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Systematic Review of Methodological Approaches for Designing, Assessing and Validating Business Analytics Maturity Models

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Abstract

Context: Applying maturity models to measure and evaluate Business Analytics (BA) in organisations is challenging. There is a lack of empirical studies on how BA maturity models are designed, assessed and validated to determine how BA contributes to business value.
Objective: To report on state of research on BA maturity models (BAMMs) and identify how BAMMs can be empirically (1) designed, (2) assessed and (3) validated.
Method: Systematic review of BA maturity model studies focuses on methodological approaches used in design, assessment and validation of BA maturity models.
Results: (1) A systematic review resulted in nine papers included for analysis. (2) Within these papers the dominant methodological design approaches for maturity models are Rasch analysis and set theory; (3) assessment approaches are Cluster, Additive Logic, Minimum Constraints using Statistical Squared Distance and Euclidian Distance; and (4) validation approaches are variance techniques using regression, correlation coefficients with tests for statistical significance against self-reported maturity, perceived benefits or performance.
Conclusion: This research contributes to a deeper understanding of how BAMMs can be designed, assessed and validated in a rigorous manner. Future research should involve more empirical studies that demonstrate the validity and usefulness of BAMMs in contributing to business value.

Keywords: Business Analytics, Maturity Model Design, Maturity Model Assessment, Maturity Model Validation, Systematic Literature Review.

1. Introduction

Business intelligence (BI) became a popular term in business and IT communities in the 1990s (H. Chen, Chiang, & Storey, 2012). In the late 2000s, business analytics (BA) was introduced to represent the key analytical component in BI. BA refers to the extensive use of data, statistical, and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport & Harris, 2007). Business intelligence (BI) can be defined as a set of processes and technologies that convert data into meaningful and useful information for business purposes. While some believe that BI is a broad subject that encompasses analytics, business analytics, and information systems (Bartlett, 2013). There are many debates on whether the concept of business analytics (BA) is a subset of BI (Davenport & Harris, 2007) or an advanced discipline within the concept of BI (Laursen, 2010). In this research, business analytics is viewed as a study of business data using statistical techniques and programming for creating decision support and insights for achieving business goals (Schniederjans, Schniederjans, & Starkey, 2014). Business analytics (BA) can be defined as a process beginning with business-related data collection and consisting of sequential application of descriptive, predictive, and prescriptive analytic components, the outcomes support evidence based decision-making and improved organisational performance (Schniederjans et al., 2014). BA systems involve the use of BA capabilities and technologies to collect, transform, analyse and interpret data to support decision-making (Cosic, Shanks, & Maynard, 2012). Prior empirical studies of BA maturity models (BAMMs) focus on technological and operational aspects. Maturity models (MMs) are a widely accepted instrument for systematically documenting and guiding development and transformation of organisations based on best or common practices (Paulk, Curtis, Chrissis, & Weber, 1993). However, there is relatively little research that considers the methodological approach to designing, assessing and validating of BAMMs. With the increasing diversity and number of published research on MMs, it is necessary to categorise and analyse this field of research in a systematic way (Wendler, 2012). This will enable the construction of an appropriate and methodologically rigorous approach to design, assessment and validation of BAMMs. In this research we undertook a systematic literature review in relation to MMs, BIMMs and more specifically BAMMs to report on the state of research on BAMMs and identify how BAMMs can be empirically (1) designed, (2) assessed and (3) validated.

2. Method

A systematic literature review (SLR) is a means of evaluating and interpreting all available research relevant to a research hypothesis, topic, or phenomenon of particular interest (EBSE, 2007). The following steps were adapted from guidelines for performing SLRs by EBSE (2007) and applied as a procedure to systematically search and select the relevant studies in this research:

1. Define research objective and hypotheses.
2. Define the search string; identify inclusion and exclusion criteria.
3. Conduct initial search.
4. Review the title, abstract, and keywords of the initially retrieved studies.
5. Revise inclusion and exclusion criteria; select potentially relevant studies.
6. Remove duplicate studies.
7. Review potentially relevant studies selected; discuss any issues.
8. Review the entire content of initially selected studies (including the references section to identify any potentially missing studies); identify relevant ones.
9. Review relevant studies selected; discuss any issues.
10. Identify the final set of relevant studies.

Science Direct is a database containing articles from about 1,500 journals in various disciplines. Google Scholar provides an easy way to broadly search for scholarly literature across many disciplines and sources. The search strings for specific terms used in this research are listed in Table 1. Figure 1 shows the refinement steps in the SLR procedure and resulting number of papers between January 2000 and December 2020.

Filter	Term	Search strings
1	Business Intelligence	“business intelligence”

2	Business Analytics	"business analytics"
3	Maturity Model	"maturity model"
4	Design	"design" or "develop" or "create"
5	Assess	"assess" or "measure" or "evaluate"
6	Validate	"validate" or "validation"

Table 1: Search strings for specific terms

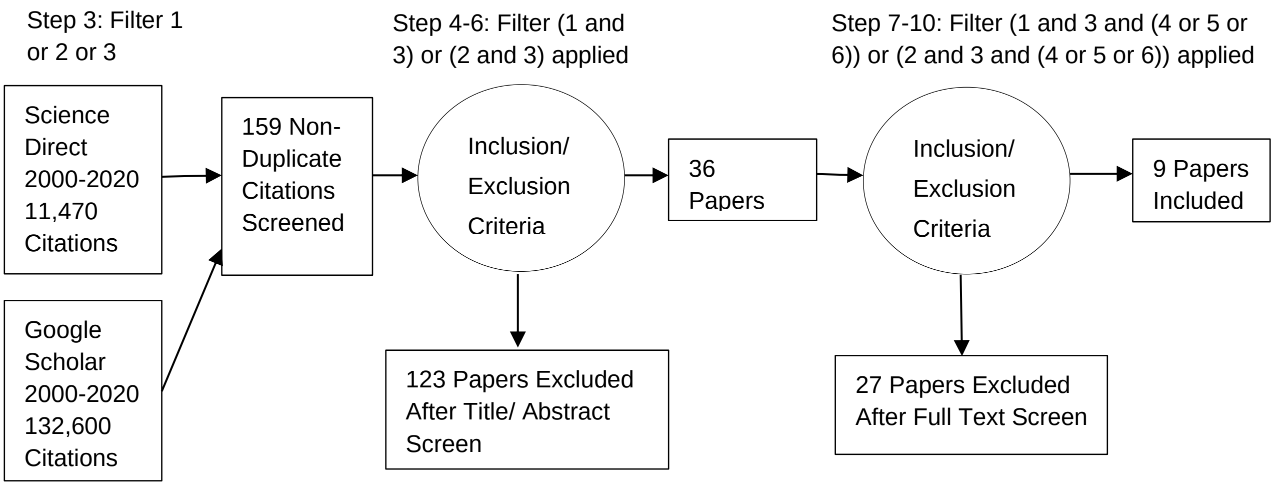

Figure 1: The refinement steps in the SLR procedure and resulting number of papers

The papers relevant to the design, assessment and validation of Business Analytics Maturity Models (BAMMs) were downloaded with abstract and results stored in Endnote. These papers were read and removed if (1) not written in English, (2) keynote-related paper editorials, or (3) content did not belong to the field of BI, BA and maturity models. As a result, nine papers related to design, assessment and validation of maturity models were identified. These nine papers are sorted by ascending year of publication and summarised in Table 2. This shows that previous research assessed BI/BA maturity models in terms of characteristics of different types of maturity models, BI maturity models, BA maturity models, methodological approaches used for design, assessment and validation of maturity models, key results and findings of analysis of BI/BA maturity models.

Author(s) (Year)	Paper Title (abbreviated)*	Maturity Model	Design	Assessment	Validation	Summary
Becker, Knackstedt, and Pöppelbuß (2009)	Developing Maturity Models for IT Management	IT Management	Yes	Yes	Yes	• Documented maturity models to provide a consolidated procedure for theoretical development and evaluation of maturity models.
Lahrmann, Marx, Mettler, Winter, and Wortmann (2011)	Inductive design of MMs: applying the Rasch algorithm	BI	Yes	Yes	No	• Positive impacts on organisational performance could be derived financially and with business functions based on actionable outcomes from BI systems.
Lukman, Hackney, Popovič, Jaklič, and Irani (2011)	BI maturity: transitional context within Slovenia	BI	Yes	Yes	No	• BI maturity considered three segmentations and viewpoints: technological, business and information quality.
Cosic (2020); Cosic et al. (2012)	BA Capability Maturity and Development; BA Capability Maturity Model (BACMM)	BA	Yes	Yes	Yes	• Holistic view of sixteen BA capabilities of organization grouped in four capability areas: governance, culture, technology and people.
Raber, Wortmann, and Winter (2013a, 2013b)	Situational BI Maturity Models: An Exploratory Analysis; Towards The Measurement Of BI Maturity	BI	Yes	Yes	Yes	• Explored influence of contextual factors on evolution of BI maturity. • Assessed BI maturity using Rasch Analysis and then Hierarchical Clustering Analysis to determine difficulty and maturity level of each measurement item and related capability for each respondent on a standardised scale. • Then assigned measurement items into maturity levels.
Halper and Stodder (2014)	TDWI Analytics Maturity Model (AMM) Guide	BA	No	Yes	No	• Five stages: nascent, pre-adoption, early adoption, corporate adoption, and mature/ visionary. • An online assessment measures analytics maturity across five dimensions essential to derive value from analytics.
The Institute for Operations Research and the Management Sciences (2017)	INFORMS Analytics Maturity Model (AMM) User Guide	BA	No	Yes	No	• Online platform for organisation to perform self-assessment that analyses three critical organisational themes. • For each 12 factor questions, it calculates overall score, category and factor scores, determine scores are Beginning, Developing, or Advanced level.
Lasrado, Vatrapu, and Mukkamala (2017)	The influence of different quantitative methods on the design and assessment of maturity models	Social media	Yes	Yes	Yes	• Analysis of data set and maturity scores computed using five quantitative methods (Additive Logic, Variance Techniques, Cluster, Minimum Constraints, and Rasch Analysis), and compared sensitivity of measurement scale and maturity stages. • Relationship between social media maturity and business value were validated using SEM Partial Least Square (PLS) technique.
Ariyarathna and Peter (2019)	BAMMs: systematic review	BI and BA	No	No	No	• A systematic literature review of BAMMs for BI and BA. • No consensus in method of assessing maturity level.
International Institute for Analytics (n.d.)	Analytics Maturity Assessment (AMA)	BA	No	Yes	No	• Software-driven MM based on Five Stages of Analytics Maturity Framework Davenport and Harris (2007). • Also based on DELTA (Data, Enterprise, Leadership, Targets, and Analysts) Model by Davenport, Harris, and Morison (2010).

Table 2: Design, assessment and validation maturity models
(* Full reference details of papers listed accessible in References list)

2.1 Maturity Models

Table 2 above shows that most systematic literature reviews of maturity models give a very general description of the characteristics and classification of maturity models but do not provide technical details on how the methodological approaches used could be applied. The property, characteristics and references of MMs are summarised in Table 3. Wendler (2012) conducted a systematic mapping study which found that most publications deal with the development of maturity models in empirical studies, but there is a lack of theoretical and reflective publications that show how maturity models can be grounded in both theory and practice.

Property	Characteristics	References
Maturity levels	• Archetypal states of maturity of object assessed. • Each level should have set of distinct characteristics that are empirically testable.	Raber et al. (2013a)
Number of stages or levels	3 to 6, depending on model and purpose.	Raber et al. (2013a); Van Steenbergen, Bos, Brinkkemper, Van de Weerd, and Bekkers (2013)
Stage fixed or Continuous	• Continuous models allow scoring of characteristics at different levels. • Staged models require all elements of one distinct level are achieved.	Raber et al. (2013a); Van Steenbergen et al. (2013)
Maturity score	Use of numeric values for benchmarking purposes. Most common way of visualising is Spider cobweb design.	Raber et al. (2013a); Van Steenbergen et al. (2013)
Dimensions	• Also termed Benchmark variables, process areas, capability, and critical success factors. • Each dimension is characterised by measures such as practices, objects or activities at each maturity level.	Lasrado (2018); Menukhin, Mandungu, Shahgholian, and Mehandjiev (2019)
Sub-categories	Second level variables on which key dimensions depend.	Van Steenbergen et al. (2013)
Assessment Approach	• Qualitative assessments use descriptions • Quantitative use numeric measures.	Lasrado (2018); Menukhin et al. (2019)
Assessment method	• Self-assessment via surveys most widely adopted instrument. • Third-party assessment or certifications are other applied techniques assessed by certified experts.	Wendler (2012)

Table 3: Characteristics of Maturity Models (Adapted from Lasrado (2018); Menukhin et al. (2019))

2.2 Business Intelligence (BI) Maturity Models

BI Maturity Models listed in Table 2 are summarised in terms of focus, design, assessment and validation in Table 4.

Maturity Model	Focus	Design	Assessment	Validation	Source
BI	BI dimensions derived from existing literature, Dimensions: Strategy, Organisation/ Process, IT support	Quantitative bottom-up approach (Rasch Algorithm supported by cluster analysis used to derive maturity levels)	Questionnaire results; 51 companies; cross-industry	No information provided.	Lahrmann et al. (2011) [Academia]
BI	BI in Slovenia	Quantitative bottom-up approach (K-Means algorithm)	Questionnaire results; 131 companies; cross-industry	No information provided.	Lukman et al. (2011) [Academia]
BI	Dimensions: Strategy, Social System, Technical System, Quality, Use/Impact	Quantitative bottom-up approach (Rasch Algorithm supported by cluster analysis used to derive maturity levels)	Questionnaire results; 51 companies; cross-industry	Discussion of final model with three industry experts on comprehensiveness, self-assessment, potential BI roadmap	Raber et al. (2013a, 2013b) [Academia]

Table 4: Comparison of BI maturity models

2.3 Business Analytics (BA) Maturity Models

In turn, the BA Maturity Models listed in Table 2 are summarised in terms of focus, design, assessment and validation in Table 5. The majority of BA maturity models were developed by practitioners with no documentation on the foundations of the design of the BA maturity model. The model development process proposed by Cosic et al. (2012) is based on the construction approach by Becker et al. (2009) which shows that BA maturity models can be adapted from maturity models developed for other IT domains such as IT Management.

Maturity Model	Focus	Design	Assessment	Validation	Source
IT Management	Problem definition and comparison of existing maturity models based on transfer of structure or contents to new domains	Determination of development strategy; Iterative maturity model development	Delphi method and creativity techniques	Names a regular validation as necessary without describing the step in detail.	Becker et al. (2009) [Academia]
Business Analytics Capability Maturity Model (BACMM)	Assess BA initiatives within large-scale Australian organisations	The model development process is based on approach of Becker et al. (2009)	16 key capabilities that can be aggregated to provide a measure of maturity for each of the four high-level BA capabilities and finally an aggregated measure for the overall BA capability.	A Delphi study with an expert panel used to validate and refine BA Capability Framework constructs	Cosic (2020); Cosic et al. (2012) [Academia] based on the construction approach by Becker et al. (2009)
TDWI Analytics Maturity Model	Predictive analytics, social media/ text analytics, cloud computing, and big data analytics approaches	No information provided.	Assess enterprises' analytics capabilities	No information provided.	Halper and Stodder (2014) [Practitioner]
INFORMS Analytics Maturity Model	Benchmarking capabilities and identifying actions to improve the analytical maturity	No information provided.	Each dimension has a potential high score of 10 points.	No information provided.	The Institute for Operations Research and the Management Sciences (2017) [Practitioner]
International Institute for Analytics (IIA) Analytics Maturity Model	Optimizing performance by improving analytics capabilities	No information provided.	Analytics Maturity Assessment is evaluated against 33 unique competencies within five DELTA model categories.	No information provided.	International Institute for Analytics (n.d.) [Practitioner]

Table 5: BA maturity models with sources

The four BAMMs in Table 5 are compared in more detail based on purpose, origin, stages/levels, dimensions and assessment in Table 6 below. According to Becker et al. (2009), a maturity model is descriptive in purpose of use if it is applied for as-is assessments when the current capabilities of the organisation under investigation are assessed against given criteria. A maturity model is prescriptive in purpose of use, if it indicates how to identify desirable maturity levels and provides guidelines on improvement measures. Most practitioners' maturity models are prescriptive and use proprietary assessment methods and measurement items.

3. Methodological Approaches used in Design, Assessment and Validation of Maturity Models

Lasrado et al. (2017) explored the influence of different quantitative methods on the design and assessment of maturity models. The quantitative methods used in design, assessment and validation of maturity models are summarised by method, assumption and application in Table 7.

<table>
<tr><td>Maturity Model</td><td>Business Analytics Capability Maturity Model (BACMM)</td><td>TDWI Analytics Maturity Model</td><td>INFORMS Analytics Maturity Model</td><td>International Institute for Analytics (IIA) Analytics Maturity Model</td></tr>
<tr><td>Purpose</td><td>Descriptive</td><td>Prescriptive</td><td>Prescriptive</td><td>Prescriptive</td></tr>
<tr><td>Origin</td><td>Cosic (2020); Cosic et al. (2012)
[Academia]</td><td>Halper and Stodder (2014)
[Practitioner]</td><td>The Institute for Operations Research and the Management Sciences (2017) [Practitioner]</td><td>International Institute for Analytics (n.d.)
[Practitioner]</td></tr>
<tr><td>Stages/ Levels</td><td>5 levels:
Level 0 – Non-existent
Level 1 – Initial
Level 2 – Intermediate
Level 3 – Advanced
Level 4 – Optimised</td><td>5 stages: Nascent, Pre-adoption, Early Adoption, Corporate Adoption, Mature/ Visionary</td><td>3 levels:
Beginning, Developing, Advanced</td><td>5 stages: Analytically impaired, Localized analytics, Analytical aspirations, Analytical companies, Analytical competitors</td></tr>
<tr><td>Dimensions</td><td>4 dimensions:
Technology, People, Culture and Governance</td><td>5 dimensions:
Organisation, Infrastructure, Data Management, Analytics, Governance</td><td>3 dimensions: Organisational, Analytics Capability, Data & Infrastructure</td><td>5 dimensions: Data, Enterprise, Leadership, Targets, Analysts</td></tr>
<tr><td>Assessment</td><td>BACMM combines framework for BA capabilities with five level maturity scale (Paulk et al., 1993).
Maturity scale is applied to each of the sixteen BA capabilities.
After maturity levels are assigned to each of the sixteen lower-level BA capabilities, they are aggregated to provide a measure of maturity for each of the four high-level BA capabilities and finally an aggregated measure for overall BA capability.</td><td>Each dimension potential high score of 20 points.<table><tr><td>Score per Dimension</td><td>Stage</td></tr><tr><td>4–7.1</td><td>Nascent</td></tr><tr><td>7.2–10.1</td><td>Pre-Adoption</td></tr><tr><td>10.2–13.3</td><td>Early Adoption</td></tr><tr><td>13.4–16.6</td><td>Corporate Adoption</td></tr><tr><td>16.7–20</td><td>Mature/ Visionary</td></tr></table></td><td>Each dimension potential high score of 10 points.<table><tr><td>Score per Dimension</td><td>Stage</td></tr><tr><td>1 – 3</td><td>Beginning</td></tr><tr><td>4 – 7</td><td>Developing</td></tr><tr><td>9 – 10</td><td>Advanced</td></tr></table></td><td>Analytics Maturity Assessment is evaluated against 33 unique competencies within five DELTA model categories.
DELTA scores are calculated on a 1.00-5.99 scale with descriptive stages of maturity assigned to each of five score ranges (1-1.99, 2-2.99, etc.) and aligned with five stages.</td></tr>
</table>

Table 6: Comparison of BAMMs: Academia (Descriptive) and Practitioners (Prescriptive)

Phase	Method	Assumption	Application Summary	Source
(1) Design	Rasch Analysis	Organisations with higher maturity have high probability of successfully implementing capabilities.	Rasch analysis combined with cluster analysis first used to empirically describe evolution of software development process in organisation using capability maturity model (CMM) questionnaire.	Dekleva and Drehmer (1997)
			Based on results of application of Rasch analysis and cluster analysis, an initial MM can be derived in design phase.	Berghaus and Back (2016); Lahrmann et al. (2011) Raber et al. (2013b)
	Set Theory: 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) were used to design a social media maturity model using six step procedure.	Lasrado et al. (2017)
(2) Assessment	Cluster: Two Step Clustering, Fuzzy Clustering (FC) or other methods depending on the data.	There are groups of organisations homogenous across particular set of maturity capabilities.	Cluster analysis was used to categorise companies in study on organisational maturity on information system skill needs.	Benbasat, Dexter, and Mantha (1980)
			Clustering was adopted to assess organisations' situational corporate collaboration maturity for handling mixed-scaled data.	Jansz (2016)
	Additive Logic: 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 organisations with higher maturity will have implemented more capabilities.	Summation, simple average, and weighted average wherein the formulation of weights is arbitrary or non-empirical are commonly used for maturity assessments.	Chung, Andreev, Benyoucef, Duane, and O'Reilly (2017); Luftman (2001); Van Steenbergen et al. (2013)
			Empirical calculation of weights using methods such as structural equation modeling (SEM) is rare.	Winkler, Wulf, and Brenner (2015)
	Minimum Constraints: (a) Statistical Squared Distance (SSD)	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.	SSD is calculated for each of the maturity levels using characteristic values of 21 items to categorise an organisation based on its respective maturity level at which it shows lowest SSD. SSD is weighted by standard deviation at capability level.	Joachim, Beimborn, and Weitzel (2011)
	(b) Euclidian Distance (EUC)		EUC is computed for specific maturity dimension of organisation between answers given to specific items of dimension (See Section 4 for details)	Raber et al. (2013b)
(3) Validation	Variance Techniques: Regression, correlation coefficients with tests for statistical significance.	Organisations with high maturity will also realise higher business benefits, performance and business value than those at a lower maturity level.	Validating maturity using regression with tests for statistical significance.	L. Chen (2010); Joachim et al. (2011); Sledgianowski, Luftman, and Reilly (2007)
			Validating maturity using correlation coefficients against self-reported maturity, perceived benefits or performance.	Marrone and Kolbe (2011)
			Calculated maturity level can be validated using structural equation models (SEM).	Lasrado et al. (2017); Raber et al. (2013b)

Table 7. Quantitative Methods used in Maturity Models Research (Lasrado et al., 2017)

Figure 2 explains (1) design and development of maturity model survey instrument in Phase A, (2) classification of each organisation into a maturity level in Phase B, and (3) validation of maturity levels in Phase C.

In (1) Design Phase, set theory is used in design of MMs to reduce the number of conditions by dropping or merging conditions (i.e. using AND, OR, any other logical set operations) and arriving at macro conditions, in order to remove measurement items that have no influence on outcomes. Rasch analysis can be used in the design phase to develop the initial maturity model by reducing the number of measurement items, and can also be used in the assessment phase to calculate maturity scores and to classify organisations based on data collected through surveys together with cluster analysis.

In (2) Assessment Phase, cluster, additive logic and minimum constraints using statistical squared distance and Euclidian distance can be used to classify organisations into a maturity level.

In (3) Validation Phase, variance techniques such as regression, correlation coefficients with tests for statistical significance, can be used to determine the extent to which an assigned maturity level an organisation's use of BA contributes to business value.

4. Methodological Approaches used in Design, Assessment and Validation of BI/BA Maturity Models

Figure 2 shows that the main methodological design approaches used in construction of MMs are Rasch analysis and Set theory. However, Rasch analysis has been adopted by most researchers for both the design and assessment phases of BI/BA maturity models. Lahrmann et al. (2011) proposed a rigorous methodological approach for the construction of MMs which applies Rasch analysis and hierarchical cluster analysis to construct MMs. Rasch analysis has been used to measure variables such as abilities, attitudes and personal characteristics for psychological and educational assessments. Rasch analysis allows for inductive allocation of organisational capacities to different maturity levels and thus supports rigorous design and development of Capability Maturity Models (CMM) (Cleven, Winter, Wortmann, & Mettler, 2014). The use of Hierarchical cluster analysis provides a rigorous rather than arbitrary approach to allocating an organisation's capability at different levels of difficulty and maturity in order to overcome subjectivity of defining maturity levels arbitrarily (Lahrmann et al. 2011: 177). Raber et al. (2013b) developed an empirically grounded MM using an approach adapted from Lahrmann et al. (2011). The measurement instrument used by Raber et al. (2013b), assessed BI maturity using Rasch analysis and then used Hierarchical clustering analysis to determine the difficulty and maturity level of each measurement item and related capability for each respondent organisation on one standardised scale and then assigned the measurement items into corresponding maturity levels. The maturity level with the smallest Euclidean distance represents the maturity level of an organisation. An example was provided by Raber et al. (2013b) showing how the measurement instrument could be used for assessing the BI maturity levels in an organisation. The BI maturity instrument developed by Raber et al. (2013b) was used to determine whether BI maturity is linked to business benefits. The assumption is that organisations with high BI maturity are able to generate greater business benefits than organisations with a lower level of BI maturity. The rigorous approach to developing a BIMM adopted by Raber et al. (2013b) is not specific to BI, it can be used for other related domains in order to overcome methodological weaknesses of other BAMMs. This approach is summarised in Figure 3, which explains (1) design and development of a BIMM survey instrument in Phase A, (2) classification of each organisation into a BI maturity level in Phase B, and (3) validation of BI maturity levels in Phase C.

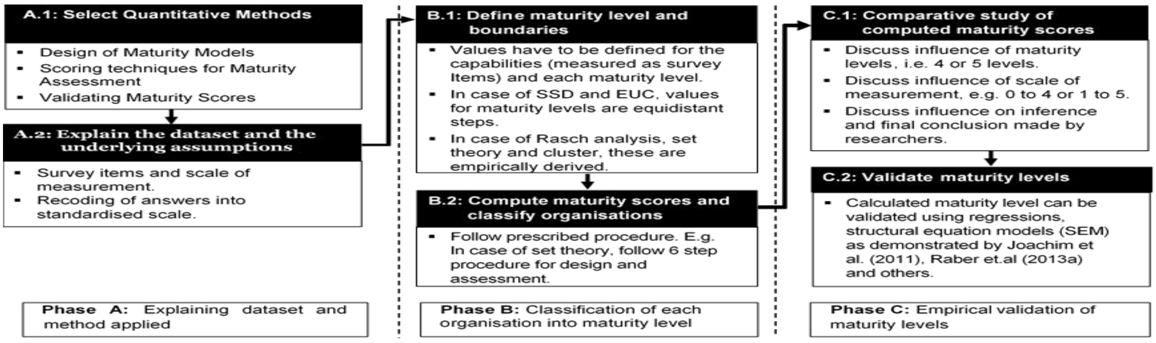

Figure 2: Methodological Framework for the Multi-Method Comparative Study of Maturity Models (Lasrado et al., 2017)

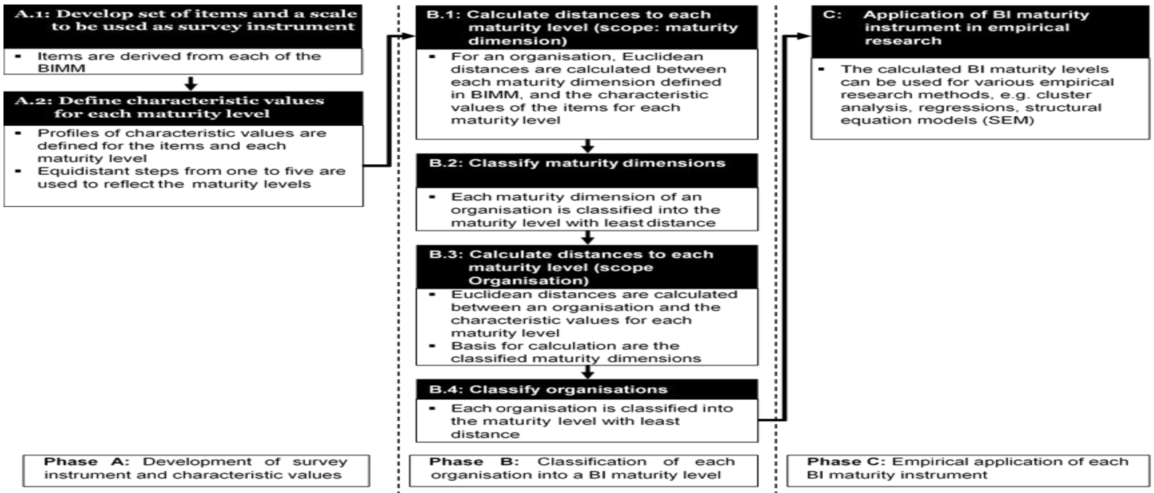

Figure 3: Methodological Approach used in Design, Assessment and Validation of BI/BA Maturity Models (Raber et al., 2013b)

5. Analysis and Results

A systematic review of methodological approaches used in design, assessment and validation of maturity models revealed that (1) main methodological design approaches used for maturity models are Rasch analysis and Set theory; (2) main methodological assessment approaches used for maturity models are Cluster, Additive Logic, Minimum Constraints using Statistical Squared Distance and Euclidian Distance; and (3) main methodological validation approaches of maturity models are variance techniques using regression, correlation coefficients with tests for statistical significance against self-reported maturity, perceived benefits or performance. The rigorous approach to developing a BIMM adopted by Raber et al. (2013b) opens a new application of Rasch analysis and cluster analysis to assess maturity levels that could be applied to construct BAMMs. Most of the BAMMs developed by academia are descriptive. In contrast our research also identified that practitioner developed BAMMs are prescriptive. These two groups have opposing aims with their respective BAMMs. Practitioners as BAMM consultants need to provide organisations with measurable outcomes so that organisations determine their current BA maturity level. Practitioners as consultants are motivated financially. Because they need to protect their intellectual property they do not describe in detail the design principles and assessment approaches used in proprietary BAMMs. Whereas BAMMs of academics are largely descriptive in that the design and assessment approaches of BAMMs are defined but often not empirically validated. Hence academic BAMMs in many instances have not been empirically validated in a real world setting. This is an important finding that emphasizes the disconnect between academic research and practice in the domain of BAMMs. Therefore, we argue that more empirical studies and evidence are also required to not only design and assess but also to empirically validate BAMMs.

6. Conclusion

There is only generic research on the design and assessment of MMs with little specific application to BA validated in real world settings. Many adopted measurement instruments using Rasch analysis were built on the assumption that the maturity increases in equidistant steps and provides a basis for determining the level of maturity in a systematic and rigorous way. Rasch analysis is the most widely used design and assessment method for the construction of MMs. Set theory using QCA and NCA is used by Lasrado et al. (2017) in the design of a maturity model by reducing the number of measurement items. However, the validity and reliability of the measurement instrument needs to be tested and confirmed by larger sample survey data. Future research should be directed towards performing more empirical studies in real world settings to demonstrate the validity and usefulness of BAMMs in contributing to quantifying the business value that can be attributed to the use of BA in organisations.

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