

Spring 6-10-2017

# WHOSE MATURITY IS IT ANYWAY? THE INFLUENCE OF DIFFERENT QUANTITATIVE METHODS ON THE DESIGN AND ASSESSMENT OF MATURITY MODELS

Lester Allan Lasrado  
*Copenhagen Business School, lal.itm@cbs.dk*

Ravi Vatrapu  
*Copenhagen Business School, vatrapu@cbs.dk*

Raghava Rao Mukkamala  
*Copenhagen Business School, Denmark, rrm.itm@cbs.dk*

Follow this and additional works at: [http://aisel.aisnet.org/ecis2017\\_rip](http://aisel.aisnet.org/ecis2017_rip)

---

## Recommended Citation

Lasrado, Lester Allan; Vatrapu, Ravi; and Mukkamala, Raghava Rao, (2017). "WHOSE MATURITY IS IT ANYWAY? THE INFLUENCE OF DIFFERENT QUANTITATIVE METHODS ON THE DESIGN AND ASSESSMENT OF MATURITY MODELS". In Proceedings of the 25th European Conference on Information Systems (ECIS), Guimarães, Portugal, June 5-10, 2017 (pp. 2918-2927). ISBN 978-0-9915567-0-0 Research-in-Progress Papers.  
[http://aisel.aisnet.org/ecis2017\\_rip/41](http://aisel.aisnet.org/ecis2017_rip/41)

# WHOSE MATURITY IS IT ANYWAY? THE INFLUENCE OF DIFFERENT QUANTITATIVE METHODS ON THE DESIGN AND ASSESSMENT OF MATURITY MODELS

*Research in Progress*

Lester Allan Lasrado, Centre for Business Data Analytics, Department of IT Management, Copenhagen Business School, Copenhagen, Denmark, lal.itm@cbs.dk

Ravi Vatrapu, Centre for Business Data Analytics, Department of IT Management, Copenhagen Business School, Copenhagen, Denmark & Faculty of Technology, Westerdals Oslo School of Arts Communication and Technology Norway, vatrapu@cbs.dk

Raghava Rao Mukkamala, Centre for Business Data Analytics, Department of IT Management, Copenhagen Business School, Copenhagen, Denmark, rrm.itm@cbs.dk

## Abstract

*This paper presents results from an ongoing empirical study that seeks to understand the influence of different quantitative methods on the design and assessment of maturity models. Although there have been many academic publications on maturity models, there exists a significant lack of understanding of the potential impact of (a) choice of the quantitative approach, and (b) scale of measurement on the design and assessment of the maturity model. To address these two methodological issues, we analysed a social media maturity data set and computed maturity scores using different quantitative methods prescribed in literature. Specifically, we employed five methods (Additive, Variance, Cluster, Minimum Constraint, and RASCH) and compared the sensitivity of measurement scale and maturity stages. Based on our results, we propose a set of methodological recommendations for maturity model designers.*

*Keywords: Maturity Models, Quantitative Methods, Rasch, QCA, NCA, Fuzzy Clustering, Regression.*

## 1 Introduction

In information systems (IS) research, maturity models are understood as tools that can aid the facilitation of internal and/or external benchmarking and showcase possible improvements and providing guidelines through the evolutionary process of organizational development and growth (Mettler et al. 2010). Being normative and prescriptive by nature, development and evaluation of methodologically rigorous and empirically validated maturity models is a subject of debate and fierce critique in IS research (Becker et al. 2010; King and Kraemer 1984; Lasrado et al. 2016a), and related disciplines (Andersen and Henriksen 2006; Kazanjian and Drazin 1989; Wendler 2012). Proponents for and opponents of maturity models have long been engaged in debates on and discussions about theoretical, methodological and empirical aspects of maturity models without much comparative analysis (Lasrado et al. 2016a). In particular, maturity models are criticised for lack of theoretical foundations (Pöppelbuß et al. 2011; Renken 2004), lack of empirical validation in the selection of variables (Lahrman et al. 2011; Wendler 2012), and being overly conceptual and simplistic (Solli-Sæther and Gottschalk

2010). Recent literature reviews of the field by multiple scholars (Lasrado et al. 2015; Pöppelbuß et al. 2011; Solli-Sæther and Gottschalk 2010; Wendler 2012) point to the rarity in use of empirical or other demonstration methods. Becker et al. (2010) summarises the status quo of maturity model research as “*Information systems research has ignored theoretical approaches to maturation – the process of becoming more mature has been understood rather vaguely.... Maturity models in IS research requires analytical perspectives better grounded in theory*”. To address the criticisms of maturity models listed above, this paper investigates how maturity is currently measured employing different quantitative methods. This paper aims to conduct a systematic comparison of the five dominant quantitative methods used in maturity model research by answering the following research question: *Does the application of different quantitative methods influence the final design of maturity models and its subsequent maturity assessment?*

The rest of the paper is organized as follows. First, we summarize prior research on application of quantitative methods for maturity models. Second, we present and discuss methodological aspects of our comparative study of different quantitative methods including a description of the social media maturity dataset used. Third, we present the analysis and report the results. Finally, we discuss the results, propose recommendations, and outline future research directions.

## 2 State of the Art: Different Methods in MM Research

Our review of maturity models in information systems research (Lasrado et al. 2016a; Lasrado et al. 2015) yielded a list of seven quantitative methods (Table 1). Two of the methods (Rasch analysis, SET) are used only for the design phase. The design phase is about empirically constructing the maturity model and involves deciding the number of maturity stages or levels, the characteristics of each of the stages, stage boundaries and the progression towards maturation.

	Method	Assumptions	Application in Information Systems
Design (D)	<b>RASCH:</b> Rasch analysis or Item response theory (IRT).	Organizations with higher maturity have a high probability of successfully implementing capabilities, both easy and advanced. Similarly, lower maturity ones have a very low probability of implementing advanced capabilities.	Rasch Analysis combined with Cluster Analysis was first used by Dekleva and Drehmer (1997) to empirically describe the evolution of the software development process in an organisation using capability maturity model (CMM) questionnaire. This method has then been applied by many scholars (Berghaus and Back 2016; Lahrmann et al. 2011; Raber et al. 2012).
	<b>SET:</b> QCA and NCA applied together.	An underlying assumption of equifinality that there exist multiple paths towards maturation.	Qualitative Comparative Analysis (QCA) with Necessary Condition Analysis (NCA) for designing a social media maturity model (Lasrado et al. 2016a). Authors prescribe a 6-step procedure for applying this method.
(A)	<b>CLUSTER:</b> Two Step Clustering, Fuzzy Clustering (FC) or other methods	There are groups of organisations that are homogenous across a particular set of maturity capabilities.	Benbasat et al. (1980) uses cluster analysis for categorizing the companies in their study on organizational maturity on information system skill needs. Jansz (2016) adopts clustering to assess organisations’ situational

	depending on the data.		corporate collaboration maturity. She also provides suggestions and guidelines <sup>1</sup> with regards to cluster analysis preparations for handling mixed-scaled data.
	<b>ADDITIVE LOGIC (ADD):</b> Summation or average of capabilities with or without weights for capabilities.	There is only one single linear path to higher maturity. The underlying assumption is that organisations with higher maturity will have implemented more number of capabilities.	Summation, simple average, and weighted average wherein the formulation of weights is arbitrary or non-empirical (Chung et al. 2017; Luftman 2000; Van Steenberghe et al. 2013) are commonly used for maturity assessments. Empirically supported calculation of weights using methods like structural equation modelling (Winkler et al. 2015) is rare.
	<b>MINIMUM CONSTRAINT:</b> (a) Statistical Squared Distance (SSD) (b) Euclidian Distance (EUC)	There is only one single linear path to higher maturity. The underlying principle is based on theory of constraints; the overall maturity is the level of maturity of the lowest capability.	There is only one instance each for application of SSD (Joachim et al. 2011) and EUC (Raber et al. 2013) who also prescribe a detailed 3-step procedure for SSD and EUC respectively. The only difference between the two methods is that SSD is weighted by the standard deviation at the capability level and EUC does not.
<b>Validation (V)</b>	<b>VARIANCE:</b> Regression, Correlation coefficients with tests for statistical significance.	Organizations with high maturity will also realise higher business benefits, performance and business value as compared to the ones at a lower maturity level.	Validating maturity using regression (Chen 2010; Joachim et al. 2011; Raber et al. 2013; Sledgianowski et al. 2006) or correlation coefficients (Marrone and Kolbe 2011) against self-reported maturity, perceived benefits or performance.

Table 1. Quantitative Methods used in Maturity Models Research.

Furthermore, as illustrated in Table 1, all the seven<sup>2</sup> methods can be applied in the assessment phase. This phase involves computing the maturity scores and classifying the organisations. Finally, only one method is applied for validating maturity.

<sup>1</sup> For the dataset used in our study, we chose Fuzzy Clustering (FC) as it is prescribed as an approach to identify complex non-linear phenomena. According to Babuška (2012), fuzzy clustering does so by partitioning the available data into groups and by approximating each group using a simple model. It can be used as a tool to partition the data in such a way that the transitions between the groups is smooth rather than abrupt. It can be used to both design a maturity model as well as classify maturity of organizations. Fuzzy clustering has prescribed validity measures (Wang and Zhang 2007) such as Partition Coefficient, Partition Entropy (Bezdek 2013) and Xie and Beni's Index (Xie and Beni 1991) to validate and identify the suitable number of clusters. In this paper, we have used Fuzzy C-means clustering algorithm (Bezdek et al. 1984) to partition the data pertaining to digital maturity of organizations.

<sup>2</sup> Here we count EUC and SSD as one method under the category of Minimum Constraint. Although the two methods are fundamentally similar, we compare the results obtained using these two methods to assess the influence of weighting by standard deviation employed in SSD but not in EUC.

### 3 Methodology & Dataset Description

To answer our research question, we employed a multi-method comparative approach on a single dataset. Our methodological approach is similar to the one adopted by Van Looy (2015) to study business process maturity scoring algorithms. However, instead of a single case study, we used a dataset measuring social media maturity of 85 organizations in Denmark (Lasrado et al. 2016a). Given the quasi-experimental design, we held the dataset constant and varied the quantitative methods. Overall our methodology comprised of three phases as summarized in Figure 1 and discussed below.

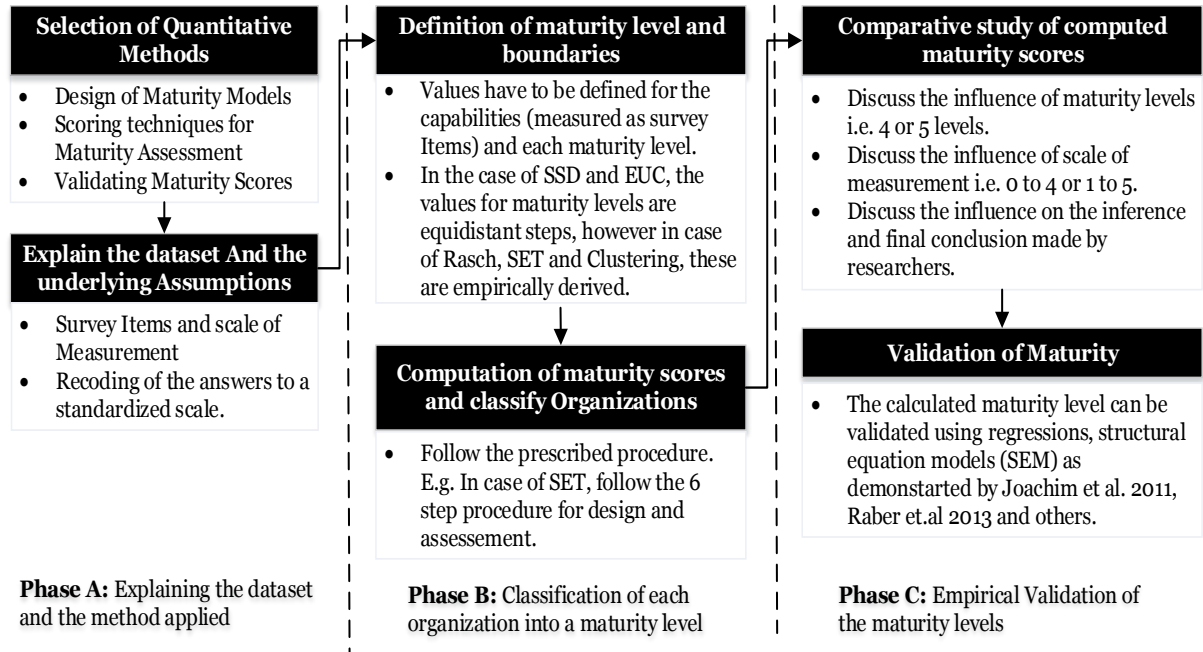


Figure 1. Methodological Framework for the Multi-Method Comparative Study.

Phase one of our methodology involves the selection of the quantitative methods from a review of the extant literature and then explaining the dataset. We select and apply all the seven methods listed in Table 1 on a dataset measuring social media maturity by Lasrado et al. (2016a). This data was collected through a cross-sectional survey whose primary purpose was comparative benchmarking of participating organizations in Denmark. As illustrated in Table 2<sup>3</sup>, there are 14 conditions or capabilities (X) grouped under 4 broader categories: Management, IT Policy, Technology and Culture. In line with our previous research papers (Lasrado et al. 2016a; Lasrado et al. 2016b) using the same dataset, we also employ business value realized in PR, Sales & Marketing (Y) as a proxy measure for maturity.

	Condition (X)	Scale; # of items	Study Recoding
Culture	The measures for Culture are based on orientation towards employee driven style of working and decision making (EEC), a	EEC: Likert Scale (-2 to 2); 4	0 = 0; -1 = 1; 0 = 2; 1 = 3; and 2 = 4. In case of decimals, then <i>round</i>

<sup>3</sup> Given the page constraints of a research-in-progress paper, we can only briefly list and explain the capabilities or conditions and their respective scales of measurement in Table 2. Furthermore, for the purpose of standardisation, we also recoded the original dataset as integers between 0 and 4. The reason for this standardisation step was to facilitate application of Rasch Analysis as there is a strict requirement that the items need to be integers.

	well-planned and structured style (PSC), and an explorative culture (NSC) wherein new IT systems are always sought after. They are measured as Completely disagree (-2) to Completely agree (2).	PSC: Likert Scale (-2 to 2); 2	<i>off</i> to the nearest integer. E.g. If EEC = 1.4, then it is rounded off to 1, if $\geq 1.5$ and above then 2.
		NSC: Likert Scale (-2 to 2); 1	
Management	Top Management encourages use	Likert (0-4); 1	Not Recorded.
	IT investment within the organization as compared to previous years	0=decreased,1=Same, 2=increased; 1	0=decreased,2=Same, 4=increased.
	Digital strategy Index (DS)	Index (0 to 4); 1	Round off i.e. DS=2.6, then rounded off to 3.
IT Policy	Allowing access to Own Devices (OD) measured on access to number of systems, and/or Providing Employees With Devices (PEWD) measured on number of employees, while having a high IT Security Index (ITS) is an organization with high social media maturity.	ITS: Index (scaled to 4); 1	Round off i.e. DS=2.6, then rounded off to 3.
		PEWD: Likert Scale (0-4); 1	Not Recorded.
		OD: Likert Scale (0-4); 1	Not Recorded.
Technology	Social media presence, measured as the number of social media channels.	Count (0 -8); 1	0 = 0; 1 = 1; 2 = 2; 3 = 3; $\geq 4 = 4$ .
	Extent of Use of social media.	Likert Scale (0-4); 2	Round off.
	Number of resources (FTE) hired specifically for social media activities, measured as none, part time, full time and more than one.	Ordinal (0,1,2,3,4); 1	Not Recorded.
	Sometimes, a marketing manager or any other employee manages social media. Hence professional skills (S) available inside the organization is measured.	Likert Scale (0-4) i.e. Not at all to Very high degree; 1	Not Recorded.
	Metrics (M) is a measure of formalized governance i.e KPI's, and workflows	Ordinal (0,0.5,1); 2	0 = 0; 0.5 = 2; 1 = 4
Y	Business Value from social media in customer facing activities.	Likert Scale (0-4); 2	Round off.

Table2. Dataset and Conditions Explained (Lasrado et al. 2016a).

## 4 Analysis & Results

We now present and discuss Phases B & C in Figure 1. All the different methods discussed in section 2 were applied on the social media maturity dataset. However, Rasch analysis proved to be ineffective in providing valid and reliable results. The reason for these ineffective results is that the survey items were not designed keeping Rasch analysis in mind, especially in keeping the scales and their intervals constant. Hence Rasch analysis was dropped from this comparative study. However, we successfully designed and assessed social media maturity of organisations using set theory (SET) while satisfying all the validity tests prescribed.

The success of SET over Rasch<sup>4</sup> can be mainly attributed to the steps involving QCA, specifically qualitative interference and calibration that makes the dataset less vulnerable to measurement errors,

<sup>4</sup> Rasch algorithm checks for the sensitivity of the final results using measures of person and item reliability (Cleven et al. 2014). A reliability greater than 0.8 is expected. However, for the social media maturity dataset, we obtained a reliability of 0.44 which is way below the prescribed minimum.

outliers and inconsistent scales across different survey items. Using SET, we empirically derived four maturity stages and classified organisations as belonging to one of these stages or levels. Next, we applied fuzzy clustering and established existence of two maturity stages. Finally, we applied statistical squared distance (SSD), Euclidian distance (EUC), and additive logic (ADD) methods to assess maturity and the results are discussed below.

#### 4.1 Comparison of Maturity Assessment Results

Comparison of the maturity assessment results using the five methods is illustrated in Figure 2. It is quite evident that the five methods produce very different results. While set theory (SET) classifies organizations across four stages ranging from no maturity to very high maturity, the other four methods (ADD, EUC, Fuzzy Clustering and SSD) classify majority of the organizations as high maturity. We find that set theory (SET) is the most conservative of all the methods with 43% of the organizations at the lowest level of maturity while ADD is the most lenient with 60% of the organizations classified as high maturity.

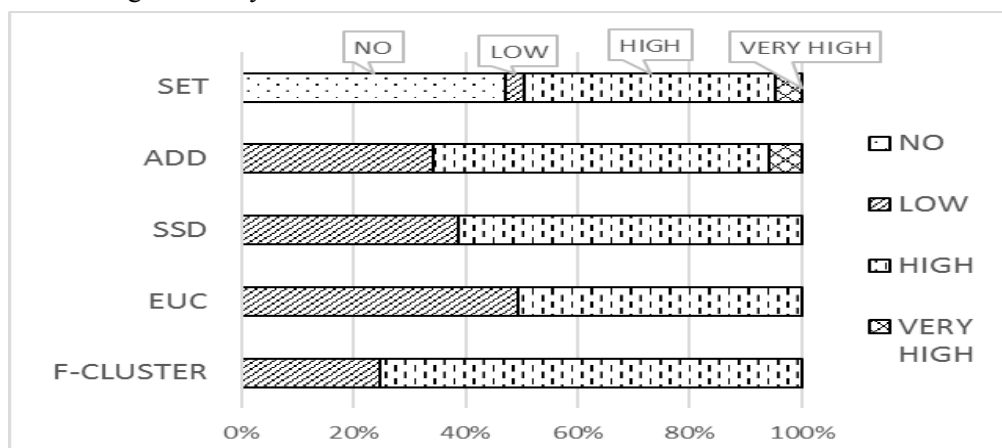


Figure 2. Variation in Maturity Assessment using Five Different Quantitative Methods.

We then investigated the commonalities or intersections of the 5 methods and found that only 25 of the 85 organisations (i.e. 29%) share common maturity results. Furthermore, a detailed inspection of intersections (denoted with  $\cap$ ) provided us with other interesting findings; (1)  $EUC \cap$  Fuzzy Clustering = 50 (59%), (2)  $EUC \cap SSD \cap ADD \cap$  Fuzzy Clustering = 44 (52%), and (3)  $EUC \cap SSD \cap ADD \cap SET = 27$  (32%). These results highlight the fact that the quantitative method chosen exerts a substantial influence on the final maturity assessment.

##### 4.1.1 Effect of Measurement Scale

Next, we investigated the effect of measurement scales on final maturity results. In particular, we investigate the impact of the two scale designs of 0-4 vs. 1-5 while keeping the intervals equidistant<sup>5</sup>. Prior research on effect of measurement scales on BPM maturity (Van Looy 2015) found that maturity scores are generally lower for a 0-4 scale than a 1-5. We tested this finding for our five quantitative methods. We find that change in measurement scale has no impact whatsoever on the maturity results using any of the four methods (ADD, SSD, EUC and SET). Now that the effect of scale of measurement has been tested, next we investigated the effect of the number of maturity stages.

<sup>5</sup> E.g. Business Value is measured as None (0), Low Value (1), Some Value (2), High Value (3), Very High Value (4). By changing to a 1-5 scale, we just add 1 to all values i.e. None (1), Low Value (2), Some Value (3), High Value (4), Very High Value (5).

#### 4.1.2 Effect of Number of Stages

The decision about selecting the number of maturity stages forms the core of any maturity model design framework (Cleven et al. 2014; Lasrado et al. 2016a). In order to test the effect of number of stages on final maturity assessments, we compared the maturity scores for 4 vs. 5 stages. While such a comparison is not possible for Fuzzy Clustering and SET method as the number of stages are empirically derived and not arbitrarily chosen, we were able to test the effect of the number of maturity stages for EUC, SSD and ADD<sup>6</sup>. We find statistically significant differences<sup>7</sup> with an increase of overall average maturity by 39.75%, 28% and 36.7% observed for EUC, SSD and ADD respectively as maturity stages are increased from four to five. These findings highlight a critical issue raised by many scholars (Cleven et al. 2014; De Bruin et al. 2005; Solli-Sæther and Gottschalk 2010) that the researcher's choice of number of maturity stages should not be arbitrary but theoretically informed during the design or assessment phase and should be empirically validated subsequently. Now that effect of number of maturity stages is established, we then conducted the validation of maturity using different methods.

#### 4.2 Validation: Maturity Results and Perceived Business Value

While Maturity Models literature predominantly uses qualitative methods (e.g. focus groups, Delphi method and interviews) for validation of maturity, there have been few scholars (Table 1) who have employed quantitative variance based methods (e.g. Correlation, OLS, and SEM). Although this approach to validating maturity has been critiqued and challenged (King and Kraemer 1984; Mullaly 2014), it is the sole quantitative method for validation used in literature till date. In line with recommendations from prior research (Joachim et al. 2011; Raber et al. 2013; Winkler et al. 2015), we investigated the relationship between social media maturity and business value (DV) using SEM analysis by Partial Least Square (PLS) technique (Hair 2011). The results are listed in Table 3.

	Method	# Stages	Scale	Mean	Std. Dev	Coefficient	R-Sq (Adj)
EUC	EUC	4	0-4	1.51	0.503	0.291*	0.085
	EUC_1	4	1-5	1.51	0.503	0.291*	0.085
	EUC_2	5	1-5	2.15	0.567	0.300*	0.090
SSD	SSD	4	0-4	1.61	0.490	0.420*	0.176
	SSD_1	4	1-5	1.61	0.490	0.420*	0.176
	SSD_2	5	1-5	2.06	0.496	0.365*	0.133
ADD	ADD	4	0-4	1.72	0.569	0.377*	0.142
	ADD_1	4	1-5	1.72	0.569	0.377*	0.142
	ADD_2	5	1-5	2.31	0.655	0.457*	0.209
	SET	4	0-4	1.07	1.055	0.468*	0.219
	Fuzzy Clustering	2	1-5	1.75	0.43	0.541*	0.29
*p-value significant at 95% level of confidence. R-Sq indicates amount of variance explained (min value 0.1) and Path coefficients indicate the strengths of the relationships.							

Table 3. Validation of Maturity.

<sup>6</sup> EUC\_2 indicates 1-5 scale. SSD\_2 also indicates 1-5 scale with 5 maturity stages.

<sup>7</sup> There was a significant difference in the maturity scores calculated using SSD\_1 (M =1.61, SD =0.49) and SSD\_1 (M =2.06, SD =0.496);  $t(84) = -8.241$ ,  $p = 0.000$ . Similarly, T tests for EUC\_1(M =1.51, SD =0.503) and EUC\_2 (M =2.15, SD =0.567); as well as ADD\_1(M =1.72, SD =0.569) and ADD\_2 (M =2.31, SD =0.655) highlighted significant differences.



As illustrated in Table 3, maturity assessments done using the four methods of Fuzzy Clustering, SET, ADD and SSD are validated irrespective of the number of maturity stages. Interestingly, a drastic drop of R-Sq (adj) in EUC and EUC\_2 is observed. Hence, EUC could not be validated as the R-Sq (adj) of 0.085 is considered very weak and below the threshold of 0.1. This is primarily attributed to the way maturity scores are calculated for this method. The theory of constraints (Van Looy 2015) plays an important role wherein the minimum scores of the dimensions pull the final maturity scores lower.

## 5 Recommendations and Future Research

Going beyond a simple comparison of different maturity measurement methods, based on the empirical findings reported and discussed above, we propose a list of recommendations for maturity model designers in Table 4 below.

Key Question	EUC	SSD	ADD	SET	RASCH	CLUSTER
Is the method suitable for Design (D) or Assessment (A) phase?	A	A	A	D+A	D+A	D+A
Is the selection of number of maturity stages arbitrary (M) or empirically driven (P)?	M	M	M	P	M	P
Has the approach prescribed the necessary validity and reliability tests for the measures? Yes (Y), No (N), Don't know or Not tested in this study (-).	N	N	N	Y	Y	Y
Does the approach need a dependant variable (DV) for design and/or assessment?	N	N	N	Y	N	Y
Would change in scale impact results?	N	N	N	N	-	-
Would change in # of stages impact results?	Y	Y	Y	-	-	-

Table 4. Recommendations for Maturity Model Designers

There are two limitations of this study. First, not all the propositions related to maturity model design and assessment could be addressed in this paper, especially with regards to Rasch Analysis. This limitation is primarily due to the social media maturity dataset used for this study failing to satisfy the prescribed validity and reliability measures. Second, the findings and subsequent recommendations are solely based on using single maturity dataset, and limited to only five different maturity computation methods. In order to address these two limitations, future research would be repeat the three phase methodological process on multiple datasets spanning academia (ITIL Maturity (Marrone and Kolbe 2011; Wulf et al. 2015) and industry (Omni channel Maturity (Houllind 2015)). Future work will also investigate incorporating new computational methods and techniques.

## Acknowledgements

We gratefully acknowledge the support and generosity of Networked Business Initiative, Denmark and their partners namely Sitecore, The Danish Chamber of Commerce, The Confederation of Danish Industry and Erhvervsstyrelsen without which the present study could not have been completed.

## References

- Andersen, K. V., and Henriksen, H. Z. 2006. "E-Government Maturity Models: Extension of the Layne and Lee Model " *Government Information Quarterly* (23:2), pp. 236-248.
- Babuška, R. 2012. *Fuzzy Modeling for Control*. Springer Science & Business Media.

- Becker, J., Niehaves, B., Poeppelbuss, J., and Simons, A. 2010. "Maturity Models in IS Research," *European Conference on Information Systems (ECIS) 2010 Proceedings, Paper 42*.
- Benbasat, I., Dexter, A. S., and Mantha, R. W. 1980. "Impact of Organizational Maturity on Information System Skill Needs," *MIS quarterly*, pp. 21-34.
- Berghaus, S., and Back, A. 2016. "Stages in Digital Business Transformation: Results of an Empirical Maturity Study," in: *MCIS 2016 Proceedings*. 22.
- Bezdek, J. C. 2013. *Pattern Recognition with Fuzzy Objective Function Algorithms*. Springer Science & Business Media.
- Bezdek, J. C., Ehrlich, R., and Full, W. 1984. "Fcm: The Fuzzy C-Means Clustering Algorithm," *Computers & Geosciences* (10:2-3), pp. 191-203.
- Chen, L. 2010. "Business-IT Alignment Maturity of Companies in China," *Information & management* (47:1), pp. 9-16.
- Chung, A. Q., Andreev, P., Benyoucef, M., Duane, A., and O'Reilly, P. 2017. "Managing an Organisation's Social Media Presence: An Empirical Stages of Growth Model," *International Journal of Information Management* (37:1), pp. 1405-1417.
- Cleven, A. K., Winter, R., Wortmann, F., and Mettler, T. 2014. "Process Management in Hospitals: An Empirically Grounded Maturity Model," *Business Research* (7:2), pp. 191-216.
- De Bruin, T., Freeze, R., Kaulkarni, U., Rosemann, M., Campbell, B., Underwood, J., and Bunker, D. 2005. "Understanding the Main Phases of Developing a Maturity Assessment Model," in: *Australasian Chapter of the Association for Information Systems*.
- Dekleva, S., and Drehmer, D. 1997. "Measuring Software Engineering Evolution: A Rasch Calibration," *Information Systems Research* (8:1), pp. 95-104.
- Hair, J. F. R., Christian M.Sarstedt, Marko. 2011. "PLS-Sem: Indeed a Silver Bullet," *Journal of Marketing Theory & Practice* (19:2), pp. 139-152.
- Houliand, R. 2015. "Hvis Det Handler Om Mig, Så Kåber Jeg!", from <http://omnichannelmarketing.dk/>
- Jansz, S. 2016. "Corporate Collaboration 2.0 Maturity Model." Universitat St.Gallen.
- Joachim, N., Beimborn, D., and Weitzel, T. 2011. "An Instrument for Measuring SOA Maturity " *International Conference on Information Systems 2011. Paper 3*.
- Kazanjanian, R. K., and Drazin, R. 1989. "An Empirical Test of a Stage of Growth Progression Model," *Management Science* (35:12), pp. 1489-1503.
- King, J. L., and Kraemer, K. L. 1984. "Evolution and Organizational Information Systems: An Assessment of Nolan's Stage Model," *Commun. Association for Computing Machinery* (27:5), pp. 466-475.
- Lahrman, G., Marx, F., Mettler, T., Winter, R., and Wortmann, F. 2011. "Inductive Design of Maturity Models: Applying the Rasch Algorithm for Design Science Research," in *Service-Oriented Perspectives in Design Science Research*. Springer Berlin Heidelberg, pp. 176-191.
- Lasrado, L., Vatrappu, R., and Andersen, K. N. 2016a. "A Set Theoretical Approach to Maturity Models: Guidelines and Demonstration," in: *International Conference on Information Systems (ICIS)*. AIS Electronic Library (AISeL).
- Lasrado, L., Vatrappu, R., and Normann, K. 2016b. "A Methodological Demonstration of Set-Theoretical Approach to Social Media Maturity Models Using Necessary Condition Analysis," in: *Proceedings of the 20th Pacific Asia Conference on Information Systems*.
- Lasrado, L. A., Vatrappu, R., and Andersen, K. N. 2015. "Maturity Models Development in IS Research: A Literature Review," in: *IRIS Selected Papers of the Information Systems Research Seminar in Scandinavia 2015. Paper 6*.
- Luftman, J. 2000. "Assessing Business-IT Alignment Maturity," *Communications of the Association for Information Systems* (4:1), p. 14.
- Marrone, M., and Kolbe, L. M. 2011. *Impact of IT Service Management Frameworks on the IT Organization an Empirical Study on Benefits, Challenges, and Processes*.

- Mettler, T., Rohner, P., and Winter, R. 2010. *Towards a Classification of Maturity Models in Information Systems*. Physica-Verlag HD.
- Mullaly, M. P. W. 2014. "If Maturity Is the Answer, Then Exactly What Was the Question?" *International Journal of Managing Projects in Business* (7:2), pp. 169-185.
- Pöppelbuß, J., Niehaves, B., Simons, A., and Becker, J. 2011. "Maturity Models in Information Systems Research: Literature Search and Analysis," *Communications of the Association for Information Systems* (29), pp. 505-532.
- Raber, D., Winter, R., and Wortmann, F. 2012. "Using Quantitative Analyses to Construct a Capability Maturity Model for Business Intelligence," in: *45th Hawaii International Conference In System Science*. IEEE Computer Society, pp. 4219-4228.
- Raber, D., Wortmann, F., and Winter, R. 2013. "Towards the Measurement of Business Intelligence Maturity," *ECIS 2013 Completed Research. Paper 95*.
- Renken, J. 2004. "Developing an Is/Ict Management Capability Maturity Framework," *Proceedings of the 2004 annual research conference of the South African institute of computer scientists and information technologists on IT research in developing countries*: South African Institute for Computer Scientists and Information Technologists, pp. 53-62.
- Sledgianowski, D., Luftman, J. N., and Reilly, R. R. 2006. "Development and Validation of an Instrument to Measure Maturity of It Business Strategic Alignment Mechanisms," *Innovative Technologies for Information Resources Management* (19:3), pp. 18-33.
- Solli-Sæther, H., and Gottschalk, P. 2010. "The Modeling Process for Stage Models," *Journal of Organizational Computing and Electronic Commerce* (20), pp. 279-293.
- Van Looy, A. 2015. "An Experiment for Measuring Business Process Maturity with Different Maturity Models," *Twenty-Third European Conference on Information Systems (ECIS 2015)*: AIS Electronic Library (AISeL), pp. 1-12.
- Van Steenbergen, M., Brinkkemper, S., Van de Weerd, I., and Bekkers, W. 2013. "Improving Is Functions Step by Step: The Use of Focus Area Maturity Models," *Scandinavian Journal of Information Systems* (25:2), p. 2.
- Wang, W., and Zhang, Y. 2007. "On Fuzzy Cluster Validity Indices," *Fuzzy sets and systems* (158:19), pp. 2095-2117.
- Wendler, R. 2012. "The Maturity of Maturity Model Research: A Systematic Mapping Study," *Information and Software Technology* (54:12), pp. 1317-1339.
- Winkler, T., Wulf, J., and Brenner, W. 2015. "Selfsurvey: A Prediction-Based Decision Support Platform for Survey Research," *Twenty-Third European Conference on Information Systems (ECIS), Münster, Germany, 2015*.
- Wulf, J., Winkler, T. J., and Brenner, W. 2015. "Measuring It Service Management Capability: Scale Development and Empirical Validation," *Wirtschaftsinformatik Proceedings 2015. Paper 43*.
- Xie, X. L., and Beni, G. 1991. "A Validity Measure for Fuzzy Clustering," *IEEE Transactions on pattern analysis and machine intelligence* (13:8), pp. 841-847.