade, brain and autonomic nervous system activity measurement has received increasing interest in the field. [60] presents a systematic literature review (SLR) of the NeuroSE literature. 89 papers were found. 47 articles presenting completed empirical research. The SLR revealed that the number of authors publishing NeuroSE research is still relatively small. The thematic focus so far has been on code comprehension, while code inspection, programming, and bug fixing have been less frequently studied. NeuroSE publications primarily used methods related to brain activity measurement (particularly fMRI and EEG), while methods related to the measurement of autonomous nervous system activity (e.g., pupil dilation, heart rate, skin conductance) has so far received less attention.

3 Methodology

The systematic mapping study method is based on [30, 46]. The main idea is to find existing literature on the use of techniques from neuro-science in the area of conceptual modelling (what we have termed neuro-conceptualization).

The investigation is similar to the one done recently in software engineering [60] as described above which can be useful to read to understand a bit more on the neuroscience-terms in this area.

In a full structured literature review, natural source would be IEEExplore, Springerlink, ScienceDirect, ACM Library, Scopus and Web of Science. Our experience from earlier studies is that by using Google Scholar we will manage to capture the same papers as these sources, and also additional literature, although that is primarily grey literature. The sufficiency of using Google Scholar is also supported by scientometric literature [17,24,38].

The search string is a combination of a traditional search string from neuro-science [51] and selected terms in the area of information systems modelling. Since the term "conceptual modelling" and "data modelling" will bring a lot of result on people modelling the brain (and not with the brain), we have chosen some more specific terms in enterprise and process modelling. Thus, the full search string was as follows:

("enterprise model*" OR "business process model*" OR "BPMN")
AND
("Blood" OR "Brain" OR "Cardiovascular" OR "Cognitive load" OR "Cognitive processes" OR "Diffusion Tensor" OR "EEG" OR "Electrocardiogram" OR "Electroencephalography" OR "Electromyography" OR "Eye Tracking" OR "fMRI" OR "fNIRS" OR "Gaze" OR "Heart rate" OR "Hormone" OR "Infrared spectroscopy" OR "Morphometry" OR "Nervous system" OR "Positron emission" OR "Saliva" OR "Skin conductance" OR "Urine")

The research question pursued in this part of the literature mapping are:

- RQ1: Who has published Neuro-conceptualization research and where?
- RQ2: Which neurophysiological methods (e.g., fMRI, EEG, eye tracking, wristband, facial landmarks) and measures were applied?
- RQ3: How were the empirical Neuro-conceptualization studies designed?

Inclusion and exclusion criteria:

Inclusion:

- Empirical investigations on the application of neurophysiological methods and/or knowledge to investigate the use of modelling techniques.
- Paper is written in English.
- Full paper is available.
- Paper from the last decade (2014-2024).

- Pass a minimum quality threshold (see exclusion criteria below).

Exclusion:

- Papers not in scientific journals or conferences (e.g. not include newspaper articles, whitepapers, papers not peer-reviewed (in different arxives), master theses and PhD theses).
- Papers in other languages than English.
- Similar to [52,60], articles applying eye tracking measurements that are not predominantly reflexive (e.g., gaze and saccade measurement) are excluded (e.g., [21]).
- Papers from 2021 or earlier with 0 citations.
- Literature reviews.

4 Overview of results

A challenge is that many result are given. We limited the search to 2014-2024 and got a total of 5896 papers. Based on title and abstract, we reduced this to 90 papers, and with the inclusion and exclusion criteria described in Section 3 we ended with 43 papers for further analysis.

RQ1: Who has published Neuro-conceptualization research and where?

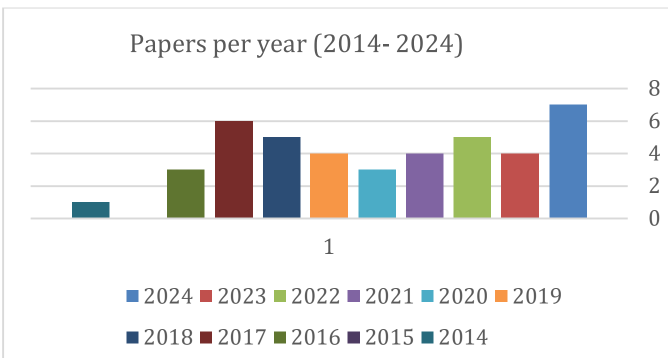

Fig. 1. Number of papers per year

As shown in Fig. 1, the papers are quite evenly distributed per year, although we can see an increasing trend especially given that the number for 2024 only includes the first 8 months of the year. On the 43 empirical paper, there is a total of 83 authors. Papers have between 2 and 7 authors. Fig. 2 show the authors that are involved in most papers.

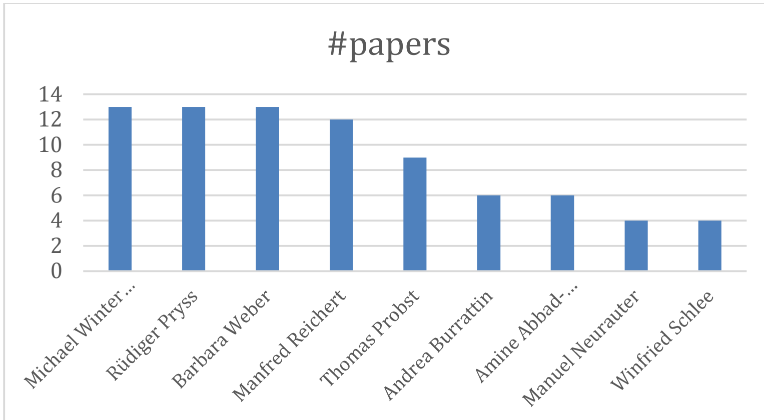

Fig. 2. Most productive authors in the neuro-conceptualization area

Two main clusters are found, around Manfred Reichert with collaboration with Michael Winter (Zimoch), Rüdiger Pryss, Thomas Probst and Winifred Schlee, and around Barbara Weber with collaborations with Andrea Burratin, Amine Abbad-Andaloussin, and Manuel Neurauter. A number of other people in information systems modelling and NeuroIS have done work in the period, but not as consistently as these groups.

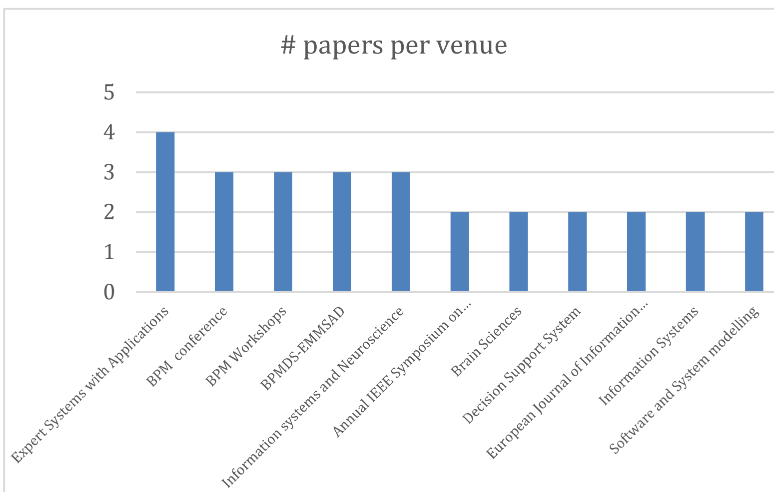

Fig. 3. Journals and conferences with most papers

The papers are published in 26 different journals (17) and conferences/workshop (9). From Fig. 3, we see that there is no dominant publication venue, and that it includes mostly traditional conferences and journals in information systems modelling plus some specific outlets for NeuroIS research.

RQ2: Which neurophysiological methods and measures were applied?

42 of the 43 investigations used eye-tracking (ET). Early use of eye-tracking for researching model comprehension is found in [44, 59], but these works focus on capturing area of interest (i.e. what the modeler is looking at). Later, eye-tracking is also used for capturing other characteristics such as cognitive load in process model comprehension [3,15,64]. The sensor-toolset has lately been extended from only using ET by some to include wristbands for capturing for instance EDA [2,65]. Use of EEG is reported in [23, 35]. Techniques from neuroscience such as fMRi and fNIRS has not been used. In some experiments, ET is combined with (retrospective) think-aloud [1]. In [35] an example of the combined use of all four modalities in MMLA (EEG, ET, facial and physiological data) is reported in connection to process model comprehension. A paper presented at NeuroIS retreat in 2024 focus on causal relationships between biometric measures, using granger-causalities [36]. The findings from the experiment reported in [35, 36], demonstrate that particular cognitive-affective states detected from using all the four different sensors in combination is relevant and influential to understand both the cognitive and affective process of model comprehension and the performance of model interpreters.

No experiment testing neuro-adaptive systems are found in the published literature.

RQ3: How were the empirical Neuro-conceptualization studies designed?

The majority of studies (40) included model comprehension tasks, in some cases combined with model validation and model creation. Those not including model comprehension explicitly looked at model creation [56,59]. Independent variable has been

- aspects of the model (e.g. ambiguities in models [15], model complexity [66], model layout [56], model modularization [54] and usage of colour [11]).
- modelling language (comparing modelling languages [11, 43, 69]).
- modelling method [4].
- characteristics of the modeler (including gender [23] and expertise [7,8, 68]).

Most of the papers is based on understanding operational process models (in both functional process models such as BPMN [7,35, 66], Petri-net [69], or EPC [70] and declarative process models [2]). There are also examples of analysis of comprehension of REA class diagrams [6], decision models [14], goal models using iStar [23] and combinations of rule and process models [58], and combination of data and process models in UML [28]. Some studies compare different modelling languages [43,69], but there are no studies that compare visual and textual models (as done in e.g. [49] using more traditional experiments). Most experiments are done in a lab with individual students. [63] describe an experiment using ET with health practitioners, but also this in a lab environment. [47] also collect data from practitioners on model comprehension. An example of following pairs of modellers with ET is found in [14] to investigate joint visual attention.

Whereas the BPMN models in [35] is reported to be made in Signavio, few papers on model comprehension report the original tool. Typically, the models are made in a standard tool and exported to a standard format, and then imported to a special environment for doing the experiment. The tools used in the reported modelling task are custom made tools for easier integration with the experiment environment.

Whereas most of the work collect a limited number of biometric parameters (e.g. cognitive load based on eye-tracking), [35] in addition find significant performance changes due to all types of sensors and measurements as listed in Table 1, illustrating how the use of all the mentioned sensors in MMLA can be used to find distinct aspects of the modelling situation. A full overview of results from the studies will be provided in a more rigorous structured literature review and is not presented here due to page limitations.

Table 1. Example of measurements that has been found significant for modelling performance

Eye- tracking	Backtracks
	Information processing index
	Average attention
	Familiarity/expertise (Perceived difficulty)
Face	Frustration
	Boredom
	Confusion
Wristband	Stress
	Engagement
EEG	Convergent thinking
	Memory load
	Drowsiness

[36] illustrate how one can identify causality between measurements from all sensors, further illustrate the utility of an MM-approach, and not using e.g. eye-tracking alone.

5 Identified knowledge gaps.

Based on the knowledge of the developments and previous research of information systems modelling and the current literature mapping, we have identified the following knowledge gaps (KG):

- KG1: Most studies in conceptual modelling have been done not taking biometrics into account in a holistic manner. E.g. studying of affective aspects for *model comprehension* are missing [41]. A lot of research has been done on especially model comprehension [37] that can be reinvestigated taking biometrics into account. Replicating studies comparing textual and visual models [49] would be interesting given that the joint visual and textual nature of conceptual models as knowledge representations provide unique challenges and opportunities since textual and visuo-spatial processing uses different areas of the brain [27,39]. Also, other differences of characteristics of models, modelling languages, modelling domains, modelling tools, modelers, and type of modelling task is interesting to investigate.

- KG2: In existing work, one has mainly collected biometrics on a limited set of *model comprehension* tasks in a laboratory setting. Thus, we want to collect biometrics to better understand *modelling, model validation and model integration* tasks*,* in addition to other *model comprehension* tasks*.* An additional challenge with some of these tasks is the necessity of more movement during the experiment, thus challenging the data quality of the data captured from the various sensors. In particular EEG-signals are susceptible to noise, although post-processing techniques are available to rectify many errors [35].
- KG3: In existing work, one has collected biometrics on the activities of individuals. Modeling is often a collaborative task, and we want to collect biometrics to better understand *collaborative modelling tasks*: In the literature study, we have found only one example of this (joint attention in pair modelling [14]).
- KG4: An important trend in NeuroIS is development of neuro-adaptive systems [57]. So far, such mechanisms have not been used for supporting conceptual modelling tasks. How can we use biometrics in neuro-adaptive modelling tools? There are examples from software development environments e.g. on the use of cognitive load, but a challenge is to find which of the large number of biometric parameters that is useful in such setting, and also which can be used and still have tools that can be according to the new AI Act, which limit the use of biometric in commercial tools for learning and work.
- KG5: In existing work, one has collected biometrics on *model comprehension* in a lab setting. Following up [40], it is also important to use such techniques also outside of the lab. To be more generally applicable we must study and collect biometric data in a less controlled setting similar to the study of model quality in [34].
- KG6: Meta-modelling is often done separately from modelling; thus, limited work has been possible to do on studying simultaneous change of models and modelling languages. New tools such as AKMM[1] enables this, and we want to collect biometrics of modelling where one performs such *leaps of abstraction,* changing the modelling language when it is found insufficient to do the task.

Studies of this sort have known limitations as for the ability of finding all relevant papers. Having close contact with the main authors of work in this area, and with people working in NeuroIS and MMLA make me more confident that most relevant work has been identified. Searching only in Google Scholar is another potential limitation, and I would suggest researchers that want to pursue the listed knowledge gaps to do additional detailed searches in the sub-area of research to ensure that one is investigating new areas. A start could be to do forward and backward snowballing based on the identified papers. Coding of work as for the use of methods and tools has been done only by the author, which is an additional limitation.

6 Conclusions and Further Work

Visual information systems models, in the form of conceptual models, enterprise models and business process models have been in use since the 70ties. Some researchers claim the applicability of these and similar types of visualization for a large number of knowledge representation tasks, which can influence a larger variety and number of

[1] https://akmmclient-alfa.vercel.app/modelling

people than currently done. To see how cognitive and emotional aspects influence the use of such knowledge representations, we find it beneficial to look at techniques within neuro-science and biometrics for capturing data as a basis for improving our understanding of these phenomenon.

A number of techniques are found to be used in related fields, such as NeuroIS and NeuroSE. Looking upon modelling tasks to a considerable extent as being tasks of learning, we have in this paper looked upon to what extend collection of biometrics using the techniques found in MMLA is used in information systems modelling research. As seen in the literature review, a limited usage of such techniques can be found, mostly looking on model comprehension using ET to detect e.g. cognitive load. On the other hand, we see examples of more extensive use of sensors to capture a wider set of data, for a larger set of modelling tasks, and have described a set of knowledge gaps that can be looked upon as inspiration for future work. This must be combined with understanding of the social processes when models evolve into socially constructed reality.

The use of sensors will to a different degree limit the ecological validity. Principally it is not possible to measure something without influencing the ecological validity, thus there is always a threat to validity when doing measurements, what needs to be done is to control the significance of this, e.g. by having a controlled lab environment or sensors that can collect data in more normal modelling situations.

References

1. Abbad Andaloussi, A., Zerbato, F., Burattin, A., Slaats, T.,Hildebrandt, T. T, Weber, B. (2021) Exploring how users engage with hybrid process artifacts based on declarative process models: A behavioral analysis based on eye-tracking and think-aloud. Softw Syst Model **20**, 1437–1464
2. Abbad-Andaloussi, A., Burattin, A., Slaats, T., Kindler, E., Weber, B. (2023) Complexity in declarative process models: Metrics and multi-modal assessment of cognitive load. Expert Systems with Applications 233
3. Batista Duarte, R., Silva da Silveira, D., de Albuquerque Brito, V. Lopes, C.S. (2021) A systematic literature review on the usage of eye-tracking in understanding process models, Business Process Management Journal, Vol. 27 No. 1, pp. 346
4. Bera, P., Burton-Jones, A., Wand, Y. (2018) Improving the representation of roles in conceptual modeling: theory, method, and evidence. *Requirements Eng* **23**, 465–491
5. Blikstein, P., Worsley, M. (2016) Multimodal Learning Analytics and Education Data Mining: using computational technologies to measure complex learning tasks. Journal of Learning Analytics, 3(2), 220-238
6. Boot, W.R., Dunn, C.L., Fulmer, B.P., Gerard, G.J., Grabski, S.V. (2022) An eye tracking experiment investigating synonymy in conceptual model validation, International Journal of Accounting Information Systems, Volume 47, 2022,–241
7. Boutin, K.D., Davis, C., Hevner, A., Léger, P.M.: Don't overthink it (2022) The paradoxical nature of expertise for the detection of errors in conceptual business process models Frontiers in Neuroscience Volume 16
8. Davis, C., Hevner, A., Labonte-LeMoyne, É., Léger, P-M. (2018) Expertise as a mediating factor in conceptual modeling. Information Systems and Neuroscience pp 85-92
9. D'Lascio, E., Gashi, S., Santini, S. (2018) Unobtrusive Assessment of Students' Emotional Engagement During Lectures Using Electrodermal Activity Sensors. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2(3), 1-21

10. D'Mello, S., Graesser, A.(2012) Dynamics of affective states during complex learning. Learning and Instruction 22, 145–157
11. Djurica, D., Kummer, T. F., Mendling, J., Figl, K. (2023). Investigating the impact of representation features on decision model comprehension. European Journal of Information Systems, 1–25.
12. Dybå, T., Dingsøyr, T. (2008) Empirical studies of agile software development: A systematic review, Information and Software Technology, Volume 50, Issues 9–10, Pages 833-859,
13. Egset, K., Wold, B., Krogstie, J., Sigmundsson, H. (2020) Magno App: Exploring Visual Processing in Adults with High and Low Reading Competence. Scandinavian Journal of Educational Research: 1-11.
14. Fındık-Coşkunçay, D., Çakır, M.P. (2022) An investigation of the relationship between joint visual attention and product quality in collaborative business process modeling: a dual eye-tracking study. Softw Syst Model **21**, 2429–2460
15. Franceschetti, M., Abbad-Andaloussi, A., Schreiber, C., Lopez, H. A., Weber, B. (2024) Exploring the Cognitive Effects of Ambiguity in Process Models Proceedings BPM 2024, Krakow
16. Fritz, I., Baggio, G. (2021) Neural and behavioural effects of typicality, denotation and composition in an adjective–noun combination task. Language, Cognition and Neuroscience, 37(5), 537–559
17. Gehanno, JF., Rollin, L. Darmoni, S. (2013) Is the coverage of google scholar enough to be used alone for systematic reviews. BMC Med Inform Decis Mak **13**, 7
18. Giannakos, M. N., Sharma, K., Papavlasopoulou, S., Pappas, I. O., Kostakos, V. (2020) Fitbit for learning: Towards capturing the learning experience using wearable sensing. International Journal of Human-Computer Studies, 136, 102384
19. Giannakos, M., Cukurova, M., Papavlasopoulou, S. (2022) Sensor-Based Analytics in Education: Lessons Learned from Research in Multimodal Learning Analytics. In: Giannakos, M., Spikol, D., Di Mitri, D., Sharma, K., Ochoa, X., Hammad, R. (eds) The Multimodal Learning Analytics Handbook. Springer, Cham.
20. Giannakos, M., Cukurova, M. (2023) The Role of Learning Theory in Multimodal Learning Analytics. British Journal of Educational Technology
21. Goldberg, J. H. (2014) Measuring software screen complexity: Relating eye tracking, emotional valence, and subjective ratings Int. J. Hum. Comput. Interact., 30 pp. 518-532
22. Gonzalez-Perez, C., Henderson-Sellers, B. (2008) Metamodelling for software engineering. Wiley
23. Gralha, C., Goulão, M., Araujo, J. (2020) Are there gender differences when interacting with social goal models? Empir Software Eng 25, 5416–5453
24. Gusenbauer, M. (2022) Search where you will find most: Comparing the disciplinary coverage of 56 bibliographic databases. Scientometrics **127**, 2683–2745
25. Gutschmidt, A., Verbruggen, C., Snoeck, M. (2024) A Study on the Impact of the Level of Participation in Enterprise Modeling. In: Almeida, J.P.A., Kaczmarek-Heß, M., Koschmider, A., Proper, H.A. (eds) The Practice of Enterprise Modeling. PoEM 2023. Lecture Notes in Business Information Processing, vol 497. Springer, Cham.
26. Henderson-Seller, B., Ralyté, J., Ågerfalk, P. J., Rossi, M. (2014) Situational Method Engineering, Springer
27. Hervé, P-Y., Zago, L., Petit, L., Mazoyer, B., Tzourio-Mazoyer. N. (2013) Revisiting human hemispheric specialization with neuroimaging, Trends in Cognitive Sciences, Volume 17, Issue 2, Pages 69-80
28. Jabbari, M., Recker, J., Green, P., Werder, K. (2022) How do individuals understand multiple conceptual modeling scripts? Journal of the Association of the AIS vol 23, issue 4
29. Kelly, S., Tolvanen, J. (2008) Domain-Specific Modeling—Enabling Full Code Generation. Wiley, Berlin
30. Kitchenham, B., Charters, S. (2007) Guidelines for performing systematic literature reviews in software engineering

31. Krogstie, J. (2012) Model-based Development and Evolution of Information Systems: A Quality Approach. Springer
32. Krogstie, J. (2016) Quality in Business Process Modeling, Springer
33. Krogstie, J. (2024) Standard process specification languages In: Grefen, P. and Vanderfeesten, I. Handbook on Business Process Management and Digital Transformation Edward Elgar Publishing
34. Krogstie, J., Heggset, M., Wesenberg, H. (2017) Business Process Modeling of a Quality System in a Petroleum Industry Company Business Process Management Cases Springer
35. Krogstie, J., Sharma, K. (2024) Enhancing Our Understanding of Business Process Model Comprehension Using Biometric Data. In: van der Aa, H., Bork, D., Schmidt, R., Sturm, A. (eds) Enterprise, Business-Process and Information Systems Modeling. BPMDS EMMSAD 2024 Lecture Notes in Business Information Processing, vol 511. Springer, Cham.
36. Krogstie, J., Sharma, K. (2024) Enhancing Our Understanding of Business Process Model Comprehension Using Biometric Data. In NeuroIS Retreat 2024, Springer, Cham
37. Malinova, M., Mendling, J. (2022) Cognitive diagram understanding and task performance in system analysis and design. Management Information Systems Quarterly 46
38. Martín-Martín, A., Thelwall, M., Orduna-Malea, E. et al. (2021) Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: a multidisciplinary comparison of coverage via citations. Scientometrics 126, 871–906
39. Martín-Monzón, I., Amores-Carrera, L., Sabsevitz, D., Herbert, G. (2024) Intraoperative mapping of the right hemisphere: a systematic review of protocols that evaluate cognitive and social cognitive functions Frontiers in Psychology 15
40. Martinez-Maldonado, R., Echeverria, V., Fernandez-Nieto, G., Yan, L., Zhao, L., Alfredo, R., Li, X., Dix, S., Jaggard, H., Wotherspoon, R. (2023) Lessons learnt from a multimodal learning analytics deployment in-the-wild. ACM Transactions on Computer-Human Interaction 31, 1
41. Mendling, J., Malinova, M. (2022) Experimental evidence on the cognitive effectiveness of diagrams Procedia Computer Science 197, 10-15
42. Michael, J., Bork, D., Wimmer, M., Mayr, H. (2024) Quo Vadis modeling? Softw Syst Model 23, 7–28
43. Molina, A. I., Redondo, A. M., Ortega, M., Lacave, C. (2014) Evaluating a graphical notation for modeling collaborative learning activities: A family of experiments, Science of Computer Programming, Volume 88, Pages 54-81
44. Nordbotten, J.C., Crosby, M.E. (1999) The effect of graphic style on data model interpretation. Information Systems Journal, 9: 139-155
45. Paas, F., Van Merriënboer, J. J. (1994) Instructional control of cognitive load in the training of complex cognitive tasks. Edu. Psych. review 6, 351–371
46. Petersen, K., Vakkalanka, S., Kuzniarz, L. (2015) Guidelines for conducting systematic mapping studies in software engineering: An update, Information and Software Technology, Volume 64, Pages 1-18,
47. Petrusel, R., Mendling, J., Reijers, H. (2017) How visual cognition influences process model comprehension. Decision Support Systems Volume 96, Pages 1-16
48. Recker, J., Lukyanenko, R., Jabbari S., Mohammad, S., Castellanos, A. (2021) From representation to mediation: a new agenda for conceptual modeling research in a digital world. MIS Quarterly: Management Information Systems, 45(1), pp. 269-300
49. Ritchi, H., Jans, H., Mendling, J., Reijers, H.A. (2020) The Influence of Business Process Representation on Performance of Different Task Types. Journal of Information Systems 1 March; 34 (1): 167–194
50. Riedl, R., Léger, P-M. (2016) Fundamentals of NeuroIS - Studies in neuroscience, psychology and behavioral economics Springer
51. Riedl, R., Fischer, T., Léger, P.-M. (2017). A decade of NeuroIS research: status quo, challenges, and future directions. In: Proceedings of the International Conference on Information Systems - Transforming Society with Digital Innovation, (ICIS), Seoul, South Korea, pp. 10–13
52. Riedl R., Fischer T., Léger P.-M., Davis, F. (2020) A decade of NeuroIS research: Progress, challenges, and future directions DATA BASE Adv. Inf. Syst., 51 pp. 13-54

53. Sandkuhl, K., Fill, H-G., Hoppenbrouwers, S., Krogstie, J., Matthes, F., Opdahl, A., Schwabe, G., Uludag, Ö., Winter R. (2018) From expert discipline to common practice: a vision and research agenda for extending the reach of enterprise modeling. Business &Information Systems Engineering, Vol 60, pages 69-80
54. Schrepfer, M., Wolf, J., Mendling, J., Reijers, H.A. (2009) The Impact of Secondary Notation on Process Model Understanding. In: Persson, A., Stirna, J. (eds) The Practice of Enterprise Modeling. PoEM 2009. LNBIP, vol 39. Springer, Berlin, Heidelberg
55. Schreiber, C., Abbad-Andaloussi, A., Weber, B. (2023) On the Cognitive Effects of Abstraction and Fragmentation in Modularized Process Models. In: Di Francescomarino, C., Burattin, A., Janiesch, C., Sadiq, S. (eds) Business Process Management. BPM 2023. Lecture Notes in Computer Science, vol 14159. Springer, Cham.
56. Tallon, M., Winter, M., Pryss, R., Rakoczy, K., Reichert, M., Greenlee, M. W., Frank, U. (2019) Comprehension of business process models: Insight into cognitive strategies via eye tracking. Expert Systems with Application Volume 136, 2019, Pages 145-158
57. vom Brocke, J., Hevner, A., Léger, P. M., Walla, P., & Riedl, R. (2020) Advancing a NeuroIS research agenda with four areas of societal contributions. European Journal of Information Systems, 29(1), 9–24
58. Wang, W., Chen, T., Indulska, M., Sadiq, S., Weber, B. (2020) Business process and rule integration approaches - An empirical analysis of model understanding, Information Systems, Vol. 104
59. Weber, B., Pingera, J., Neurater, M., Zugal, S., Martini, M., Furtner, M., Sachse, P., Schnizer, D. (2016) Fixation Patterns During Process Model Creation: Initial Steps Toward Neuro-Adaptive Process Modeling Environments, 49th Hawaii International Conference on System Sciences (HICSS), Koloa, HI, USA
60. Weber, B., Fischer, T., Riedl, R. (2021) Brain and autonomic nervous system activity measurement in software engineering: A systematic literature review Journal of Systems and Software, 178
61. Weick, K. (1995) Sensemaking in Organisations. Sage, London
62. Wertheimer, M. (1923) Untersuchungen zur Lehre von der Gestalt II. Psychologische Forschung (4:1), pp. 301-350
63. Winter, M., Bredemeyer, C., Reichert, M., Neumann, H., Probst, T., Pryss, R. (2021) How Healthcare Professionals Comprehend Process Models-An Empirical Eye Tracking Analysis. IEEE 34th Annual IEEE Symposium on Computer-Based Medical Systems
64. Winter, M., Neumann, H., Pryss, R., Probst, T., Reichert, M. (2023) Defining gaze patterns for process model literacy – Exploring visual routines in process models with diverse mappings Expert Systems with Applications, Volume 213
65. Winter, M., Bredemeyer, C., Reichert, M., Neumann, H., Pryss, R. (2023) A Comparative Cross-Sectional Study on Process Model Comprehension driven by Eye Tracking and Electrodermal Activity Research Square preprint https://doi.org/10.21203/rs.3.rs-3705553/v1
66. Winter, M., Pryss, R. (2024) The effects of modular process models on gaze patterns - A follow-up investigation about modularization in process model literacy, Expert Systems with Applications, Volume 237, Part A
67. Xiong, J., Zuo, M. (2020) What does existing NeuroIS research focus on? Information Systems, Vol 89
68. Zimoch, M., Pryss, R., Probst, T., Schlee, W., Reichert, M. (2017) Cognitive insights into business process model comprehension: Preliminary results for experienced and inexperienced individuals. Proceedings Enterprise, Business-Process and Information Systems Modeling pp 137–152
69. Zimoch, M., Pryss, R., Schobel, J., Reichert, M. (2017) Eye tracking experiments on process model comprehension: lessons learned. Proceedings Enterprise, Business-Process and Information Systems Modeling pp 153-168
70. Zimoch, M., Mohring, T., Pryss, R., Probst, T., Schlee, W., Reichert, M. (2018) Using Insights from Cognitive Neuroscience to Investigate the Effects of Event-Driven Process Chains on Process Model Comprehension. In: Teniente, E., Weidlich, M. (eds) BPM Workshops. BPM 2017. Lecture Notes in Business Information Processing, vol 308. Springer