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Defining a Learning Metric for DSS Success Monitoring

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Abstract*: *The decision-making process is a knowledge-intensive activity, supported by DSS, that warrants close monitoring in most enterprises to ensure its success. Numerous frameworks for the evaluation of DSS effectiveness were proposed in the literature. However, many use metrics that are survey-based to reflect users' perception of the system's value. Based on the premise that metrics should be as objective as possible, this paper proposes a learning metric that assess the cognitive effects of DSS and their impact on decision performance. Drawing from the current tendency of using DSS in e-learning platforms, we define a learning metric that includes factors such as time spent on tasks, decision-aids use versus cumulated personal experience from previous usage, regret avoidance, decision outcome, and decision rejection/acceptance from higher management. Based on a criteria application process, we validate the proposed metric by first specifying its intent of use to determine the appropriate validation criteria, then demonstrating its viability against these criteria. An experimental case study is conducted to further attest to the validity of the proposed learning metric.

Keywords*: *DSS, DSS evaluation, user learning, metric validation

I.INTRODUCTION

The decision-making process is a knowledge-intensive activity where stakeholders use the knowledge representation of a specific issue within a business context to help them understand the problem and make adequate choices [2]. In this sense, understanding cognitive effects related to the use of DSS and their impact on decision performance is worthy of interest [3]. Traditionally, effects of DSS on users have been evaluated through the "User-satisfaction" metric, defined by [4] as the extent to which an application contributes to users' value creation within the organization. However, satisfaction is based on the level at which a user perceives the value of the system and can only reflects a subjective stance of users towards the DSS effectiveness. In fact, disconfirmation theory [5] confirms that there is a disproportion between a user's rating and the system's expected performance. Which consequently affects the user's actual satisfaction. Evaluating DSS needs to take into account the effect on users while considering metrics that are less subjective. This paper aims to explore the viability of user-learning as a metric for DSS evaluation.

DSS provide the opportunity for decision makers to build on knowledge learnt from the decision process' workflow and contribute to both implicit and intentional learning. They help improve the process of decision making through "Decisional guidance", offering users directives and information [6] throughout their interactions with the system. Decisional guidance is the backbone for user learning and implementing strategies for problem-solving, but it also offers users a participative toolbox to help them identify essential information for decision-making. Improved user learning can thus be considered a crucial measure in DSS evaluation and should be incorporated in the evaluation process. This paper aims to define and validate user learning as a metric for DSS evaluation. For that purpose, it is organized in three sections: the first section defines the learning metric and its constituents, the second presents the metric's validation process, and the third introduces an experiment to further validate the learning metric. The paper concludes with an outlook to future work.

II.LEARNING IN DSS

Learning theoreticians consider that individuals acquire and build knowledge out of their experiences and more specifically when they are involved in the activity of building objects/accomplishing missions [7, 8]. This active exploration leads them to develop a knowledge representation of the differences between their current state of learning and their accumulated experience. Learning is generally associated to social constructivism, since it happens in a social context. In such a context, individuals explore the environment by collaborating with others, reflecting and assimilating the aquired knowledge [9,10]. If we apply problem-based learning, case-based reasoning, and situated learning theories [11] to knowledge inciting systems (including DSS, Education-Games, e-learning platforms, etc..), we can argue that the user's interaction with the system creates contextualized and authentic learning related to the accomplished tasks. Moreover, the skills acquired are transferable to future situations [12].

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Drawing from the current tendency of embedding DSS in e-learning platforms [13,14], we adapted a number of factors that reflect the progression of users learning. These factors include, and are not limited to, time spent on tasks, decision aids use versus cumulated personal experience from previous usage, regret avoidance, decision outcome, and decision rejection/acceptance from higher management [15]:

▪ Time: Average time spent on tasks; this element is the only one to represent the time factor. It refers to the element of speed processing and is also an indicator of memory performance.

▪ Decision aids use: Represented by the frequency of simulation scenarios used and the frequency of external links clicks. The main purpose was to quantify how much the user tends to rely on his previous experiences with the system in similar scenarios.

▪ Regret avoidance: calculated based on the number of decision withdrawals by the user before it reaches higher management, indicating the regret or confidence.

▪ Process quality: Based on the Number of decision process steps that the user creates. An efficient process includes an inferior number of steps.

▪ Decision Outcome: Indicated by the number of decisions that were rejected by a hierarchical authority due to errors and incoherence. It represents the key element in dynamic assessment.

▪ Decision acceptance and rejection: Number of decisions sent back for further details/clarifications/corrections, also a way for dynamic assessments.

The factors can be adapted to the system at hand, are measured through the monitoring of DSS usage (log data), and are later aggregated to constitute the proposed learning metric.

III.LEARNING METRIC VALIDATION PROCESS

In the perspective of incorporating learning in the evaluation process of DSS, we choose to proceed to validating learning as a software metric. The rationale being that what applies to Information systems should apply to their subcategories as well. For the research community, a metric can be considered valid when it is found acceptable according to its use intent. Hence the defining of the intended use is very critical to the metric validation process. [16]. Meneely et Al. introduced a criteria application process based on a matrix combining the criteria and their advantages of use [16]. Choosing the appropriate validation criteria for a metric is a process that begins with defining the purpose of use for the metric related to the context of the evaluation activity. After that, their matrix is used to highlight the advantages that are related to the defined intent of use and hence extract criteria that are tied to the chosen advantages. The remaining task will be demonstrating the viability of the metric against these criteria. Table I presents the mapping of criteria with their advantages for the learning metric. The process is applied on the proposed Learning metric in order to confirm its viability for DSS evaluation.

IV.LEARNING AS A METRIC

A. Intent of Use

The intent of use for learning as a metric/measure for evaluating DSS is reducing the subjectivity of the user related metrics in an evaluation process. From a software conception perspective, our intent is improving DSS's capability to incorporate rich knowledge-intensive content to its users.

B. Defining advantages

Once the intended use is determined, specific properties that are appropriate to the metric can be inferred. These properties are called advantages, and for the proposed learning metric can be summarized as follows:

- Mathematical Soundness: It's the ability of the metric to endure mathematical operations without misrepresenting the attribute.
- Practicality: A metric is being practical when it can be effectively used in a software development project.
- Correctness: Being able to get correct values of the criteria that represent the metric.
- Difference-Detecting: The values resulting in incorporating the metric must indicate significant differences between the use cases.
- Meaningfulness: reflects the existence of a conceptual relationship between the measured attribute and the metric that is easy to understand and intuitive.
- Quality-Focused: Criteria related to this advantage indicate that the metric has an intent to improve the quality of the software.

C. Deducing criteria

After defining the advantages related to the metric of learning, we can identify the criteria associated with these advantages. The criteria are then marked as applicable to our context or not. The results are represented in Table II.

In order to validate the following criteria: Dimensional Consistency, Interaction Sensitivity, Non-uniformity, Actionability, Causal Relationship Validity, Usability, Instrument Validity, Non-collinearity; a case study had been conducted to confirm the validity of learning as a software metric and is presented in the next sections.

V.EXPERIMENTAL VALIDATION

For the sake of validating our proposed metric, we assessed learning on a corporate DSS called PLAFIN, based on the usage data. PLAFIN was implemented within the company to support the organization-wide budget allocation process and global financial decisions. The system is equipped with various functionalities supporting users in selecting, aggregating, estimating, simulating, equalizing and optimizing financial information. Users can consult financial transactions on a daily basis and/or explore historical transactions, make budget simulations and conduct what-if analyses, make decisions and forward them to hierarchical authority within the organization for consolidation and final approval.

Table I: **Mapping from Criteria to Advantages**

#	Criterion	Mathematical Soundness	Practicality	Correctness	Efficiency	Hypothesis-Strengthening	Meaningfulness	Decision-Informing	Quality-Focused	Theory-Building	Consensus Contribution	Difference-Detecting
1	A Priori Validity					X						
2	Actionability		X					X				
3	Appropriate Continuity	X					X				X	
4	Appropriate Granularity											X
5	Association							X		X		
6	Attribute Validity						X				X	
7	Causal Model Validity		X					X		X		
8	Causal Relationship Validity		X					X		X		
9	Content Validity						X				X	
10	Construct Validity			X							X	
11	Constructiveness							X		X		
12	Definition Validity										X	
13	Discriminative Power		X					X		X		
14	Dimensional Consistency	X					X					
15	Economic Productivity		X					X				
16	Empirical Validity					X				X		
17	External Validity							X	X	X		
18	Factor Independence					X	X					
19	Improvement Validity				X							
20	Instrument Validity	X		X								
21	Increasing Growth Validity	X									X	
22	Interaction Sensitivity	X									X	
23	Internal Consistency						X					
24	Internal Validity						X					
25	Monotonicity	X										
26	Metric Reliability			X								
27	Non-collinearity					X			X			
28	Non-exploitability		X									
29	Non-uniformity	X					X					X
30	Notation Validity			X							X	
31	Permutation Validity						X					
32	Predictability		X						X	X		
33	Prediction System Validity		X					X	X			
34	Product or Process Relevance		X									
35	Protocol Validity			X							X	
36	Rank Consistency					X		X	X			
37	Renaming Insensitivity						X					
38	Repeatability					X				X		
39	Representation Condition	X					X					
40	Scale Validity	X										
41	Stability			X								X
42	Theoretical Validity						X					
43	Trackability					X		X				
44	Transformation Invariance											X
45	Underlying Theory Validity									X		
46	Unit Validity						X					
47	Usability		X		X				X			

TableII: Criteria applicable to Learning as a metric

Advantage	Criteria	Applicable	Demonstration
Mathematical Soundness	Appropriate Continuity	Yes	The concept of learning is continuous and do not present disruption
	Dimensional Consistency	Yes	The learning metric is linear over time (As demonstrated in the experiment)
	Instrument Validity	NA	
	Increasing Growth Validity	Yes	
	Interaction Sensitivity	Yes	Users interacting with two different systems might have different learning scores (As demonstrated in the experiment)
	Monotonicity	NA	
	Non-uniformity	Yes	Different systems produce different results (As demonstrated in the experiment)
	Representation Condition	Yes	Learning metric can be identified to numerical values following a scale
	Scale Validity	Yes	Learning metric follows an ordinal scale
Practicality	Actionability	Yes	Learning metric allows to make an empirically informed decision based on the software product's status (As demonstrated in the experiment)
	Causal Model Validity	Yes	It can be used in a causal model that explains a quality factor: Satisfaction for example
	Causal Relationship Validity	Yes	The causal relationship between learning and system use to be demonstrated in the experiment
	Discriminative Power	Yes	The case of a system where no learning is gained by the user is a discriminative case
	Economic Productivity	Yes	Learning is a benefit of using a system hence the contribution to the cost and benefit question
	Non-exploitability	Yes	Learning cannot be manipulated by developers
	Predictability	NA	
	Prediction System Validity	NA	
	Product or Process Relevance	Yes	Learning metric can be tailored to specific product and processes
	Usability	Yes	The metric can be cost-effectively implemented in a quality assurance program (As demonstrated in the experiment)
Correctness	Construct Validity	Yes	The gathering of the metric's measurements is suitable for the definition of the targeted attribute
	Instrument Validity	Yes	The instrument measure is valid and properly calibrated (As demonstrated in the experiment)

Metric Reliability	Yes	The measurements of learning can be systemized hence accurate and repeatable
Notation Validity	Yes	The measurements of learning are mathematical precise values
Protocol Validity	NA	
Stability	Yes	The measurements produced by a system will remain the same.
Appropriate Granularity	Yes	The learning metric's finest granularity is one user
Transformation Invariance	NA	
Attribute Validity	Yes	The measurements correctly exhibit the attribute that the metric is intending to measure
Content Validity	Yes	The learning metric captures the entire notion of learning (Memory, processing, logical operations...)
Factor Independence	Yes	The individual measurements used in the metric formulation are independent of each other (True, as for the demonstrating experiment, learning scores are composed of elements issued form successive processes)
Internal Consistency	Yes	All of the elementary measurements of learning are assessing the same construct (Knowledge) and are interrelated
Internal Validity	Yes	Demonstrated via theory and experiment
Permutation Validity	Yes	Order of elements do not affect the result
Renaming Insensitivity	Yes	
Theoretical Validity	Yes	Validated via literature review
Unit Validity	NA	
External Validity	Yes	Learning has been linked to usage
Non-collinearity	Yes	Correlation with satisfaction has been discussed in the experiment
Rank Consistency	Yes	Learning metric induces ranking by its nature.

The system is also equipped with a process management module to manage the group decision-making processes and collect/consolidate decisions made across the organization.

The learning metric was computed based on the following factors: Number of steps, number of errors, time on task, withdrawals, external clicks, simulation use, sent-backs.

In order to monitor learning evolution, we establish an overall score formula (1) based on these factors and their corresponding weights, in a given period of time. The weights were defined in a way that reflects the importance of the factors as illustrated in the literature.

$$FoM = 1/\sum W(i) * E(i) \quad \text{With} \quad \sum W(i) = 1 \qquad (1)$$

This overall score designated "figure of merit (FoM)" constitutes a user's learning score in a given time interval. Larger values indicate that learning progress is considerable. From the formula, and according to feedback from domain experts, we drew the conclusion that the learning metric exhibits dimensional consistency, usability, instrument validity, and is linear over time.

An ETL process has been developed to collect the usage data of the DSS corresponding to stakeholders involved in the decision-making process on a 2 years period, extract the relevant data, then compute and store the learning scores. (Figure 1).

Figure 1. Collecting usage data and computing FoMx

V.RESULTS

We observed the evolution of user's scores each quarter for six quarters of regular system use. The learning scores were computed for each user then combined for a global view on the effects of system use. Average, median and mean values were calculated to check the overall evolution of the learning scores over time periods for all the users, values are shown in Table III.

Table - III. Scoring values for period 2016/Q1 to 2017/Q2

Period of Evaluation	Median	Average score	Standard Deviation
2016/Q1	11.12	10.66	2.11
2016/Q2	11.12	11.74	1.72
2016/Q3	12.95	14.39	1.93
2016/Q4	14.79	16.34	1.62
2017/Q1	20.06	19.70	1.02
2017/Q2	23.22	22.75	1.23

The results indicated that the computed learning score has augmented over time for all DSS' active users. The metric exhibits non-uniformity as it produces various values for at different entities. It also helps infer recommendations for action, which reveals its actionability. The metric's interaction sensitivity, causal relationship validity and non-collinearity have been demonstrated in a prior work [17].

VI.CONCLUSION

The increasing complexity of organizational management, the rising flow of information, and the variety of business areas make the investment in DSS costly and risky and drive the need of evaluation frameworks that address effectiveness and efficiency. Global frameworks capable of providing a holistic view on the performance of such systems are hence required. The aim of this research was to contribute to the ongoing discussion on DSS success, by defining a new evaluation criteria that will later be included in a global evaluation framework. The proposed Learning metric is built on the premise that a successful DSS implementation should positively impact the usage frequency and cognitive capabilities of users. Which should lead to an improvement of the overall decision-making process and outcome. We thus defined a metric that accounts for learning factors such as: Number of steps, number of errors, time on task, withdrawals, external clicks, simulation use, and sent-backs. We then addressed the validation of the learning metric using a criteria application process that maps the relevant validation criteria with the properties of the metric then demonstrates its viability against these criteria. We found that the proposed learning metric exhibits dimensional consistency, usability, instrument validity, non-uniformity, actionability, and is linear over time. An experiment was also conducted to further demonstrate the validity of the metric in a business context. Although, throughout our experiment, experts feedback has confirmed that the metric is viable, it is worth mentioning that our experiment concerns users of similar backgrounds. Some extra-work is needed to widen the scope of the theory and strengthen the generalizability of the findings. It is in our perspectives to test and validate the metric in more diversified environments, including a controlled group to be used as a benchmark against which our results will be measured.

REFERENCES

1. V. L. Sauter, "Decision Support Systems for Business Intelligence", 2nd ed.,. Hoboken, NJ: Wiley, 2010.
2. Z. Shabani, M. Eshaghian, "Decision support system using for learning management systems personalization," in American Journal of Systems and Software, Vol. 2, No. 5, 2014, pp. 131-138.
3. A. Kamis, M. Koufaris, T. Stern, "Using an attribute-based decision support system for user-customized products online: an experimental investigation", in MIS Quarterly, Vol. 32, No. 1, 2008, pp. 159–177.
4. W. H. Delone, E. R. McLean,"The Delone and McLean model of information systems success: a ten-year update," in Journal of management information systems, Vol. 19, No. 4, 2003, pp. 9-30.
5. R.L. Oliver, "A cognitive model of the antecedents and consequences of satisfaction decisions" in Journal of Marketing Research, Vol. 17, No. 4, 1980, pp. 460–469.
6. S. Antony, R. Santhanam, "Could the use of a knowledge-based system lead to implicit learning," in Decision Support Systems, Vol. 43, No. 1., 2006, pp.141-151.

7. Y. Kafai, "Minds in play: Computer game design as a context for children's learning". Mahwah, NJ: Lawrence Erlbaum, 1995.
8. S. Papert, "Mindstorms: Children, computers, and powerful ideas". New York: Basic Books. 1980.
9. J. Piaget, "Construction of reality in the child". London: Routledge & Kegan Paul. 1957.
10. L. Vygotsky, "The role of play in development," in Mind in society, Cambridge, MA: Harvard University Press, 1978, pp. 92–104
11. J.S. Brown, A. Collins, P. Duguid, "Situated cognition and the culture of learning" in Educational Researcher, Vol. 18, No. 1, 1989, pp. 32–42.
12. E. De Vries, "Students' construction of external representations in design-based learning situations" in Learning and Instruction, Vol. 16, 2006, pp. 213–227.
13. M. Mitri, "Using Decision Support Systems to Enhance Learning in Higher Education" in Journal of Computer Information Systems, Vol. 42, No. 4. 2002.
14. S.B. Kotsiantis, "Use of machine learning techniques for educational proposes: a decision support system for forecasting students' grades" in Artificial Intelligence Review, Vol. 37, No. 4, 2012.
15. K. Boukhayma, A. ElManouar, "Evaluating decision support systems" in 15th International Conference on Intelligent Systems Design and Applications (ISDA), Marrakech, 2015, pp. 404-408
16. A. Meneely, B. Smith, L. Williams, "Validating software metrics: A spectrum of philosophies" in ACM Trans. Softw. Eng. Methodol. Vol. 21, No. 4, 2012, pp. 1-28
17. K. Boukhayma, A. ElManouar, "Evaluating Decision Support Systems' Effect on User Learning: An Exploratory Study", in Trends and Advances in Information Systems and Technologies, vol 746, 2018.

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