Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute
InformingScience.org

IJIKM.org

Volume 18, 2023

Analysis of the Scale Types and Measurement Units in Enterprise Architecture (EA) Measurement

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Abstract

Aim/Purpose	This study identifies the scale types and measurement units used in the measurement of enterprise architecture (EA) and analyzes the admissibility of the mathematical operations used.
Background	The majority of measurement solutions proposed in the EA literature are based on researchers' opinions and many with limited empirical validation and weak metrological properties. This means that the results generated by these solutions may not be reliable, trustworthy, or comparable, and may even lead to wrong investment decisions. While the literature proposes a number of EA measurement solutions, the designs of the mathematical operations used to measure EA have not yet been independently analyzed. It is imperative that the EA community works towards developing robust, reliable, and widely accepted

Accepting Editor Dimitar Grozdanov Christozov │ Received: December 27, 2022 │ Revised: March 7, March 28, April 20, 2023 │ Accepted: April 30, 2023.
Cite as: Abdallah, A., Abran, A., Qasaimeh, M., Ahmad, A., & Al-Refai, A. (2023). Analysis of the scale types and measurement units in enterprise architecture (EA) measurement. *Interdisciplinary Journal of Information, Knowledge, and Management*, *18,* 321-352. https://doi.org/10.28945/5113

measurement solutions. Only then can senior management make informed decisions about the allocation of resources for EA initiatives and ensure that their investment yields optimal results.

Methodology In previous research, we identified, through a systematic literature review, the EA measurement solutions proposed in the literature and classified them by EA entity types. In a subsequent study, we evaluated their metrology coverage from both a theoretical and empirical perspective. The metrology coverage was designed using a combination of the evaluation theory, best practices from the software measurement literature including the measurement context model, and representational theory of measurement to evaluate whether EA measurement solutions satisfy the metrology criteria. The research study reported here presents a more in-depth analysis of the mathematical operations within the proposed EA measurement solutions, and for each EA entity type, each mathematical operation used to measure EA was examined in terms of the scale types and measurement units of the inputs, their transformations through mathematical operations, the impact in terms of scale types, and measurement units of the proposed outputs.

Contribution This study adds to the body of knowledge on EA measurement by offering a metrology-based approach to analyze and design better EA measurement solutions that satisfy the validity of scale type transformations in mathematical operations and the use of explicit measurement units to allow measurement consistency for their usage in decision-making models.

Findings The findings from this study reveal that some important metrology and quantification issues have been overlooked in the design of EA measurement solutions proposed in the literature: a number of proposed EA mathematical operations produce numbers with unknown units and scale types, often the result of an aggregation of undetermined assumptions rather than explicit quantitative knowledge. The significance of such aggregation is uncertain, leading to numbers that have suffered information loss and lack clear meaning. It is also unclear if it is appropriate to add or multiply these numbers together. Such EA numbers are deemed to have low metrological quality and could potentially lead to incorrect decisions with serious and costly consequences.

Recommendations for Practitioners The results of the study provide valuable insights for professionals in the field of EA. Identifying the metrology limitations and weaknesses of existing EA measurement solutions may indicate, for instance, that practitioners should wait before using them until their design has been strengthened. In addition, practitioners can make informed choices and select solutions with a more robust metrology design. This, in turn, will benefit enterprise architects, software engineers, and other EA professionals in decision making, by enabling them to take into consideration factors more adequately such as cost, quality, risk, and value when assessing EA features. The study's findings thus contribute to the development of more reliable and effective EA measurement solutions.

Recommendations for Researchers Researchers can use with greater confidence the EA measurement solutions with admissible mathematical operations and measurement units to develop new decision-making models. Other researchers can carry on research to address the weaknesses identified in this study and propose improved ones.

Impact on Society Developers, architects, and managers may be making inappropriate decisions based on seriously flawed EA measurement solutions proposed in the literature and providing undue confidence and a waste of resources when based on bad measurement design. Better quantitative tools will ultimately lead to better decision making in the EA domain, as in domains with a long history of rigor in the design of the measurement tools. Such advancements will benefit enterprise architects, software engineers, and other practitioners, by providing them with more meaningful measurements for informed decision making.

Future Research While the analysis described in this study has been explicitly applied to evaluating EA measurement solutions, researchers and practitioners in other domains can also examine measurement solutions proposed in their respective domains and design new ones.

Keywords Enterprise Architecture (EA), metrology, software metrics, scale types, admissible mathematical operations

INTRODUCTION

To adapt to changes across business domains and technologies, enterprises must establish an integrated environment to support corporate alignment between business and information technology (IT) (Dumitriu & Popescu, 2020; Effendi et al., 2021). Enterprise architecture (EA) has been used to develop and implement an integrated view that encompasses an organized collection of management systems, structures, relationships, and interconnections, where EA serves as a blueprint for a company's operations and guides decision-making processes (Banaeianjahromi & Smolander, 2014; Ilin et al., 2017; Nurmi., 2019; Tallé & Uche, 2021).

EA aims to align technology with business goals to improve decision making, reduce IT costs, optimize investment decisions, streamline business processes, and promote resource reuse across all domains (Alwadain, 2020; Bonnet, 2009; Canada & Halawi, 2021; Dang & Pekkola, 2017; Dumitriu & Popescu, 2020; Effendi et al., 2021; Niemi & Pekkola, 2020; Šaša & Krisper, 2011; Van den Berg et al., 2019). However, to verify the extent to which EA benefits are realized, EA-adapted measurement solutions are needed to measure EA performance and progress towards strategic goals (Brückmann et al., 2009; Cameron & McMillan, 2013; Wan et al., 2013).

On the one hand, EA measurement solutions with a strong metrological design can be of great benefit to enterprise architects, software engineers, and other professionals to ensure accurate and reliable information for informed decision-making, ultimately contributing to the success of the organization's IT initiatives. On the other hand, poorly designed EA measurement solutions may lead to poor decision-making and result in unintended consequences for the organization, such as increased costs and increased failures.

Effective EA measurement is needed to enable architects to evaluate alternative designs and make informed decisions about trade-offs between EA attributes, such as cost, quality, risk, and value (Effendi et al., 2021). Within the set of measurement solutions proposed in EA literature, the measurement process must be applied to various types of entities and attributes within the EA architectural layers of business, applications, and technologies, and much of the existing research in this area has relied on qualitative measures. Very few studies have identified the limitations of current EA measurement practices, calling for further refinement and improvement (Mirsalari & Ranjbarfard, 2020).

The measurement of EA functions and processes remains a challenge due to several factors. For example, there is a lack of standard practices for evaluating all EA functions and processes, limitations to evaluation methods for EA (Nikpay et al., 2017) and organizational difficulties (Cameron & McMillan, 2013). Furthermore, the field of EA is also hindered by the absence of well-defined terminology commonly found in more rigorous scientific and engineering disciplines (Abdallah & Abran, 2019).

The research study reported here aims to provide a deeper understanding of the mathematical operations used in EA measurement solutions from a metrology perspective. The objective is to highlight the limitations and shortcomings of these solutions, to help users and researchers make informed decisions, and to avoid misunderstandings or improper conclusions. This study is innovative in its examination of the measurement units and scale types of input data and its discussion of the validity and interpretation of the mathematical transformations of outputs. It employs various metrological criteria for the design of measurement methods, including the measurement context model, the representation theory of measurement, and measurement scale types.

The scope of this study does not analyze whether the measures proposed in the EA literature are objective; instead, this study analyzes them objectively using measurement scale types and measurement units to determine whether their designs have significant weaknesses that make them less useful to practitioners, and even harmful in some instances. For example, the analysis of the scale types and measurement units in well-known software metrics led to the following conclusions:

- The measurement units in Halstead Metrics are inadequately handled, and subsequent measures derived from the same design have inherited similar flaws and limitations – see chapter 7 in Abran (2010).
- The Use Case Points (UCP) measurement method assigns numbers to several entities (actors, use cases, requirements, etc.) and attributes (complexity, difficulty, etc.), without considering their measurement units and scale type, combining many concepts at once: while the outcome is a ‘number’, the end-result is of an unknown and unspecified entity type and UCP method calculations are based on several algebraically inadmissible scale type transformations – see chapter 9 in Abran (2010).

The structure of this paper is as follows: the subsequent section provides an overview of the related work on the measurement of EA, representation theory for measurements, and types of scales. This is followed by a description of the research methodology, which includes a metrological examination of the mathematical operations employed for measuring EA solutions. Subsequently, the research findings, benefits, and implications are discussed. Finally, the findings are summarized, and some recommendations are provided for practitioners and researchers.

RELATED WORK

RELATED WORK ON ANALYSIS OF EA MEASUREMENT SOLUTIONS

The evaluation and measurement of EA functions and processes remain a challenge due to several factors. For example, there is a lack of standard practices for evaluating all EA functions and processes (Nikpay et al., 2017). Additionally, there are numerous limitations to the current EA evaluation methods (Nikpay et al., 2017). Measuring the value of EA also presents organizational difficulties (Cameron & McMillan, 2013). These issues highlight the need for the continued improvement and refinement of EA evaluation and measurement practices.

Ilin et al. (2017) investigated the state of EA measurement to identify any shortcomings and gaps in measuring EA components, structures, and interrelationships from a technological perspective. The study emphasized the use of measurement concepts to support the alignment, monitoring, and assessment of software projects within an EA framework. The key findings of the research were aligned using a balanced scorecard (BSC) measurement approach and focused on measuring software structures and functionality within a service-oriented architecture (SOA) context. This study highlights the importance of implementing effective measurement strategies for EA- and software-related projects.

A comprehensive review of EA measurement was conducted by Abdallah and Abran (2019) who analyzed various proposals in the field. The study found that these solutions were approached from a range of perspectives, such as:

- a conceptual model for EA value measurement for organizations implementing EA (Cameron & McMillan, 2013).
- an approach to justifying EA investments by incorporating a balanced scorecard framework that considers multiple perspectives such as financial, customer, internal, and learning (Plessius et al., 2012; Schelp & Stutz, 2007).
- measurement of the EA functional size based on the COSMIC function points - ISO 19761 - and the EA modeling language (ArchiMate) (Abdallah et al., 2019; Ilin et al., 2021).
- measurement of complexity in EA proposals at the design stage (González-Rojas et al., 2017).
- measurement of the complexity of an enterprise architecture (Schütz et al., 2013).
- factors that could impact the implementation of enterprise architecture (Bakar et al., 2016).
- quantification of EA value on IT projects (Kurek et al., 2017).

Abdallah et al. (2019) proposed a measurement design based on metrology principles for quantifying the software components of IT infrastructure within an EA context. The solution involves the adoption of the Open Group Architecture Framework (TOGAF) EA layers, modeling the EA layers using ArchiMate (Slagter et al., 2017), integrating COSMIC – ISO 19761 concepts into the ArchiMate model, and measuring the functional size of the EA layers (Abran et al., 2021). This approach provides a structured and comprehensive method for evaluating the software components of IT infrastructure in an EA context.

A systematic literature review (SLR) conducted by the authors (Abdallah et al., 2021) analyzed 23 primary studies on EA measurement solutions. The study revealed the following key findings:

- Most of the input data used in EA measurement solutions are subjective opinions of EA practitioners rather than objective data.
- The types of mathematical operations used in EA range from commonly accepted financial formulas, such as ROI, to custom-made formulas without examining their mathematical structure.
- A lack of specification for the measurement units, to the exception of costs.

Additionally, this SLR observed a scarcity of references to metrology concepts in the EA community and no agreed-upon framework or method for verifying and validating the metrology rigor of EA measurement solutions.

The subsequent study (Abdallah et al., 2022) proposed a metrology-coverage evaluation method to evaluate each EA measurement solution for each EA entity type. This was achieved through a blend of the evaluation theory by López (2000), the measurement context model by Abran (2010), and the representational theory of measurement by Fenton and Bieman (2014). This combination was used to assess the compliance of EA measurement solutions with the metrology criteria. The results show that:

- The metrology-coverage for EA architecture has weaknesses in both theoretical and empirical designs, while EA projects have the highest metrology coverage.
- The metrology-coverage for EA frameworks has a relatively high coverage in theoretical designs, but there is a lack in the empirical designs.
- The metrology-coverage for the EA program is low in theoretical designs and the measurement unit is missing in empirical designs.

This study highlighted the need for improving the metrology-coverage of EA measurement solutions to ensure the trustworthiness and consistency of measurement results.

Related Work on Measurement Representation Theory and Scale Types

The purpose of measurement is to gain an understanding of a subject under study. The representational theory of measurement considers measurement to be the transformation of the physical reality (empirical) into numerical values (Abran, 2010; Fenton & Bieman, 2014). According to this theory:

- The empirical world refers to what is being measured.
- The numerical world represents the world of numbers from which measurement results are expected.

The criteria established by the measurement context model (Abran, 2010) and representational theory of measurement (Fenton & Bieman, 2014) can be used to validate the design of a measurement solution and ensure its metrological qualities. This helps ensure that the measurements produced are reliable. The representational theory asserts that the data obtained from measurement should accurately reflect the properties of the objects being studied and that the manipulation of the data should maintain the relationships between the objects.

The accuracy of the measurement depends heavily on the design of the measurement method. To ensure that the measurement results are reliable and representative of the measured entity, it is crucial that the following criteria are met in the design of the measurement method:

1. The attribute being measured should be clearly defined.
2. A clear characterization of the attribute, including its sub-attributes, should be provided.
3. The relationship between the sub-attributes and the main attribute should be unambiguous, for example using a meta-model. The measurement context model outlines these theoretical design criteria to ensure that the measurement process accurately captures the desired information about the entity being measured.

The criteria for designing an appropriate measurement method are crucial for obtaining accurate results. The measurement context model outlines empirical factors that must be considered to create an effective measurement strategy. The following points must be considered when designing a measurement method:

- Identification of the source of the measurement data; for example, measurement tools, sensors, etc.
- Definition of the type of data to be collected: for instance, the data collected may be of ratio scale type.
- Specification of the mathematical operations that are allowed to be used; for example, operations involving multiplication of ratio scale data inputs.
- Definition of universally recognized measurement units; for instance, the COSMIC Function Points (CFP) from ISO 19761.

Furthermore, the measurement process should ensure that the numerical results accurately reflect the properties of the entities measured in the real world. The relationship between the elements in the empirical system corresponded to the numerical measurements obtained. This is known as the representation condition for the measurement (Fenton & Bieman, 2014).

- Empirical Relational System: <E, {R1..Rn}>, where E represents a set of entities, and {R1..Rn} represents a set of empirical relationships defined for E with respect to a specified attribute (such as the EA value).
- Numerical Relational System: <N {S1..Sn}>, where:
    - N represents a set of numerical values,
    - {S1..Sn} denotes a set of numerical relationships defined within N.
- Measure: M is a measure of <E{R1).Rn}> with respect to a given attribute if
    - M: E → N: A measure is a mapping from entities to numbers or symbols.

- Ri (e1, e2, ... ek) ⇔ Si (M(e1), M(e2), ... M(ek)): The measurement procedure (M) that meets the representation requirement is known as a homomorphism. This term signifies that there is a connection between the empirical and numerical domains, making the measurement valid.

The results of the measurement process should accurately reflect the attributes and relationships of the measured entities. This implies that the numerical representation must retain the same characteristics and comparisons as those in the real world. To illustrate this point, if Joe is taller than Fred, then the measurement of Joe's height must result in a larger number than the measurement of Fred's height.

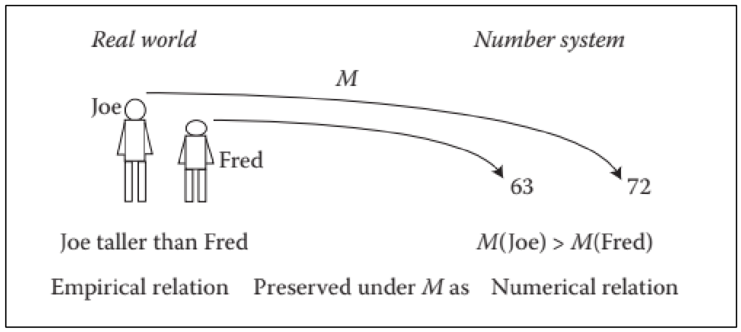

Figure 1. Example of the representation condition (Fenton & Bieman, 2014)

The representational theory of measurement follows strict guidelines to guarantee the validity and consistency of measurements. For the measurement to correspond to the empirical world, it must be a homomorphic representation, indicating a clear connection between empirical and numerical worlds. This requires identifying and adhering to the quantification rules that map an attribute to a numerical world through a mathematical system, resulting in a numerical value with a corresponding unit of measurement. To ensure accurate data analysis, mathematical operations on these numbers must conform to the rules outlined in Figure 2 for the measurement scale type as follows:

- The nominal scale type is qualitative, and the values are non-numeric. The only mathematical operation that can be applied to nominal data is counting or frequency. For example, the number of projects that use agile or waterfall methodologies can be counted. It is important to use the correct mathematical operation for nominal data because using the wrong operation can lead to incorrect or meaningless results. For example, trying to calculate the mean or median of nominal data does not make sense, because there is no meaningful order for the values. Additionally, nominal data cannot be used in mathematical operations, such as addition or subtraction, as nominal values are labels and not numerical values.

- The ordinal scale type is qualitative, and the values have a meaningful order. The mathematical operations that can be applied to ordinal data include counting, frequencies, and measures of central tendency such as the median or mode. We can also use non-parametric tests to compare ordinal data between the groups. Using the correct mathematical operation for ordinal data is important because using an incorrect operation can lead to inaccurate results. For example, using the arithmetic mean on ordinal data can produce results that do not make sense because the values are not equally far from each other. Instead, the median can be used, which represents the central tendency of the data and is less sensitive to outliers.

- The interval scale type is quantitative, and the values have a meaningful order with equal intervals. The mathematical operations that can be applied to interval data include measures of central tendency, such as the mean or median, and statistical tests, such as t-tests or ANOVA. Using the correct mathematical operation for interval data is important because the zero point on an interval scale is arbitrary and does not represent the true absence of a measured attribute. Instead, measures such as percentage change or relative change should be used to compare the interval data.

- The ratio scale type is quantitative, and the values have a meaningful order with a true zero point. The mathematical operations that can be applied to ratio data include measures of central tendency, such as the mean or median, and statistical tests, such as correlation or regression analysis. Using the correct mathematical operation for the ratio data is important because the zero point on a ratio scale represents the true absence of the measured attribute. Therefore, we can calculate ratios on the ratio data, such as saying that 100 lines of code are twice as many as 50 lines of code.

Using an appropriate mathematical operation for each measurement scale type is important for accurate data analysis and interpretation. Using an incorrect mathematical operation will result in incorrect or meaningless results.

Scale type	Admissible Transformation	Operations	Examples	
Nominal	(R,=)	f unique	Name, distinguish	Colors, shapes
Ordinal	(R,>=)	f strictly increasing monotonic function	Rank, Order	Preference, hardness
Interval	(R,>=,+)	$f(x)= ax + b, a > 0$	Add	Calendar time, temperature (degrees Celsius)
Ratio	(R,>=,+)	$f(x) = ax, a > 0$	Add, multiply, divide	Mass, distance, absolute temperature (degrees Kelvin)
Absolute	(R,>=,+)	$f(x) = x$	Add, multiply, divide	Entity count

Figure 2. Mathematical rules for each scale type (Abran, 2010)

Research Methodology

The inputs for the study reported here come from the findings of two previous studies (Abdallah et al., 2021, 2022) on EA measurement solutions as follows:

1. The systematic literature review (SLR) by Abdallah et al. (2021) identified four entity types that were measured in the proposed EA measurement solutions:
    - An EA architecture provides a blueprint for the organization's IT systems and infrastructure (Table 1).
    - An EA project provides a structured approach to the design and implementation of the organization's IT strategies (Table 2).
    - An EA framework aims to improve the alignment between the organization's business and IT systems (Table 3).
    - An EA program focuses on managing and evolving an organization's IT systems over time to support changing business needs (Table 4).

Table 1. Measurement for the EA architecture entity
(from Abdallah et al., 2021)

EA Measurements solution (EAMS)	Authors	Title	Source
EAMS1	Fasanghari et al., 2015	A novel credibility-based group decision making method for enterprise architecture scenario analysis using data envelopment analysis	Applied Soft Computing
EAMS2	Razavi et al., 2011	An AHP-based approach toward enterprise architecture analysis based on enterprise architecture quality attributes	Knowledge and Information Systems
EAMS3	Gammelgård et al., 2007	An IT management assessment framework evaluating enterprise architecture scenarios	Information Systems and e-Business Management
EAMS4	Velitchkov, 2009	Enterprise architecture metrics in the balanced scorecard for IT	Information Systems Control Journal
EAMS5	Brückmann et al., 2009	Evaluating enterprise architecture management initiatives - how to measure and control the degree of standardization of an IT landscape?	Enterprise Modeling and Information Systems Architectures

Table 2. Measurement for the EA project entity
(from Abdallah et al., 2021)

EA Measurements solution (EAMS)	Authors	Title	Source
EAMS6	Rico, 2006	A framework for measuring ROI of enterprise architecture	Journal of Organizational and End User Computing
EAMS7	Foorthuis et al., 2016	A theory building study of enterprise architecture practices and benefits	Information Systems Frontiers
EAMS8	Bradley et al., 2011	Enterprise architecture, IT effectiveness and the mediating role of IT alignment in US hospitals	Information Systems Journal
EAMS13 EAMS9	Tamm et al., 2011	How does EA add value to organizations?	Communications of the Association for Information Systems
EAMS10	Aier, 2014	The role of organizational culture in grounding, management, guidance, and effectiveness of enterprise architecture principles	Information Systems and e-Business Management
EAMS11	Nikpay et al., 2017	A hybrid method for evaluating enterprise architecture implementation	Evaluation and Program Planning
EAMS12	Lange et al., 2016	An empirical analysis of the factors and measures of enterprise architecture management success	European Journal of Information Systems
EAMS13	Safari et al., 2017	Identifying and evaluating enterprise architecture risks using FMEA and fuzzy VIKOR	Journal of Intelligent Manufacturing
EAMS14	Lee et al., 2016	Transformational and transactional factors for the successful implementation of enterprise architecture in the public sector	Sustainability
EAMS15	Alzoubi et al., 2018	A measurement model to analyze the effect of agile enterprise architecture on geographically distributed agile development	Journal of Software Engineering Research and Development
EAMS16	Shanks et al., 2018	Achieving benefits with enterprise architecture	Journal of Strategic Information Systems
EAMS17	González-Rojas et al., 2017	Multilevel complexity measurement in enterprise architecture models	International Journal of Computer Integrated Manufacturing

Table 3. Measurement for the EA framework entity
(from Abdallah et al., 2021)

EA Measurements solution (EAMS)	Authors	Title	Source
EAMS18	Zandi & Tavana, 2012	A fuzzy group multi-criteria enterprise architecture framework selection model	Expert Systems with Applications
EAMS19	Morganwalp & Sage, 2004	Enterprise architecture measures of effectiveness	International Journal of Technology, Policy and Management
EAMS20	Melita, 2006	Evaluation of ARIS and Zachman frameworks as enterprise architectures	Journal of Information and Organizational Sciences
EAMS21	Bijarchian & Rosmah, 2014	Usability elements as benchmarking criteria for enterprise architecture methodologies	Journal of Teknologi (Sciences and Engineering)

Table 4. Measurement for the EA program entity
(from Abdallah et al., 2021)

EA Measurements solution (EAMS)	Authors	Title	Source
EAMS22	Jahani et al., 2010	Measurement of enterprise architecture readiness	Business Strategy Series

2. The subsequent study (Abdallah et al., 2022) proposed a metrology coverage evaluation method to evaluate each EA measurement solution for each EA entity type. This was achieved through a blend of the evaluation theory (López, 2000), the measurement context model (Abran, 2010), and the representational theory of measurement (Fenton & Bieman, 2014). This combination was used to assess the compliance of EA measurement solutions with the metrology criteria including theoretical and empirical criteria. The following metrology criteria were employed in the development of the metrology evaluation:
    1) Theoretical Design Criteria
        - Are the measured or quantified concepts defined in the measurement solution?
        - Are the measured or quantified concepts decomposed to a granular level that will allow quantification?
        - Are the measured or quantified sub-concepts defined within the measurement solution?
        - Is the intended use of the measurement results identified?
    2) Empirical Design Criteria
        - Is the point of view (perspective) of quantification identified?
        - Is the data input (subjective or objective) determined?
        - Are the rules on how to quantity the EA entity and its concepts identified?
        - Is there any mathematical operation performed on the collected input data prior to its use in the analysis models?
        - Is there a standard measurement unit used when quantifying the EA entity?

To evaluate whether EA measurement solutions satisfy the metrology criteria, which is referred to as 'metrology coverage', the metrology coverage is calculated using (1):

$$\text{Metrology coverage} = \frac{\sum_{i=1}^{n} \text{Metrology coverage score}}{n} \tag{1}$$

Where:

- n = the number of metrology criteria (theoretical or empirical).
- Metrology coverage score = 1 when the measurement solution satisfies the metrology criteria (theoretical or empirical).
- Metrology coverage score = 0 when the measurement solution does not satisfy the metrology criteria (theoretical or empirical).

Tables 5 and 6 illustrate an example of the metrology coverage evaluation for the EA architecture entity type.

Table 5. Metrology coverage evaluation for EA architecture for the theoretical design criteria

EA Entity	Primary study	Define the attribute	Decompose attribute to sub-attribute	Define the sub- attributes	Decompose the sub-attribute	Identify intended use of measurement	% Metrology coverage
Architecture	EAMS1	0	0	0	0	1	20%
	EAMS2	1	1	0	1	1	80%
	EAMS3	0	1	1	1	1	80%
	EAMS4	0	1	0	1	1	60%
	EAMS5	1	0	0	0	1	40%

Table 6. Metrology coverage evaluation for EA architecture for the empirical design criteria

EA Entity	Primary study	Source of input identified	Type of input identified	Quantification rule	Math on input data	Math on output data	Measurement unit	% Metrology coverage
Architecture	EAMS1	1	1	1	1	1	0	83%
	EAMS2	1	1	1	0	1	0	66%
	EAMS3	1	1	1	0	0	0	50%
	EAMS4	0	1	1	1	0	0	50%
	EAMS5	1	1	1	1	0	0	66%

The study reported here presents a more in-depth analysis of the findings from our previous research, the systematic literature review (SLR) (Abdallah et al., 2021), and the metrology coverage evaluation method (Abdallah et al., 2022) to investigate the mathematical operations within these EA measurement solutions, and this for each EA entity type. The methodology approach selected was to analyze the input, transformation, and output of the measurement units and scale types of each mathematical operation used in the design of the EA measurement solutions (Table 7 and Figure 3):

- The measurement unit is described when the measurement units of the inputs, transformations, and outputs (also known as the derived units) are specified. Otherwise, the measurement unit will be labeled with "undetermined."
- Each mathematical operation is examined in terms of the input, transformation, and output of the measurement scale types.
- The measurement scale is described if the measurement scale input, transformation, and output are specified. Otherwise, the measurement scale is labeled as "undetermined."

Table 7. Analysis framework for measurement units and scale types

Inputs	Mathematical operation	Measurement unit/scale		
		Input unit/scale type	Transformation unit/scale	Output unit/scale
{EA measurement solution from the SLR}	{Mathematical operation used in the measurement solution}	{Input unit/scale type of the input data to the measurement solution}	{Transformation of the unit/scale in the input data of the measurement solution}	{Output unit/scale type of the output data from the measurement solution}

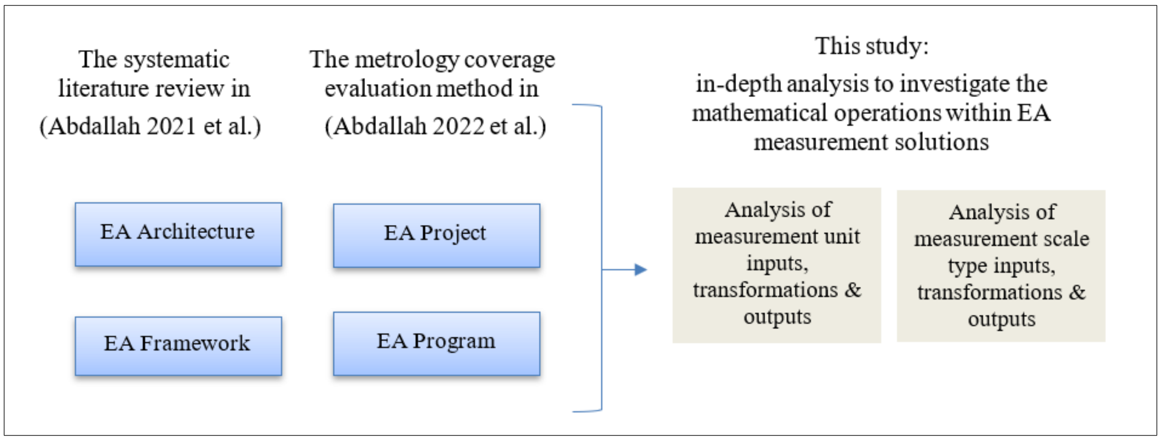

Figure 3. Research methodology for the analysis of the mathematical operation in the design of EA measurement solutions

RESULTS: SCALE TYPES AND MEASUREMENT UNITS IN EA MEASUREMENT DESIGNS

MEASUREMENT OF EA ARCHITECTURE

The five studies proposing measurement solutions for the EA architecture were analyzed to determine the scale types of the input data, the validity of the mathematical operations used in these studies, whether the scale type of the outputs could be identified, and if so, which scale type was used – Table 8. The admissibility of mathematical operations refers to whether they comply with the mathematical operations admissible according to the scale types mentioned in Figure 2 as outlined below:

- EAMS4 and EAMS5 use the number of applications and business process elements as quantitative inputs to the proposed mathematical equation: these inputs are therefore numbers on a ratio scale type, meaning that the input data have a defined meaning for both the magnitude and direction of differences between values. These can then be used in mathematical operations such as addition, multiplication, etc. The output data also follow a ratio scale, meaning that they provide a meaningful comparison of relative sizes.
- EAMS1, EAMS2, and EAMS3 have input data on an ordinal scale type, such as the pairwise comparison scale using AHP an undocumented transformation scale, an undetermined output scale, an admissibility of scale transformation, and an undetermined output scale type.

Table 8. Scale types in EA architecture measurement

Study	Input Scale Type	Scale type transformation in maths formula	Scale type transformation admissibility	Output scale type	Operation admissibility
EAMS1	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS2	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS3	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS4	Ratio	Not documented	Undetermined	Ratio	Admissible
EAMS5	Ratio	Not documented	Undetermined	Ratio	Admissible

The results of the analysis of the measurement units and their utilization in mathematical operations within the proposed measurement solutions for the EA architecture are presented in Table 9. It offers a thorough understanding of the units utilized in the measurement solutions for EA architecture, as outlined below:

- EAMS1, EAMS2, EAMS3, and EAMS5 contain input data with an undetermined measurement unit, undocumented transformation unit, and undetermined output unit.
- EAMS4 has a number of applications and business processes as input data for measurement units. However, the transformation and output units are undetermined.

Table 9. Measurement units in EA architecture measurement

Study	Input unit	Unit transformation in maths formula	Unit transformation admissibility	Output unit	Operation admissibility
EAMS1	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS2	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS3	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS4	Applications, Business Processes	Not documented	Undetermined	Undetermined	Inadmissible
EAMS5	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible

Overall, no primary study has specified an input or output measurement unit that is standardized and internationally accepted. To illustrate some of the weaknesses identified in the previous section, a more detailed analysis of the metrology issues found in the design of EA architecture measurement solutions is presented next using three examples.

Example 1: The design for measuring EA efficiency

The approach proposed in EAMS1 for measuring EA involves using the Data Envelopment Analysis (DEA) model to identify the optimal EA scenario, such as architecture. DEA is a benchmarking technique that evaluates the efficiency of different decision-making units, known as alternatives and has proven successful in the field of operations research (Bouyssou, 1999). It uses linear programming to analyze productivity and minimize inputs while maximizing outputs.

To measure EA efficiency, the measurement solution is based on soliciting the opinions of EA practitioners regarding the outputs of various EA scenarios. These opinions are linked to the Control Objectives for Information and related Technologies (COBIT), such as creating a strategic IT plan, defining the information architecture, and managing IT investment. The method begins by viewing EA scenarios as decision-making units and collecting fuzzy scores from practitioners on a scale of 0 to 10. The scores are next used in mathematical operations to calculate the efficiency scores for each EA scenario. For example, efficiency = 0.80 represents the efficiency calculated for the EA scenario using a specific formula. The value of 0.80 indicates the level of efficiency determined by the EA practitioner for the scenario. Additionally, rank = 8 is a numerical value assigned to the EA scenario based on its efficiency level. This rank allows the comparison and evaluation of the efficiency of different EA scenarios in relation to each other. However, without a well-defined and meaningful measurement unit, the validity of these numbers and the accuracy of comparison and evaluation are uncertain.

$$Ideal\ EA\ scenario\ efficiency = \sum_{r=1}^{k} u_r y^s{}_{ro} \tag{2}$$

- u_r: the weight assigned to the r-th outcome of an EA scenario, as perceived by the s-th expert, is represented by a numerical value. This value represents the relative importance the expert places on this particular outcome in comparison to the other outcomes being measured. The calculation of these weights is based on the expert's subjective evaluation using a specified scoring system, such as a 0-10 scale. The resulting values represent the opinions of the experts on the relative significance of each outcome and are used to determine the overall efficiency score of the EA scenario.
- $y^s{}_{ro}$: the j-th outcome of a decision-making unit is evaluated based on the s-th expert perspective.

The efficiency score obtained from experts' opinions on EA scenarios was found to have certain limitations in the initial study. These issues are noted as follows:

1. The type of measurement scale used for $y^s{}_{ro}$ the output of the DMU as perceived by the s-th expert is not specified.
2. It is uncertain if the mathematical operation combining the weight of the r-th EA output and the j-th output of the DMU in u_r and $y^s{}_{ro}$, according to the s-th expert opinion, is compliant with the established measurement scale rules.
3. It is unclear how the fuzziness of EA practitioners' opinions regarding EA scenarios translates into a numerical efficiency score. The nature of the scale on which the efficiency score is expressed was not defined in the original study.
4. It is not clear whether a reference measurement unit has been designated for the efficiency score number obtained from the opinions of EA practitioners.

Therefore, the calculation of the efficiency score raises concerns from a metrology standpoint, as it is unclear how the opinions of EA practitioners were transformed into this numerical value, and whether it was assigned a proper reference measurement unit. As a result, this number could be difficult to interpret and might not have any meaningful value. This conclusion is supported by the statement by Bouyssou (1999) regarding the DEA model, which requires that manipulations be made on interval or ratio scale types to avoid conceptual and computational difficulties.

Example 2: The design for measuring EA standardization

EA management is often challenged by the diversity of IT ecosystems within various organizations. The utilization of IT objects (ITO) in hardware, database, operating systems, applications, development tools, and programming languages can lead to complications. By consolidating ITO, costs can be reduced, security and reliability can be improved, and service delivery becomes more efficient. Standardization is key to successful EAM, as it simplifies administration and maintenance, while also accelerating development.

In EAMS5, a solution was presented to measure the standardization of an IT landscape in terms of ITO. The solution considers the unique characteristics of major IT enterprises and uses fuzzy-logic principles. A simple conceptual model was applied to express IT landscapes, and a sequential standardization process was implemented for IT landscape consolidation. The proposed method uses a computational formula to objectively quantify the standardization level of ITO. The formula considers the lifecycle stages of ITO:

- The test phase refers to when the ITO is in the testing phase.
- The productive phase refers to when the ITO is integrated into the application.

- The standard phase refers to when the ITO is publicly launched and can be used for other applications.

The formula proposed provides a quantifiable way to measure the standardization level of ITO in an IT landscape. The ITO standardization degree (SD) is given by Equation (3):

$$(SD) = \begin{cases} \dfrac{\sum_{ITO \in K} g_{ITO} \ \delta_{ITO}}{ST_{sub} + Prod_{sub}}, & if\ 1 \leq ST_{sub} \leq 2 \\ 0, & otherwise \end{cases} \tag{3}$$

Where:

- ST_{sub} represents the number of ITOs with a Standard lifecycle status.
- $Prod_{sub}$ represents the number of ITOs with a Productive lifecycle status.
- Additionally, the formula uses the parameter, δ_{ITO}, which collects the status of an ITO.

$$\delta_{ITO} = \begin{cases} 1, & if\ status\ (ITO) = standard\ or\ productive \\ 0, & otherwise \end{cases} \tag{4}$$

Where, g_{ITO} is defined for each ITO such that:

$$g_{ITO} = \begin{cases} 1, & if\ status\ (ITO) = standard \\ gP_{ITO}, & if\ status\ (ITO) = productive \end{cases} \tag{5}$$

The procedure for determining an ITO's lifetime status, as acknowledged in EAMS5, relies on subjectivity, and lacks objective means of measurement. The management team and the EA architects worked together to define this status. The team evaluates the need for a new ITO, assesses whether current ITOs can fulfill demand, and determines whether the request holds strategic importance. Given the subjective nature of the process, it is crucial for clear communication and mutual understanding between EA architects and the management team to accurately establish the lifecycle status of ITO.

In the computational formula presented in EAMS5, another parameter, gP_{ITO} , is used to compute the contribution of ITO in the productive phase. This parameter is defined for each ITO in the productive phase and used to determine the standardization degree (SD) of the IT landscape. By considering the contribution of each productive ITO, the formula provides a comprehensive measurement of the standardization level.

$$gP_{ITO} = \begin{cases} 0, \quad if \quad \dfrac{\#applications \mid ITO \ \in application}{\#\ applications} \leq TV \\ \dfrac{\#applications \mid ITO \ \in application}{\#\ applications}, & otherwise \end{cases} \tag{6}$$

In this research, the threshold value (TV) for the $SD\ (K)$ formula was set by enterprise architects, who determined this value based on their understanding of the business needs. A value of 0.05 was chosen for this study. Our analysis of the $SD\ (K)$ formula and its constituent elements revealed several metrology concerns, including:

- The two variables δ_{ITO} and g_{ITO} , are multiplied to obtain numbers in (3) and (4), where:

- Based on the classification of ITO (standard, productive, or otherwise), the variable δ_{ITO} is given labels with numbers (1 or 0) as opposed to letters. This label number is utilized for addition and multiplication and serves as a representation of the state of ITO.
- The numbers are assigned to the variable *g* as labels (1 or 0) based on the categories (standard or productive) of ITO (ITO). This label number, which was later used for addition and multiplication, illustrates the role of ITO in applications.

- The gP_{ITO} variable indicates ITO status. If it is standard, it is assigned the value 1; if it is productive, it is given a fraction; and if its contribution falls below the threshold value (TV), it is assigned a value of zero. The numerator is comprised of two separate units of measurement, each reflecting a different aspect of ITO - one measuring its contribution to applications and the other measuring its status. However, the outcome of these multiplications is not explicitly stated to have a unit of measurement.

$$(SD) = \begin{cases} \dfrac{\sum_{ITO \in K} (contribution\ of\ ITO\ in\ applications)\ (status\ of\ ITO)}{standarized\ ITOs + productive\ ITOs}, & if\ 1 \leq ST_{sub} \leq 2 \\ 0, & otherwise \end{cases} \tag{7}$$

- In the denominator of the $SD\ (K)$ formula, ITO is added to result in a total number. This total number represents the combined ITO but does not provide information about the individual status of the ITOs, such as whether they are standardized or productive. The measurement units of the ITOs remained unchanged throughout this addition process, leading to a loss of information about their status.

- The outcome of the $SD\ (K)$ formula is presented as a fraction ranging from 0 to 1; however, the basis for this calculation is not clearly defined. The primary study failed to ensure that both the numerator and denominator were on the same measurement unit, leading to a potential loss of accuracy and validity of the results.

In addition, it is important to acknowledge the impact of subjective inputs on the formulas used. This can lead to varying degrees of standardization of ITO. Moreover, in calculating the scores and weights for certain EA indicators, arithmetic operations are performed on ordinal scales, which may not be ideal.

Example 3: The design for measuring EA quality and value

Due to concerns about the value of IT, a number of initiatives, including enterprise architecture (EA) and IT governance, have been undertaken to better align business and IT. However, the majority of systems offer a comprehensive system for one issue while offering fragmented solutions for others, while the measurement solution in EAMS4 offers more details on measuring connected IT goals, particularly those related to EA, based on models for strategic IT management supported by the balanced scorecard (BSC) method.

The EA measurement solution in EAMS4 proposes a number of computation formulae for the EA quality and value. For example, to quantify usability, a quality characteristic, Equation (8) is proposed to quantify the "possible client application family (PCAF)"

$$(PCAF) = 1 - \frac{\#\ IT\ Applications}{\sum_{i=1} IT\ Applications\ \times\ NPCA} \tag{8}$$

Upon examination of the PCAF formula, several concerns can be identified:

- The numerator in the formula lacks a measurement unit specified in the measurement solution. For demonstration purposes, we will assume the unit to be "application," as in ten applications (units).
- The denominator involves the multiplication of two distinct measurement units, "applications" and "families of applications."
- The result of this formula is a value that does not possess a clear measurement unit.

$$(PCAF\ ) = 1 - \frac{\#\ IT\ Applications\ (unit\ 1)}{\sum_{i=1} IT\ Applications\ (unit\ 1)\ \times\ NPCA\ (unit\ 2)} \tag{9}$$

MEASUREMENT OF EA PROJECT

The studies offering measurement solutions for an EA project were examined to determine the scale types of the input data, the validity of the mathematical operations used in these studies, whether the scale type of the outputs could be identified, and if so, which scale type was used (Table 10). This included the analysis of the input data, transformation scale type, and admissibility of the mathematical operations. In summary:

- Only EAMS6 explicitly identifies the measurement scale type of the inputs and outputs, which are all designed on a ratio scale.
- EAMS13 and EAMS14 have input data of an undetermined scale type with an undocumented transformation scale and an undetermined output scale.
- EAMS7, EAMS8, EAMS9, EAMS10, EAMS11, and EAMS12 have input data on an ordinal scale with an undocumented transformation scale and an undetermined output scale.

Table 10. Scale types in EA project measurement

Study	Input scale type	Scale type transformation in maths formula	Scale type transformation admissibility	Output scale type	Operation admissibility
EAMS6	Ratio	Not documented	Undetermined	Ratio	Admissible
EAMS7	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS8	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS9	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS10	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS11	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS12	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible
EAMS13	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS14	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS15	Ratio	Not documented	Undetermined	Undetermined	Inadmissible

The results of the analysis of the measurement units and their utilization in mathematical operations within the proposed measurement solutions for EA projects are presented in Table 11. This includes the units for the input data, the transformation unit if one is applied, and output data.

- Only EAMS6 is explicit regarding the measurement unit ($).
- EAMS15 contains input data for an undetermined unit with an undocumented transformation unit and a specified structural complexity unit (SCU) as the output unit.
- EAMS7, EAMS8, EAMS9, EAMS10, EAMS11, EAMS12, and EAMS13 contain input data for an undetermined unit with an undetermined transformation unit and an undetermined output unit.

Table 11. Measurement units in EA project measurement

Study	Input unit	Unit transformation in maths formula	Unit transformation admissibility	Output unit	Operation admissibility
EAMS6	$	Not documented	Undetermined	$	Admissible
EAMS7	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS8	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS9	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS10	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS11	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS12	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS13	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS14	Undetermined	Not documented	Undetermined	Undetermined	Inadmissible
EAMS15	Undetermined	Not documented	Undetermined	SCU	Inadmissible

A more thorough examination of the metrology problems discovered in the design of EA project measurement is offered next with Examples 4 and 5 to highlight some of the weaknesses reported in Tables 10 and 11.

Example 4: The design for measuring EA complexity

The EA measurement design of structural complexity in EAMS15 of an EA project involves combining two factors, functionality (F) and dependency (D), using a simple addition - see Equation (10).

$$Structural\ Complexity\ (SCU) = F^{3.11} + D^{3.11} \tag{10}$$

However, the validity of this calculation is uncertain due to the lack of information about the measurement units and scale types of the inputs:

- The unit of measure for functionality is not defined.
- The scale type of dependency is not specified.

As a result, it is unclear whether the resulting number, the structural complexity unit (SCU), has a meaningful and trustworthy representation of the complexity of the EA entities. Additionally, the use of mathematical operations, such as addition, to combine the inputs raises further questions about the validity of the SCU as a measurement of complexity in the context of EA.

The calculation of the structural complexity unit (SCU) requires further validation and clarification to ensure that it is a sound and well-proven engineering measurement method with strong metrological properties. From a measurement viewpoint, the use of arithmetic addition to compare "functionalities" and "dependencies" can lead to imprecise conclusions and poor decision-making. Adding two distinct units of measurement, (F) and (D), does not result in a new complexity unit (SCU). The method used to derive the complexity unit (SCU) from the sum of "functionalities" and "dependencies" in the context of EA complexity measurement has not been proven theoretically sound and Equation 11 is questionable in this regard.

$$Structural\ \ Complexity\ (SCU\ ?\ ) = F^{3.11}(unit?\ ) + D^{3.11}(unit?\ ) \tag{11}$$

The validity of the equation used to measure the complexity of EA entities has not yet been determined. The assumption that the outputs are of the ratio-scale type has not been demonstrated. As a result, using the numbers generated from this formula to make decisions carries significant risk.

Example 5: The design for measuring EA success

In EAMS9, a project success model is proposed using relationships across over 20 factors in EA, which impact EA principles and organizational culture on success. These factors were determined from a survey of EA practitioners' opinions. It should be noted that such numbers are subjective, based on the opinions and expertise of the survey participants, not reproducible or repeatable, and typically on an ordinal scale rather than a ratio scale. Consequently, the numbers obtained in this type of quantification should not be used in additive or multiplicative mathematical operations.

MEASUREMENT OF EA FRAMEWORK

The two primary studies EAMS18 and EAMS19 proposing measurement solutions for the EA framework were analyzed to determine the scale types and measurement units of the input data, the validity of the mathematical operations used in these studies, whether the scale type of the outputs could be identified, and if so, which scale type was used, including the input data, transformation scale type, and measurement units, and admissibility (i.e., whether the mathematical operation adheres to the rules in Figure 2) of the mathematical operation of each EA measurement solution – Tables 12 and 13. In summary:

- both primary studies use interval and ordinal scale types of input data and have an undetermined transformation scale, admissible transformations, and output scale type.
- none of the primary studies has specified a measurement unit.

Table 12. Scale types in EA framework measurement

Study	Input Scale Type	Scale type transformation in maths formula	Scale type transformation admissibility	Output scale type	Operation admissibility
EAMS18	Interval	Not documented	Undetermined	Undetermined	Inadmissible
EAMS19	Ordinal	Not documented	Undetermined	Undetermined	Inadmissible

Table 13. Measurement units in EA framework measurement

Study	Input unit	Unit transformation in maths formula	Unit transformation admissibility	Output unit	Operation admissibility
EAMS18	Undetermined	Undetermined	Undetermined	Undetermined	Undetermined
EAMS19	Undetermined	Undetermined	Undetermined	Undetermined	Undetermined

To illustrate some of the weaknesses identified in this section, more detailed analyses of the metrology issues found in the design of EA framework measurement solutions are presented in Examples 6 and 7.

Example 6: The design for measuring EA risk

EA frameworks can increase the effectiveness and efficiency of organizations and guarantee the interoperability of information technologies. Prior to adopting a specific EA framework, a company must consider and assess potential alternative frameworks before choosing the best one, in a joint effort with all important stakeholders. The study presented in EAMS18 introduces a fuzzy logic-based multi-criteria quantification technique to quantify the risk associated with different EA frameworks and ultimately determine the most suitable framework, which involves a series of steps as follows:

1. In the first step, EA practitioners were asked to subjectively evaluate the impact, likelihood of occurrence, and likelihood of detecting specific risks associated with choosing an EA framework. To accomplish this, practitioners were tasked with assigning a numerical impact value (I) to each framework using a fuzzy set scale of 1-10. The inputs were then expressed as trapezoidal fuzzy numbers. Similarly, the same fuzzy set of 1-10 was used to estimate the probability of occurrence and detection of the EA risks.
2. In the second step, the opinions of multiple EA practitioners were combined. A weighted average was calculated based on their subjective evaluation of the impact, probability of occurrence, and probability of detection of different EA risks. For instance, to determine the impact value of each EA framework, the practitioners used a 1-10 fuzzy set to assign a

numerical value (I) to each framework. This was calculated by considering trapezoidal fuzzy numbers as the inputs.

$$Weighted\ Impact(I) = \frac{\sum_{k=1}^{l}(w(vp)_k)\ [\tilde{e}\ (I)]}{\sum_{k=1}^{l}(w(vp)_k)} \tag{12}$$

Next is an illustrative example to explain the formula:

Step 1. The calculation of the impact value involves aggregating the opinions of the EA practitioners. The formula $[\tilde{e}\ (I)]$ * $(w(vp)_k$ is used, where $[\tilde{e}\ (I)]$ represents the trapezoidal fuzzy number for the impact of a given EA risk, and $(w(vp)_k$ represents the voting power of each EA practitioner. For example, if two EA practitioners have voting power of 5 and 4 respectively, the impact of the EA risk is estimated to be 1 and 2 based on their opinions.

Step 2. The impact value is then calculated by multiplying these values with the respective voting powers – see equation 13.

$$Weighted\ Impact\ (I) = \frac{\left(5_{voting\ power} \times 1_{impact}\right) + \left(4_{voting\ power} \times 2_{impact}\right)}{9_{voting\ power}} \tag{13}$$

In the weighted impact formula, a number of concerns can be raised:

1. The product of voting power and impact creates a value with an undefined measurement unit.
2. Dividing this value by voting power leads to another result with an indeterminate unit.
3. Even though the outcome may seem to be on a ratio scale, it lacks interpretability. For example, in the illustration, the calculation results in 1.44, but it is unclear what this value represents.

$$Weighted\ Impact\ (I_{unit:\,?}) = \frac{(5_{unit:\,?}) + (8_{unit:\,?})}{9_{voting\ power}} = 1.44 \tag{14}$$

Step 3. Compute the fuzzy risk priority number (RPN) matrix. The estimated impact, probability of occurrence, and probability of detection of EA risks were combined into a mathematical formula. The formula is used to determine the overall risk level for each EA framework being considered, which is then used to decide on the most appropriate framework to select. The RPN matrix is a key component in this process to ensure that all the relevant factors are considered in the decision-making process.

$$RPN = \tilde{e}\ (I) \times \tilde{e}\ (L) \times \tilde{e}\ (D) \tag{15}$$

The fuzzy risk priority number (RPN) matrix is created by multiplying the impact value, likelihood value, and detection value of each EA framework. The impact value is represented by $\tilde{e}\ (I)$, the likelihood value by $\tilde{e}\ (L)$, and the detection value by $\tilde{e}\ (D)$. These values worked together to provide a comprehensive evaluation of the risks associated with each EA framework.

However, this calculation has weaknesses from a metrology perspective. The inputs to the calculation depend on subjective estimates from EA practitioners and their voting power, leading to a number with an unknown measurement unit. The results of this calculation may not provide meaningful and easily interpretable values.

Thus, making decisions based on these numbers without a clear understanding of their meaning and measurement scale type is problematic. It is unclear if these numbers can be compared from a metrological standpoint, or if mathematical operations can be performed on them. The methodology used in EAMS18 also mixes different types of measurement scale types, which can lead to inconsistent results. For example, the transformation from an ordinal scale to a ratio scale is unsupported, leading to numbers with an undetermined scale type and measurement unit.

Example 7: The design for measuring EA Quality

The EA measurement solution in EAMS19 proposes a method for measuring the total EA quality score by multiplying the scores of each attribute by its weight. The overall EA effectiveness achievement percentage can then be calculated by comparing the total score gained to the total score possible (Morganwalp & Sage, 2004). The method outlined in this study involves a series of formulas (Equations 16-18).

$$Total\ score\ earned\ = \sum(attribute\ score\ x\ attribute\ weight) \tag{16}$$

$$Overall\ achievement\ percentage\ = (total\ score\ earned\ /\ total\ possible\ score)\ x\ 100 \tag{17}$$

Where, the total possible score is the sum of the weights assigned to each attribute.

$$Weight\ of\ attribute\ = (Importance\ score\ of\ attribute\ /\ sum\ of\ importance\ scores\ of\ all\ attributes) \tag{18}$$

Where, the importance score of each attribute is determined by collaborating subject-matter experts to determine the weight of each EA attribute. This type of calculation has a number of weaknesses:

- The inputs to the calculation depend on subjective estimates from EA practitioners, leading to a number with an unknown measurement unit.
- The result of this calculation may not provide a meaningful and easily interpretable value. It is important to note that the multi-criteria evaluation techniques proposed in EAMS19 have limitations in terms of the measurement scale types. Therefore, it is crucial to ensure that the measurement scales used are appropriate and well-defined to ensure the validity and reliability of the results obtained.

In multi-attribute evaluation methodologies, EA practitioners assign the measured attributes varying weights based on their significance. To evaluate one item (in this case, the EA framework), EA practitioners would have worked together to determine the weight of each EA attribute. They would then score how well an object satisfies each attribute (Morganwalp & Sage, 2004).

From a metrological viewpoint, the limitations of multi-criteria evaluation techniques lie in the transformation from an ordinal scale type (subjective assessments by experts in the field) to a ratio scale type (weights). Approaches such as the analytic hierarchy process (AHP), which are similar to other multi-attribute evaluation techniques, have been criticized for lacking well-defined and meaningful measurement units and scale transformations. As stated by Fenton and Bieman (2014), multi-criteria evaluation techniques, including AHP, lack clear specifications for measurement units and scale types, leading to uncertainty regarding the validity of their results and conclusions. This raises questions about the reliability of the EA measurement solution's dependence on AHP and multi-criteria evaluation techniques in the context of EA quality assessments.

DISCUSSION

Many mathematical operations proposed in EA measurement ignore established measurement units and scale types, which makes them weak from both a mathematical and metrological perspective. These operations often generate numbers that lack units and are the result of undocumented assumptions rather than precise quantitative knowledge. Consequently, the significance of these numbers is uncertain, and they may have lost important information and lacked clear meaning. It is also unclear whether it is mathematically appropriate to add or multiply these values together. These numbers could potentially lead to incorrect decisions that have serious and costly consequences. However, as the discipline of EA matures and becomes more data-driven, it is increasingly important to adopt more rigorous and quantifiable evaluation methods.

By adopting a more rigorous and quantifiable approach to EA measurement, researchers and practitioners can support the development of more effective and valuable EA solutions and help to drive innovation and improvement in the field. The absence of well-defined scale types and measurement units in EA measurement solutions has several implications for both researchers and practitioners. For instance:

- Researchers will not be able to compare the results of their work with other studies and practitioners will not be able to make informed decisions based on the measurement results.
- Results of EA measurements can be misleading and misinterpreted: EA practitioners may draw incorrect conclusions from their work and practitioners may make incorrect decisions leading to misallocation of resources, decreased effectiveness, and ultimately, negatively impact the overall success of EA projects. Table 14 presents the implications of these mathematical operations in EA measurement.

Table 14. Implications of the mathematical operations used in EA measurement

EA Entity Type	Examples from Primary Studies	Admissibility of mathematical operations	Implications
EA Architecture Measurement	EA efficiency	Questionable	The design of EA efficiency measurement without a well-defined and meaningful measurement unit might deliver a misleading evaluation of the efficiency of different EA scenarios in relation to each other.
	EA standardization	Questionable	The design of EA standardization measurement might increase costs, affect security and reliability, and service delivery might become less efficient.
	EA quality and value	Questionable	The design of EA usability measurement might lead to inaccurate results. For example, if the ordinal scale is used instead of the interval scale, the difference between the values will not be meaningful, and the measurement will be inaccurate.
EA Project Measurement	EA complexity	Questionable	The design of EA complexity measurement can lead to misleading important conclusions, such as poorly determining which EA design solution is more or less complex. This might affect organizations to poorly control EA project scope, duration, and budget.
	EA success	Questionable	The design of EA success measurement can lead to improper decisions related to EA principles, EA consistency, and EA utility. This might lead to misleading recommendations on how to deal with selected design decisions when introducing and developing EA principles in an organization.
EA framework measurement	EA risk	Questionable	The design of EA risk measurement can lead to misleading quantification of risk associated with different EA frameworks and ultimately may not determine the most suitable EA framework.
	EA quality	Questionable	The design of EA effectiveness measurement can lead to wrong decisions that might hinder the reuse of hardware and software components and architecture development, limit the communication, cooperation, and information sharing, lower the development of economical systems.

The use of well-defined measurement units and scale types in the mathematical operations in EA measurement offers a number of advantages:

1. The ability to provide a clear and objective evaluation of EA solutions. Metrology is the science of measurement that provides a systematic and rigorous framework for evaluating and comparing measurement results. In the EA context, metrology can be used to evaluate a wide range of EA attributes such as EA quality, cost, value, benefits, size, complexity, and accuracy of EA solutions in a consistent and objective manner, without relying on subjective opinions or personal biases. This can help to increase the transparency and accountability of EA solutions and support better decision-making.
2. Another benefit of using well-defined measurement units and scale types in EA measurement is the ability to compare and benchmark EA solutions. By applying consistent measurement criteria, it is possible to compare the performance and value of different EA entities (architecture, framework, project, and program) and identify areas for improvement.

The next three points present some simple examples of the proper usage of well-defined measurement units and scale types from real-life scenarios:

- Adding the number of apples is correct since it is on a ratio scale.
- Speed: distance divided by time = km per hour is correct since both distance and time are measured through a ratio scale type.
- Evaluation using a 5-star rating scale (ordinal scale type): it is not possible to add, multiply, or average the stars because they are not on a ratio scale type. The median can be calculated, but it is not possible to compute an 'average'.

Example 8 presents an illustration of the correct usage of a measurement unit and scale types and discusses the benefits and implications of this correct usage for both EA researchers and practitioners.

Example 8: Measuring the EA functional size based on ISO 19761

The COSMIC measurement unit for the functional size of software was designed by the 'Common software measurement international consortium – COSMIC' and accepted in 2002 by ISO/IEC as ISO/IEC 19761. It contains the collection of definitions and rules to determine the functional size of a given piece of software. Its measurement unit is specified as 1 data movement of 1 data group and is labeled as '1 COSMIC Function Points' or 1 CFP.

Four categories of data movements are identified by COSMIC (see Figure 4):

- Entry (E): data group moved from the functional user to the software.
- Exit (X): data group moved from the software to the functional user.
- Write (W): data group moved from the software to persistent storage.
- Read (R): data group moved from persistent storage to the software.

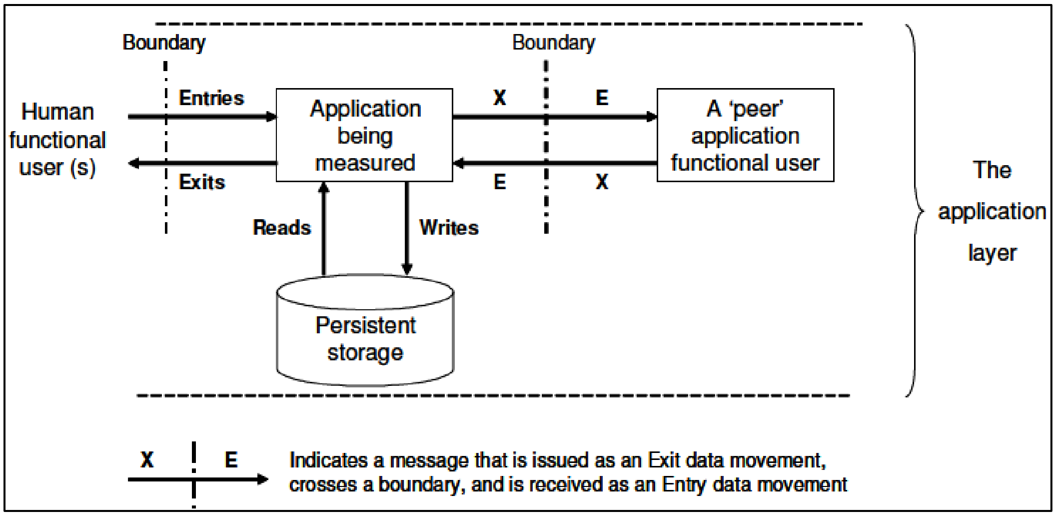

Figure 4. COSMIC four types of data movements

The functional size in COSMIC is calculated by adding the number of data movements based on the functional user requirements – see Equation (19).

$$Functional\ Size\ (CFP) = \sum Size_{Entries} + Size_{Exits} + Size_{Reads} + Size_{Writes} \qquad (19)$$

Where:

- $Size_{Entries}$ is the number of the Entry data movements to the software.
- $Size_{Exits}$ is the number of the Exit data movements from the software.
- $Size_{Reads}$ is the number of the Read data movements in the software.
- $Size_{Writes}$ is the number of the Write data movements in the software.

In most organizations, and based on The Open Group Architecture Framework (TOGAF), enterprise architecture has different architectural layers as follows:

1. Business architectural layer: responsible for defining the organization's business strategy, goals, and objectives, and creating the necessary processes and structures to achieve them.
2. The application architectural layer defines the organization's application systems and their relationships with each other. It identifies the applications that support each business process and function and describes the technology platforms and tools used to develop and support those applications.
3. Technology architectural layer: responsible for defining the hardware, software, and network infrastructure that supports an organization's application systems and business operations.

COSMIC size is valuable for EA, as it allows EA practitioners to measure the functional size of IT systems in order to understand the organization's technology infrastructure. Figure 5 illustrates an example of the EA application architecture layer of a registration system. It shows the functional processes and the data movements in the system as follows:

- Data movements in application process 1: Entry (E) and Exit (X), Read (R) and Write (W)
- Data movements in application process 2: Entry (E) and Exit (X), Read (R) and Write (W)
- Data movements in application process 3: Entry (E) and Exit (X), Read (R) and Write (W)

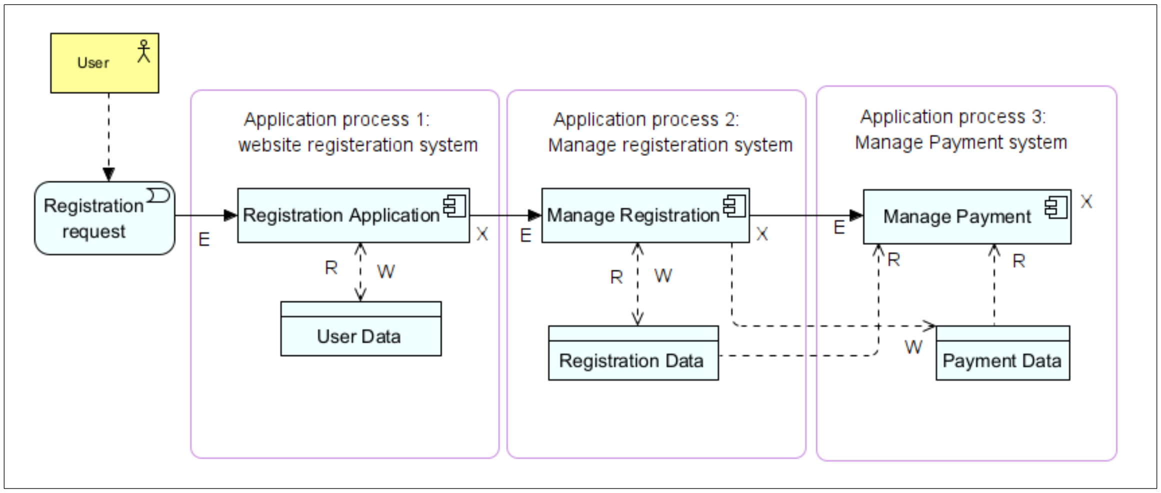

Figure 5. EA application architecture layer of a registration system using ArchiMate modeling language

The following illustrates the data movements observable at the EA application layer, along with the appropriate functional sizes:

$$Functional\ Size\ for\ application\ process\ 1 = \sum 1_{CFP} + 1_{CFP} + 1_{CFP} + 1_{CFP} = 4\text{ CFP} \quad (20)$$

Where:

- The registration application in the system has two data movements: 1 CFP for Entry data movement and 1 CPF for Exit data movement.
- The user data in the system has two data movements: 1 CFP for Write and 1 CFP for Read data movement.

$$Functional\ Size\ for\ application\ process\ 2 = \sum 1_{CFP} + 1_{CFP} + 1_{CFP} + 1_{CFP} + 1_{CFP} = 5\text{ CFP} \quad (21)$$

Where:

- Manage registration in the system has two data movements: 1 CFP for Entry data movement and 1 CPF for Exit data movement.
- Access registration data in the system has two data movements: 1 CFP for Write and 1 CFP for Read data movement.
- Payment data in the system has one data movement: 1 CFP for Write.

$$Functional\ Size\ for\ application\ process\ 3 = \sum 1_{CFP} + 1_{CFP} + 1_{CFP} + 1_{CFP} = 4\text{ CFP} \quad (22)$$

Where:

- Manage payment's data in the system has two data movements: 1 CFP for Entry data movement and 1 CPF for Exit data movement.
- Access registration data in the system has one data movement: 1 CFP for Read data movement.
- Payment data in the system has one data movement: 1 CFP for Read data movement.

Based on equations 20-22, the functional size for the EA application layer is the sum of the sizes of all the functional processes as follows:

$$Functional\ Size\ for\ EA\ application\ layer\ = \sum 5_{CFP} + 4_{CFP} + 4_{CFP} = 13 \text{ CFP} \qquad (23)$$

The mathematical operations used to measure the functional size in the EA application layer explicitly identify well-defined and established measurement scale type of inputs, and outputs, which are all designed on a ratio scale (Table 15).

Table 15. Scale types of EA measurement using COSMIC – ISO 19761

Input Scale Type	Scale type transformation in maths formula	Scale type transformation admissibility	Output scale type	Operation admissibility
Ratio	Ratio	Admissible	Ratio	Admissible

The mathematical operations used to measure the functional size in the EA application layer explicitly use well-defined and established measurement unit of inputs, and outputs, which are all designed to COSMIC Function Points (CFP) (Table 16).

Table 16. Measurement unit of EA measurement using COSMIC – ISO 19761

Input unit	Unit transformation in maths formula	Unit transformation admissibility	Output unit	Operation admissibility
CFP	CFP	Admissible	CFP	Admissible

The application of COSMIC functional size measurement on enterprise architecture measurement, including the application of a well-defined and established measurement unit and scale type standardized and established from ISO/IEC 19761, provides a standardized and objective way to measure the size of an application system as follows:

- Measurement unit: A COSMIC Function Point (CFP) is used to quantify the functional size of the software. This represents one data movement of one data group.
- Measurement scale type: the COSMIC measurement scale type is on a ratio scale and is based on counting the number of data movements between functional users and the software application.

Because the measurement units, scale types, and mathematical operations are admissible, EA practitioners can trust the numbers resulting from COSMIC functional size measurement as follows:

1. quantify potential issues such as duplication of functionality, reuse of functions, etc.
2. better estimate the effort required to develop or maintain IT systems, which is useful in project planning and resource allocation.

Estimation models can be used as statistical techniques to establish a relationship between a dependent variable (e.g., effort and cost) and one or more independent variables (Figure 6). In the context of EA, regression analysis can be used as an example to estimate the effort and cost of an EA project. For example, the functional size of an EA project can be used as an independent variable to estimate the effort (in hours) required to complete an EA project.

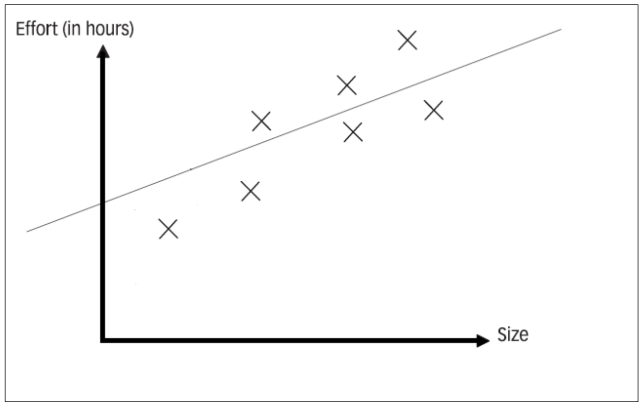

Figure 6. Example of an estimation model
(adopted and reworked from Abran, 2015)

On the other hand, this research study reveals that using multi-criteria evaluation techniques (such as fuzzy sets and fuzzy logic in Example 1 to measure EA efficiency, multi-criteria evaluation in Example 2 to measure EA standardization, and the Analytic Hierarchy Process (AHP) in Example 7 to measure EA Quality), can result in subjective data with unknown measurement units and scale types, reflecting practitioner opinions. Therefore, caution should be exercised when using these numbers as inputs in measurements and decision-making.

Decisions made based on EA measurements can have a significant impact on the organization, such as reducing IT redundancy, improving development time, and enhancing system availability and reliability. However, when proposed EA measurement solutions lack metrological rigor, such as weak application of measurement units and scale types, the resulting decisions may lead to undesired consequences, such as increased costs instead of reduction, or increased system failures.

By applying the metrology analysis presented in this paper, it becomes feasible to identify well-defined scale types and measurement units from the weak ones used in EA measurement and analyzes the admissibility of the mathematical operations used:

1. EA practitioners can rely on numbers resulting from well-defined measurement units and scale types to measure EA quality, cost, IT standardization, and other EA attributes and produce valid numbers from the metrology perspective.
2. EA practitioners can rely on numbers resulting from well-defined measurement units and scale types to better estimate the effort required to develop or maintain IT and enterprise systems through decision making models, which is useful in project planning and resource allocation.

CONCLUSIONS AND FUTURE RESEARCH

EA is widely recognized for establishing an integrated view that facilitates the alignment between business and information technology (IT). It achieves this by organizing a collection of management systems, structures, relationships, and interconnections. EA acts as a blueprint for a company's operations, guides decision-making processes, and supports corporate alignment.

The need for robust and effective EA measurement solutions has become increasingly important as organizations seek to optimize EA initiatives and investments. However, the majority of measurement solutions proposed in the EA literature are based on researchers' opinions and lack empirical validation and weak metrological properties. This means that the results generated by these solutions may not be reliable, trustworthy, or comparable, and may even lead to incorrect investment decisions.

In prior research, Abdallah et al. (2021) identified and classified EA measurement solutions based on EA entity types. In a subsequent study, Abdallah et al. (2022) evaluated their metrology coverage using a combination of evaluation theory and empirical methods. The research study reported here has identified the scale types and measurement units used in EA measurement and analyzed the admissibility of the mathematical operations used for each EA entity type, in terms of the scale types and measurement units of the inputs, their transformations through mathematical operations, and the impact in terms of scale types and measurement units of the EA measured outputs. The findings revealed that both measurement units and scale types have been overlooked in the design of EA measurement solutions proposed in the literature. The results revealed several shortcomings related to the quantification of these solutions and emphasized the need for more stringent and standardized measurement practices in the EA field.

In summary:

1. A large number of mathematical operations proposed do not consider scale types and established measurement units and are flawed.
2. A number of proposed mathematical operations produce numbers with unknown units and scale types and are often the result of an aggregation of undetermined assumptions rather than explicit quantitative knowledge. The significance of such aggregation is then uncertain, leading to numbers that have suffered information loss and lack clear meaning. For instance, it is often unclear whether it is appropriate to add or multiply these numbers together.

This metrology-based analysis highlights that the current proposals for measuring EA are not well established or robust from a metrological standpoint. The numbers produced by these methods lack strong metrological properties and are not considered reliable or valid measurements. Instead, they can be considered as preliminary attempts to quantify EA, without considering the principles of sound measurement.

Therefore, further improvement and refinement are required in the development of EA measurement solutions to achieve reliable and trustworthy results. Until then, enterprise architects, software engineers, and other practitioners of enterprise architecture cannot yet fully benefit from EA measurement solutions. When choosing between EA features, such as cost, quality, risk, and value, EA architects, for example, will not be able to analyze alternative EA designs or make well-informed selections. The impact of these flawed EA measurement solutions is significant, as they may result in inappropriate decisions being made by developers, architects, and managers, leading to undue confidence and a waste of resources when based on bad measurement design. Better quantitative tools will ultimately lead to better decision-making in EA domains. Such advancements will benefit enterprise architects, software engineers, and other practitioners, by providing them with more accurate and meaningful measurements for informed decision-making.

The metrological analysis presented in this study provides future researchers with a new perspective for creating EA measurement solutions with more robust metrological designs. This study adds to the body of knowledge related to EA measurement by offering a metrology-based analysis that can help in the design of EA measurement solutions that satisfy the mathematical validity according to the scale types, allows measurement consistency, and can be used in decision making models, as well as a detailed analysis.

Future work will explore additional EA measurement solutions identified in our previous study (Abdallah et al., 2022). Additionally, by using COSMIC - ISO 19761 principles on the ArchiMate model and measuring the functional size of EA layers, EA researchers can develop metrology-strong EA measurement designs for quantifying the software components of an IT infrastructure.

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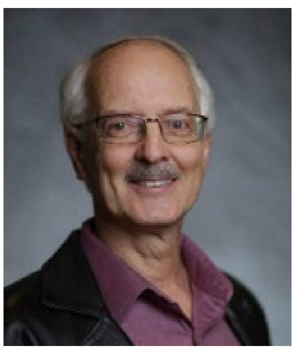

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