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An Empirical Analysis of Approach-Based Metrics Model for Architectural Erosion Detection

Ahmed Baabad[1,2] | Hazura Binti Zulzalil[1] | Sa'adah Hassan[1] | Salmi Binti Baharom[1]

[1]Department of Software Engineering and Information System, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, Serdang, Malaysia | [2]Department of Management Information Systems, Administrative Sciences, Hadhramout University, Al Mukalla, Yemen

Correspondence: Hazura Binti Zulzalil (hazura@upm.edu.my)

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ABSTRACT

Context: Software architecture plays a crucial role in the success or failure of software development and design. Over time, architectural degradation—known as architectural erosion—can compromise system quality and maintainability. Metrics-based approaches have become a prevalent method for identifying and addressing this phenomenon.

Objective: This study aims to (1) investigate whether various metrics-based approaches can effectively determine architectural erosion and support the development of a formal model, and (2) assess the construct reliability and validity of the proposed model.

Methods: A formal model was constructed based on selected metrics approaches derived from the literature. A questionnaire-based survey was conducted with 130 software engineering professionals experienced in architectural erosion and metrics. Structural Equation Modelling (SEM) was employed to evaluate the model's construct reliability, construct validity, and research hypotheses.

Results: The analysis revealed significant relationships between most classifications of metrics-based approaches and architectural erosion. However, no substantial relationships were found for the classifications of architectural complexity and architectural technical debt.

Conclusion: The proposed model offers a valuable foundation for the formal definition and evaluation of metrics-based approaches to architectural erosion. Its empirical validation provides meaningful insights for both researchers and practitioners aiming to assess or mitigate architectural erosion in software systems.

1 | Introduction

In the software engineering community, the past decade has seen a rise in focus on software architecture (SA). SA plays a significant role in a stage of software development overall, particularly in research and industry [1] as well as software development [2]. SA is regarded as the fundamental structural block of every system, since it is the significant and crucial factor in defining, succeeding, and developing systems design [3] along with quality standards [4], making it one of the most essential problems in software design and development today. Software engineering should place a significant emphasis on SA, since the decisions that are made at the beginning of the development process have a direct bearing on the quality and the level of success of the products that are produced. Even though SA achievements are tremendous, some challenges remain. Hence, SA is

eroded over time [5, 6] due to a variety of factors: time pressure, adding architectural debt, fixing bugs, design decisions, code complexity, inconsistent requirements, an unintended cyclic dependency among components, and new features, as well as technical requirements for changes (i.e., programming languages, hardware, new platforms, and operating system), All of these architectural issues may manifest unnoticed and undiscovered for a long time until they grow and become difficult to maintain. Evidently, this is not a new issue; rather, it has a lengthy history in the field of software engineering. Interestingly, the deterioration of the architecture causes the system to change at a higher frequency, with greater difficulty, and greater complexity than it did previously [7]. This phenomenon is commonly referred to as Architectural Erosion (AE) [8–13], Software Architecture Degradation (SAD) [14–17], Architectural Decay (AD) [18–20]. According to a survey of the studies conducted by the researchers working in this field, the term Architecture Erosion (AE) or Architectural Erosion (AE) is the one that is used in most of their studies. As a result, we have decided to utilize this term in our own study as well.

In this regard, a variety of potential solutions to the problem of AE have been suggested in [17]. As a consequence, the metrics strategy is the one that is utilized the most frequently and has the highest level of success among the various accessible alternatives [17, 21]. Software metrics are collected at numerous points in the software development lifecycle to improve and track the progress of various software engineering products and processes [22]. The fundamental logic is that "you cannot control what you cannot measure" [23]. In addition, many systems lack an explicit and precise description of prescriptive architecture in practice. A study [24] found that just 5% of open-source projects record software architecture. This means architectural specifications must be generated from scratch. This can be difficult for systems with hundreds of thousands of lines of code. Furthermore, the original developers of a system, who knew its architecture, are often no longer available. So, sometimes creating an architectural specification is impossible. In the event, the architectural documentation is missing, the code is frequently the primary source of information concerning potential architectural violations [15, 25]. As a result, the metrics play a major role in identifying whether there are problems with the code or the architecture.

Despite the empirical studies that highlight the widespread use of the metrics approach in addressing issues related to architectural erosion, evaluating the architectures of software implemented, and identifying architectural deviations, there is a significant lack of knowledge regarding the provision of a comprehensive perception of the elements required to evaluate the phenomenon of architectural erosion. This gap emerges due to the use of these metrics based on the researcher's point of view, without considering specificity and clarity due to the variation in the approaches used in presenting these metrics, which leads to increased ambiguity and confusion. This, in turn, causes difficulty in understanding the basic concepts of these metrics and increases challenges in terms of reducing the widespread acceptance of their concept.

Additionally, there is a need for a model for selecting the appropriateness of the adopted metrics approaches and the reliance on an appropriate classification that clarifies ambiguous definitions regarding metrics, their adopted approaches, and its categories, as well as investigates complicated, inaccurate, or incomplete approaches of the adopted metrics. The certain shortcomings and obstacles regarding architectural erosion have already provided substantial motivation for researchers to formulate an initial metrics approaches model for architectural erosion based on academic-related literature [13].

In this paper, a model for identifying architectural erosion based on the adopted metrics approaches is presented. This model can serve as the basis for a formal definition of generic approaches and adopted metrics. A model is based on systems monolithic architecture, which includes (1) generic approaches that are used for software metrics in the context of identifying architectural erosion (AE), (2) classification of adopted metrics and placement under the appropriate approach in order to recognize the AE, and (3) essential quality attributes regarding the identification of the AE. This model will investigate the empirical evidence concerning the relationship between the classification of metrics approaches and architectural erosion. This investigation will be based on an assessment of the reliability and validity of the model that was developed in collaboration with experts and related professionals. Additionally, empirical analysis will be utilized in order to determine how various classifications of different metrics approaches can identify the AE.

This paper presents a significant contribution to the field by introducing three new folds: First, A broad categorization for the purpose of determining architectural erosion, containing particular and consistent metrics that can be used to investigate and assess a wide range of approaches relevant to this context. Second, a deeper understanding along with interesting and novel insights into the potential identification of various types of metrics and their approaches to tackle architectural erosion from several perspectives. This can help researchers and developers devise or integrate solutions and approaches that play a prominent role in reducing architectural erosion based on criteria of convergent measures and achieving performance in a more effective and efficient manner. This can also be of assistance to researchers in the process of creating new solutions and approaches. Third, this model has been subjected to both an empirical evaluation and an evaluation from the perspective of software engineering professionals, yielding a wealth of information (such as erosion classifications, approach metrics, and quality attributes) that can serve as guidelines or references for researchers and practitioners for tackling the problem of architectural erosion.

The remaining parts of this paper are structured as described below. Section 2 outlines the related work. Section 3 proposes the research model and hypotheses. Section 4 describes the research methodology. Section 5 presents data analysis and results. Section 6 explains the discussion of obtained results. Section 7 illustrates implications for research and practice. Section 8 clarifies threats to Validity of the study. Section 9 concludes the paper and provides directions for future work.

2 | Related Work

Despite studies relevant to our work, no model development based on these criteria and approaches has been adopted and

validated. However, we will review the literature on those approaches that have been proposed to determine architectural erosion, based on measures that are key indicators in this context.

2.1 | Architectural Change Approach

Changes at different levels of abstraction and from multiple architectural views can induce architectural degradation and instability. An investigation was conducted to assess whether architectural instability is mitigated by the maturity level of a software system. Throughout the study, unstable software components were identified through the analysis of metrics for project design instability and project call instability [26]. Unintentional architectural changes, decay, and the presence of vulnerabilities, as well as the identification and tracking of architectural decay across the evolution history of a software system, all require a reliable determination and understanding of architectural change based on architecture-to-architecture and cluster coverage measures [27–30].

Software architecture degrades when changes violate design-time architectural intents. Erosion makes maintenance harder and slows software evolution. In study [31] that used change dispersion, relationship-based similarity, architectural stability, and Move-Join (MoJo) measures to identify architecture degradation, system architecture changes can have unforeseen repercussions. So, study [32] investigated a metric for class fault-proneness based on structural distance. Concerning co-changes between modules [19], Authors represented cross-module co-changes and inner-module co-changes metrics to identify modifications that occur simultaneously within or across modules [33]. proposed a metric-based, multidimensional approach for analyzing the structural stability of the system (package abstractness (A) and instability (I)) measures.

2.2 | Historical Data Revision Approach

Historical data revision analyses project files for bugs and changes prone throughout maintenance, revealing serious architectural flaws. Detecting architecture anti-patterns [34] and measuring and predicting architecture quality, as well as identifying architecture issues [35, 36] by analyzing revision history based on bug change frequency, bug churn, change frequency, ticket frequency, and pair change frequency measures.

To forecast architectural decay from evolutionary history [19], proposed multiple architectural perspectives, including architectural quality prediction models using an effective set of prediction metrics (i.e., number of changes and number of co-changed files). In study [15] highlighted several measures were highlighted to indicate software architecture degradation, such as the number of commits. A severity metric for code smells, which is based on the change history of a software system, was introduced to prioritize symptoms of architectural issues [37].

2.3 | Architectural Cohesion Approach

Architectural cohesion refers to the degree to which a module's elements are functionally connected. Inconsistencies between intended architecture, as detected as symptoms of architectural degradation, are investigated by many source code metrics, such as lack of method cohesion metric [15] and lack of cohesion metric for packages [31, 38]. Dependency optimization-based metrics are used to identify source code anomalies and architectural erosion through package cohesiveness quality metric to examine internal package dependencies [39] and tight class cohesion [40]. Correlations and interactions between architecture changes and decay [27] are significant concepts to measure actual cluster interactions to possible cluster interactions using the ratio of cohesive interactions metric.

2.4 | Architectural Modularization Approach

The term "architecture modularization" is used to describe the degree to which a system or piece of software is divided into independent modules that have little effect on one another when modified. In studies [39, 41], proposed package quality measures (inter-package modularization dependencies, inter-package modularization connections, inter-package modularization cyclic dependencies, and inter-package modularization cyclic connections) cover a wide range of software quality, including vulnerability detection, fault-proneness, and violation of coding standard. The aim is to assess the sufficiency of software architecture quality and to determine whether it erodes with time. Decoupling Level (DL) is a metric introduced by studies [42, 43] to assess how well a software system is separated into independent modules. On the other hand, a modularization quality metric has been presented to measure the entire system in order to simplify the system's understanding and restrict certain types of changes to particular modules [27].

2.5 | Architectural Technical Debt Approach

In the context of the software development lifecycle, the term "architectural technical debt" refers to designs that are suboptimal, incomplete, immature, or otherwise lacking in appropriate artifacts. Since software architecture deterioration causes inconsistency between a system's implementation and major design decisions [15], presented several metrics to detect architectural discrepancy (e.g., Sqale index and Sqale debt ratio).

Minimizing architecture debt is anticipated to make software less costly and more adaptable to change via decoupling level and propagation cost measures [42], evaluation of architectural violations based on architectural debt index [44], and analysis of system coupling for numerous components in each system to find defect-related activity [45, 46], which are directly related to software architecture to be maintained and evolved.

2.6 | Software Architecture Size Approach

The term "software architecture size" relates to the estimation of the size of a system or component to determine software productivity, anticipate fault locations in testing, and plan for maintenance. It refers to the overall, data, or functional measure of the system.

To characterize the evolution or degradation of architecture in terms of size, highlight architecture and code-level problems that might affect system change costs, and reduce architectural model understandability, which may lead to erosion, several size-related aspects have been proposed [15, 31, 47–49], including the number of lines of code, the number of statements, the number of calls, the number of comments, the number of connectors, the number of components, and class elegance.

2.7 | Architectural Complexity Approach

Architectural complexity relates to a system's structure, stored knowledge on how it operates, and makeup, which may be difficult to understand or solve. To ensure that systems maintain their stability and can continue to deliver the necessary functionalities as they evolve, it is crucial to understand the pattern of software architecture change as the systems evolve over time [33, 50]. Thus, structural complexity and the complexity of a defect have been proposed based on analysis of structural over-complexity [51], cognitive complexity [37], the excessive complexity [33], weighted methods per class, cyclomatic complexity [15, 52], and defect persistence [53] measures to identify a defect and architectural problems.

2.8 | Architectural Bad Smells Approach

Architectural bad smells are architectural decisions that negatively affect system quality and may refer to architectural degradation. Measures for architectural elements [54], architectural concern-based metrics [54, 55], and architecture-sensitive metrics [56] have all been proposed as heuristics to help in the prioritization of key code anomalies. In addition, study [57] performed strategies based on metrics for identifying architecturally significant smells.

Furthermore, architectural anomalies can be identified by analyzing correlations and co-occurrences among architectural and design smells [58] or among each other [59], utilizing various metrics. A tool introduced by studies [60, 61] for the detection of architectural smell is based on a metrics engine that computes all Martin metrics [62].

2.9 | Architectural Dependency Coupling Approach

Dependency coupling in architecture is the relationship between abstraction-level entities within a module that is dependent on another module, whether that dependency is direct or indirect. Researchers have shown considerable interest in examining the interdependency between conceptual architecture and various factors such as architecture changes, erosion, vulnerabilities, problem violations, and defect-related activities. This area of investigation has been a major focus in numerous studies. These studies employ coupling metrics at different levels, such as between models, objects, packages, and classes, to assess the condition of the system architecture with respect to evolution or degradation [15, 27, 31, 35, 39, 45, 61, 63–66]. For example, coupling metrics such as coupling between objects, afferent coupling, efferent coupling, data abstraction coupling, number of coupled classes, sum of coupling, module dependency strength (MDS), and dependency frequency are used.

Using architecture-sensitive strategies, proposed metrics for detecting code anomalies related to architectural elements [54]. These metrics encompass external fan-out, external fan-in, and architectural element locality. In essence, a suggested approach for investigating architectural erosion involves assessing architectural defects, architectural smells, and the quality of modularization. This is achieved by measuring the dependencies between modules [19]. Additionally, there is a recommendation to enhance the Architecture Description Language (DSL)-based approach to architecture abstraction. This enhancement aims to analyze the understandability of generated architectural models and identify architecture erosion through metrics measuring incoming and outgoing interdependence [48].

Based on the approaches that have been reviewed, it can be concluded that there is a wide range of approaches that have been proposed for determining architectural erosion. Each approach focuses on different key indicators and metrics that are considered important for detecting and quantifying architectural erosion.

Overall, these approaches offer different perspectives on architectural erosion and provide a range of metrics that can be used to quantify and detect erosion in software systems.

3 | Research Model and Hypotheses

The initial development of a software metrics model for analyzing architectural erosion was conducted using systematic mapping [13]. Meanwhile, there is a major disparity and deficiency in realizing and assessing the metrics criteria that fundamentally drive and identify architectural erosion; Therefore, the research hypotheses were developed on the basis of (1) the literature review that was presented in this study and (2) the results of a previously conducted systematic mapping study, which demonstrated the significance of taking metrics into consideration when determining the presence of architectural erosion. In this study, measurement is conceptualized as an essential task in the process of software measurement and quality attributes. Based on an evaluation of two criteria for the primary studies (i.e., the study objective and the approach adopted to address architectural erosion), the methods of architectural erosion analysis have been categorized into nine broad categories that can be taken into account when assessing architectural erosion: Architectural change (ACH), Historical data revision (HDR), Architectural dependency coupling (ADC), Architectural bad smells (ABS), Architectural cohesion (ACO), software architecture size (SAZ), Architectural technical debt(ATD), Architectural complexity (ACP), and Architecture modularization(AM). A complete description of the measurement items used in this research can be found in the Supporting Information.

These classifications reflect the authors' diverse strategies for tackling the issue of architectural erosion through analysis of the mechanisms of adopted metric approaches that have been proven to handle this issue. Most of the approaches and methods

proposed by researchers to address the phenomenon of erosion fall into the categories of architectural dependency coupling analysis, architectural bad smells, and architectural change because of the large number of metrics included in these groups and the large number of studies based on the analysis of relationships and dependencies among architectural artifacts of a given system.

A research model, shown in Figure 1, was constructed based on the aforementioned literature analysis and the facts, as well as the results of our own pre-conducted studies [13, 17]. Considering this, two-tailed hypotheses have been developed as follows:

Hypothesis 1. *Architectural change significantly identifies Architectural Erosion.*

Hypothesis 2. *Historical data revision significantly identifies Architectural Erosion.*

Hypothesis 3. *Architectural dependency coupling significantly identifies Architectural Erosion.*

Hypothesis 4. *Architectural bad smells significantly identify Architectural Erosion.*

Hypothesis 5. *Architectural cohesion significantly identifies Architectural Erosion.*

Hypothesis 6. *Software architecture size significantly identifies Architectural Erosion.*

Hypothesis 7. *Architectural technical debt significantly identifies Architectural Erosion.*

Hypothesis 8. *Architectural complexity significantly identifies Architectural Erosion.*

Hypothesis 9. *Architecture modularization significantly identifies Architectural Erosion.*

4 | Research Methodology

It is possible to solve a research problem using models, procedures, and methods. Research methodology outlines the process by which hypotheses are produced and how they are tested [67]. It is important to know the purpose of a study's design in order to effectively conduct research. Therefore, this methodology includes literature analysis, instrument validity and reliability, sampling and data collection, data preparation, measurement, and structural model assessment. This section provides a detailed explanation of the procedures and analysis that were used to fulfill the study goals.

4.1 | Literature Analysis

The initial step in the study process was to identify the problem that needed to be addressed by looking at the challenges and gaps left by prior studies. A literature review was used to gather the necessary information. In our previous research, we conducted a review of the literature on software architecture degradation and the metrics used to measure architectural erosion.

To create a proposed model for architectural erosion contexts, a systematic mapping study (SMS) was performed [13]. The study encompassed 92 metrics and 10 quality attributes. Each of the measures studied was allocated to an approach of

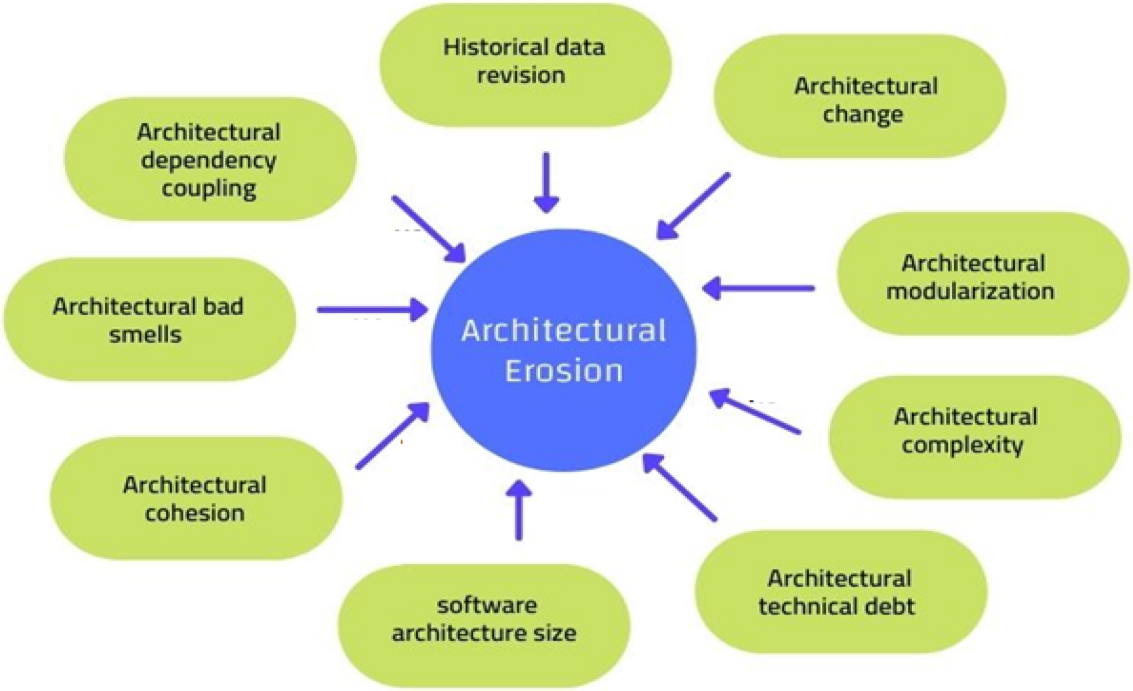

FIGURE 1 | Proposed model.

architectural erosion (historical data revision, architectural bad smell, architectural dependency coupling, architectural cohesion, architectural change, architectural technical debt, architectural complexity, architecture modularization, and software architecture size). The prior approaches were deduced based on the most widespread analysis of proposals for architectural degradation.

4.2 | Instrument Validity and Reliability

The quality of quantitative measurement could be judged by the validity and reliability of the data being collected. An instrument's reliability is demonstrated by its ability to consistently deliver the same results when tested in a variety of scenarios. In terms of validity, one definition states that it is when "what the instrument claims to measure is what it is measuring." [68]. As a result, the study instrument's validity and reliability were evaluated. Instrument validity and reliability testing are described in detail in the following sections. In the Supporting Information, you will find a summary of the survey measuring items that were utilized in this study.

4.2.1 | Content Validity

Analysis of a scale of content validity is critical for researchers who want to improve the instrument's construct validity, which is why content validation should be a primary concern [69]. Content validity focuses on the extent to which an item's sample of relevant factors adequately represents the construct of interest [70]. In general, the content validity of a model or instrument is determined by the analysis of its concept by a panel of experts [71, 72]. In the research, a questionnaire was developed and distributed to researchers and practitioners with prior experience in the context of architectural erosion. These researchers were selected through systematic studies of their published works and their relevance to the study, based on their interest in the study.

According to study [73], the model should be evaluated by at least three experts; however, the presence of more than ten experts is unnecessary [74]. Many academics believe that the model should be validated by at least five experts in order to be considered reliable [75]. In this study, 30 emails were sent to experts, but only 8 responded and filled out a questionnaire.

Diverse perspectives existed regarding the appropriate number of measurement scales, such as even-numbered (2, 4, 6, 8, 10, or) or odd-numbered (3, 5, 7, 9, or) scales [76]. The odd-numbered scale's middle numbers represent neutral, unbiased, not sure, don't know, or not applicable. In contrast, the even-numbered scale represents positive or negative responses. Odd-numbered scale can adjust the model more accurately than even-numbered scale [77, 78]. This study employed a five-point Likert scale to measure response appropriateness and intelligibility. Therefore, this study's questionnaire used a 5-point scale ranging from 1—strongly disagree to 5—strongly agree to reflect experts' opinions.

This study used a content validity ratio (CVR) model that was based on [79] to measure the individual scale items, and Judgment calculation means [78]. The model is feasible due to the study's number of panelists, which is fewer than 10 [80]. The formula could be written as follows:

$$CVR = (Ne - N/2)/(N/2)$$

where Ne, the proportion of experts who rated the item as a 4 or 5 on a 5-point scale; N, the total number of experts.

For the eight panellists in content validation, the CVR value was set at 0.75. Table 1 demonstrates component CVR values.

For the purpose of computing the mean for each item, the values reported in the questionnaire were converted as follows: [78]:

Strongly Agree (5) or Agree (4)—was replaced by 2.

Neither disagree or agree (3)—was replaced by 1.

Strongly Disagree (1) or Disagree (2)—was replaced by 0.

If the expert mean value of an item's assessment is more than 1.5, it is accepted for final items. As a result, the mean is more likely to be "Strongly Agree" or "Agree" than the expert judgement value of "0" or "No Idea". As an alternative, if the mean judgement of experts falls below 1.5, the item would be rejected since experts found the item to be unsuitable for measuring the construct in question. However, the CVR must be equal to or higher than 1.5 for the items to be accepted. Table 2 shows the finalizing criteria for the measures.

4.2.2 | Reliability Study

A pilot study was done before main data collection to validate and test research instruments. It's the initial step in designing a

TABLE 1 | Minimum CVR value based on study [79].

Numbers of panelists	Min CVR value
5	0.99
6	0.99
7	0.99
8	0.75
9	0.78
10	0.62
11	0.59
12	0.56
13	0.54
14	0.51
15	0.49
20	0.42
25	0.37
30	0.33
35	0.31
40	0.29

TABLE 2 | Summary of criteria for finalizing the items.

Criteria	Status
If CVR ≥ 0.75 only for panelist = 8	Accept
0 ≥ CVR ≤ 0.75 AND Mean ≥ 1.5	Accept
If CVR ≤ 0 AND Mean ≤ 1.5	Reject

survey questionnaire. It helps validate the research instrument and reduce errors [81]. Most scholars recommend a sample size of 20–40 [82, 83]. Thirty respondents from software engineering research groups, familiar with architecture erosion metrics, were purposively sampled.

The pilot study's data was analyzed using SPSS. Cronbach's alpha internal consistency test was used to assess the survey's measurement items for reliability. From 0 to 1, which indicates a high level of reliability. Values more than 0.9 are excellent; values between 0.8 and 0.9 are good; values between 0.7 and 0.8 are acceptable; values below 0.6 are considered poor [83]. Three criteria were used to assess the model's reliability:

1. Each construct's Cronbach's alpha value must be at least 0.70.
2. Corrected item-total correlation should be > 0.2.
3. If an item is eliminated, Cronbach's alpha must be lower than Cronbach's alpha for the construct.

4.3 | Sampling and Data Collection

Data collection is one of the key elements of model evaluation. Data collection entails gathering helpful ideas and information about research issues from target respondents [84]. Numerous methods to data collecting are described in literature, including face-to-face, telephonic, email, and use of online media [85]. Email and various forms of online media were used in the collection of data for this study. When methods are combined, both time and cost could be saved. In this research, a questionnaire was used to collect data, which is a realistic and convenient tool for data collection [86].

Given the impossibility of obtaining an accurate representation of the entire population, a representative sample was selected. This study used a technique known as "purposive sampling." The study's main emphasis is on the researcher's strategic use of chance to find potentially helpful respondents [74]. Therefore, in this research, software engineering professionals who are related to the area (e.g., software metrics, software architecture, architectural decay/degradation/erosion, software quality, architectural smell/code smell, architectural technical debt, and software maintenance and evolution) were selected as respondents. Also, in perspective industrial, Product Manager, System Architect, IT Consultant, Software Engineering Manager/Lead, and Automation Technical Leader, who have wide knowledge of software architecture erosion. Table 3 outlines respondent demographics.

An online questionnaire was designed to gather survey data, using Smart Survey tool for ease of response. It was determined

TABLE 3 | Profiles of the respondents' demographics that were collected ($n = 130$).

Demographic variable	Category	Frequency (n)	Percentage (%)
Field	Academic	89	68.5
	Industry	18	13.8
	Academic/industry	23	17.7
Current position	Researcher	89	68.5
	Software development engineer	11	8.5
	Researcher/software development engineer (both)	22	16.9
	Others	8	6.1
Year of experience	Over 15	70	53.8
	11–15	22	16.9
	6–10	24	18.5
	3–5	8	6.2
	1–2	6	4.6

that Google scholar would be the most effective tool for finding relevant researchers for the survey. Additionally, authors of studies relevant to our research were invited to participate in this survey. LinkedIn was chosen as the best way to recruit software engineers, especially those who are working in industrial companies worldwide, to participate in the survey. Moreover, the online questionnaire was shared on social media in LinkedIn and Facebook groups that are concerned with software engineering and development.

The size of the sample matters a great deal when conducting statistical analysis. Thus, the choice of sample size should be made considering the specific statistical method that will be employed to analyze the data collection. In this study, statistical methods such as structural equation modelling (SEM) and SPSS were used for analysis. There is no consensus regarding the exact sample size for SEM, and researchers have various opinions on the matter. In order for a SEM estimation to be reliable and valid, an adequate sample size is required. According to [87], a sufficient sample size for SEM requires at least five respondents for each construct and a total of no fewer than 100 persons for the entire set of data. Almost any SEM may be unworkable with less than 100 cases unless a very simple model is tested [88]. The model is considered simple because it lacks the complex variables that are associated with multi-ranking, and the sample of the target population is restricted to specific experts around the world; online questionnaires were distributed to get as many responses as possible responses and ultimately, 130 completed questionnaires were returned.

4.4 | Data Preparation

The responses were pre-processed after the data had been collected. Therefore, the steps involved in each stage of data

pre-processing are outlined in the following points, and a complete description of data investigation and descriptive statistics for constructs and their items in this research can be found in the Supporting Information.

4.4.1 | Missing Data

Incomplete data gathering is a problem [89]. In addition, missing data affects statistical tests that examine the correlations between variables [72]. Data was collected online in this study. All questionnaire responses are required and responders can not skip any. Statistical Package for Social Sciences (SPSS) was used to examine the raw data. Thus, no data was lost.

4.4.2 | Outliers

Another challenge that can arise when using statistical methods is that of outliers. An observation that stands out as being dramatically dissimilar to other value observations is known as an outlier [72, 88]. There was no univariate outlier in this study due to the Likert Scale 5-scale range being employed for responses. Outliers were determined by SPSS, and no outliers were found.

4.4.3 | Normality

To determine the shape of the sample distribution, data normality testing was employed. According to [90] study, the appropriate range for skewness is between −2 and +2, whereas the appropriate range for kurtosis is between −7 and +7 [91]. In addition, some researchers consider a score of +1 to −1 for skewness and +3 to −3 for kurtosis to be normal values [92]. In this study, the normality of the data was evaluated using SPSS to identify the range of skewness and kurtosis, ensuring that the prescribed limit was not exceeded.

4.5 | Measurement Model Assessment

The term "measurement models" refers to the models, either implicit or explicit, that relate the latent variable to its indicators. The evaluation of the PLS-SEM model begins with a look at the measurement models. Using PLS-SEM estimations, researchers can determine the reliability and validity of the construct measurements. Specifically, multivariate measurement is the use of multiple variables (i.e., multi-items) to assess a construct [93]. The PLS algorithm was employed in Smart PLS to assess the measurement model. Factor Loadings, internal consistency, convergent, and discriminant validity were used to evaluate the measurement model [93].

4.5.1 | Internal Consistency Reliability

Internal consistency reliability is often the first criterion to be assessed. To measure internal consistency, Cronbach's alpha is used, which traditional criterion and estimates the reliability based on intercorrelations between observed indicator variables and their correlations. Due to Cronbach's alpha's restrictions, a new measure of internal consistency reliability, known as composite reliability (CR), is more technically acceptable [93, 94]. Internal consistency reliability is indicated by an a-value of 0.7 or above [83, 95]. Thus, any a-value that is more than 0.70 is regarded as reliable and acceptable.

4.5.2 | Convergent Validity

The degree to which one measure correlates positively with other available measures of the same construct is what is meant by the term "convergent validity." [72, 88, 93]. Average variance extracted (AVE) is a common measure of concept convergent validity. This criterion is the grand mean of the construct's squared loadings (i.e., the sum of the squared loadings divided by the number of indicators). The following formula is used to determine the AVE [93]:

$$\text{AVE} = \frac{\sum x^2}{N}$$

where $\sum x^2$ s is the sum of all squared standardized factor loadings and n represents the items number. An appropriate value is more than 0.5, which indicates that latent variables have convergent validity [93, 96].

4.5.3 | Discriminant Validity

The degree to which a construct is empirically distinguishable from other constructs is known as discriminant validity. A construct's ability to distinguish itself from others in the model is an important step in the process of proving discriminant validity [72, 88, 93].

We assessed the discriminant validity based on the HTMT approach to determine a threshold that has been used in most of the research. Technically, HTMT estimates the correlation between two constructs if they are perfectly quantified (i.e., if they were perfectly reliable). Disattenuated correlation refers to real correlation. A correlation near 1 shows a lack of discriminant validity [93]. According to previous research and the findings of those studies [97], determined a 0.90 threshold for conceptually similar path model structures. Above 0.90, HTMT shows a lack of discriminant validity.

4.6 | Structural Model Assessment

The primary purpose of the structural model is to investigate the relationship between the independent and dependent variables. This model also makes it possible to ascertain the impact that the independent factors (exogenous variables) have on the variables that are being studied (endogenous variables) [72]. A structural model is a perspective of a system that focuses on the structure of the objects, including the relationships between those objects, their characteristics, and the activities those attributes they perform [98]. Through investigating their relationship within a structural model, we can infer the effect of the independent factors on the dependent variable. Following are the key considerations that were taken into account in the

evaluation of the structural model: (1) Structural Model Path Coefficients (Hypotheses Testing), (2) Coefficient of Determination (R^2 Value), (3) Effect Size F^2, (4) Predictive Relevance Q2 (5) Goodness of Fit of the Model—GoF.

4.6.1 | Structural Model Path Coefficients (Hypotheses Testing)

It is possible to identify the individual impact of an exogenous variable on an endogenous variable by carrying out a slope test. In order to demonstrate that the exogenous variables have a significant influence on the endogenous variables, the *p*-value should be less than 0.05, and the *t*-value should be more than the critical value (C.R), which should be greater than 1.96 [93, 99].

4.6.2 | Coefficient of Determination (R^2 Value)

The coefficient of determination (R^2 value) is the standard method for assessing the quality of a structural model. In order to evaluate how well a model can predict future values for a specific endogenous construct, researchers use a coefficient defined as the square of the correlation between those values and the model's predictions. According to study [100], values of R^2 that are greater than 0.67 are considered to be high; values that fall within the range of 0.33 to 0.67 are considered to be moderate; values that fall within the range of 0.19 to 0.33 are considered to be low; and any R^2 values that are less than 0.19 are deemed unsatisfactory.

4.6.3 | Assessment of Effect Size (F^2)

During the evaluation of the structural model, effect size (F^2), measured by Cohen's, is used to evaluate the impact of a given construct on an endogenous variable (the independent variable). According to the guidelines for evaluating F^2, the value above 0.35 represents large; whereas F^2 ranging from 0.15 to 0.35 are considered medium effect size; whereas F^2 ranging from 0.02 to 0.15 are considered small effect size. The absence of an effect can be inferred from effect size values that are lower than 0.02 [101].

4.6.4 | Assessment of Predictive Relevance (Q^2)

In addition to assessing the magnitude of the R^2 values as a measure of prediction accuracy, researchers should also evaluate Stone-Geisser's Q [2] value [102, 103]. This measure is an indicator of the model's predictive strength or predictive relevance when it is applied to data that is not contained within the sample. We used blindfolding procedures to achieve cross-validity redundancy [101] to assess the model's predictive usefulness. For a cretin's endogenous constructs, the model can be predictively useful if Q^2 is greater than zero, as shown by [93].

4.6.5 | Goodness of Fit of the Model—GoF

As an overall measure of how well a model fits the data, the goodness-of-fit model (GoF), has been developed for use with PLS-SEM. GoF, as described by [104], is the geometric mean of AVE and the average of R^2 of the endogenous variable. The goal of GoF is to provide how suitability of the study model at two levels—the measurement level and the structural level—with focus on the model's performance as a whole [105, 106]. The calculation formula of GoF is as follow:

$$\text{GoF} = \sqrt{\left(R^2 * \text{AVG}\right)}$$

According to [107], a GoF of 0.36 or higher is deemed to be large, while a GoF of 0.25 to 0.36 is considered to be medium, and a GoF of 0.1 to 0.25 is deemed to be small, and a GoF of less than 0.1 is deemed to be a "No fit."

5 | Data Analysis and Results

The results will be provided in this section in such a way that each section of the methodology contains analyses of the results referred to, such that the results are sequenced in a sequential series since each subsequent section depends on the preceding section, and so on.

5.1 | Content Validity

We conducted an evaluation round for content validity between Dec 2021 and Mar 2022. Based on the literature, the approach defines the construct clearly and precisely and provides a novel taxonomy of the construct for this research. Therefore, the round for content validity and questionnaires are provided in Appendices A and B.

Out of the 41 experts identified, only 8 of them responded to the questionnaire and completed the content validity survey. Table 4 contains the basic research-related information of the content validity experts.

A large number of items from previous studies were included, totaling 102 items spread across 10 different constructs. Therefore, these items will need to be reconsidered by experts through

TABLE 4 | Summarizes the experts' basic knowledge in content validity.

No	Designation field	Current profession	Experience
1	Academic	Researcher	> 15
2	Academic/industry	Researcher/software development engineer	> 15
3	Academic	Researcher	11–15
4	Academic	Researcher	> 15
5	Academic/industry	Researcher/software development engineer	3–5
6	Academic	Researcher	> 15
7	Academic/industry	Researcher/software development engineer	> 15
8	Academic/industry	Researcher/software development engineer	> 15

one of two concepts: either rejecting this item altogether or combining it with another item that has a similar concept based on the comment that was provided by experts.

In Table 5 which was used to present the findings of CVR and Mean for the content validity, significant points in accepting, rejecting, or merging items are indicated according to the consensus reached by the eight experts. In the historical data revision construct, combining HDR1 with HDR4 made sense since the two items complement each other and are generally accepted in terms of CVR and mean value. Regarding HDR3 and HDR10 items, they were rejected due to the CVR value being less than 0 (−0.25, −1.00) and the Mean being less than 1.5 (1.3, 0.63) respectively. The CVR value for the ABS8 and ABS10 items in the architectural bad smell construct was found to be less than 0 (−0.50 and − 0.25), and the Mean value was found to be less than 1.5 (1.00 and 1.25) respectively; hence, these items were not accepted.

Concerning the architectural dependency coupling construct which has 22 constructs, the greatest number of any construct, ADC1, ADC3, and ADC5 items were merged into a single item, as well as ADC2, ADC4, and ADC6 were merged into a single item because of how well their complementary concepts meshed and each of which may be considered valid. On the other hand, the values of the items ADC9, ADC10, ADC12, ADC13, ADC14, ADC19, ADC20, and ADC22 showed that the CVR value was found to be less than 0 (−0.25, −0.25, −0.25, −0.25, −0.25, −0.25, −0.50, −0.50) and the Mean value was found to be less than 1.5 (1.25, 1.25, 1.25, 1.25, 1.25, 1.38, 1.13, 1.00), respectively. Therefore, they were removed.

Regarding architecture modularization construct, AM1, AM6, AM7, AM8, AM9 items provided CVR values (−0.25, −0.50, −0.25, −0.25, 0.00) were less than 0 respectively. However, the last value of the AM9 item, which is 0.00, was acceptable; on the contrary, the AM9 item did not meet the Mean value, which is greater than or equal to 1.5 as illustrated in Table 2, whereas the Mean obtained value of the AM9 item is 1.38. In addition, the Mean values of the rest of the items were also less than 1.50 (1.38, 1.00, 1.13,1.25, and 1.38), respectively. As a result, these items were removed from this construct.

Concerning architectural change construct, ACH7 and ACH11 items achieved CVR values that were less than 0, which are −0.25, −0.25, respectively. Moreover, Mean values were found to be less than 1.50, which are 1.25 and 1.13, respectively. In the same context, ACH8, ACH9, and ACH8 items achieved all acceptable CVR values are acceptable which are 0; however, all Mean values of the stated items were found to be less than 1.50, which are 1.38, 1.38, and 1.38, respectively. Conclusively, all stated items were removed as demonstrated in Table 5.

With regard to architectural cohesion and software architecture size constructs, ACO4 item was removed from architectural cohesion since it did not meet the CVR and Mean values found to be less than 0 and 1.5, respectively. While SAZ5, SAZ6, SAZ8, and SAZ9 items were removed from software architecture size for the same reason mentioned above. In relation to the architectural erosion construct, all items were accepted; however, AE7, AE8, AE9, and AE10 items were combined within the AE6 item because they are considered sub-items or have the same concept. This decision was made based on the suggestions and comments of experts in the questionnaire to achieve content validity.

In its final version, the software metrics model for architectural erosion quality consisted of 66 items, grouped into 10 constructs: 7 items for Historical data revision, 9 items for Architectural bad smell, 10 items for Architectural dependency coupling, 7 items for Architectural complexity, 5 items for Architecture modularization, 8 items for Architectural change, 5 items for Architectural technical debt, 4 items for Architectural cohesion, 5 items for Software architecture size, and 6 items for Architectural erosion as illustrated in Table 6.

5.2 | Internal Consistency Reliability

Based on the findings from the content validity analysis, the model was subjected to additional testing to determine its internal consistency reliability using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In this study, a selection of profiles was provided, each of which included a designation, the participant's current profession, and familiar experience with architectural erosion and its measures. The survey was completed by a representative sample of 30 professionals in the field of software engineering; these professionals are directly related to architectural erosion and its measures.

Most of the respondents were from the academic field ($N = 22$, 73%) while the remaining respondents were distributed between industry and a combination of the academic and industry fields simultaneously ($N = 4$, $N = 4$, 13%, 14%), respectively. The current profession of the majority of respondents was researcher ($N = 22$, 73%), followed by software development engineer ($N = 3$, 10%), software development engineer and researcher at the same time ($N = 3$, 10%), product manager ($N = 1$, 4%), and industrial researcher ($N = 1$, 3%). Most respondents had excellent experience of architectural erosion and its metrics, which is more than 15 years ($N = 14$, 47%), followed by between 11–15 and between 6–10 years ($N = 7$, 23%, $N = 7$, 23%), while between 3–5 and 1–2 years ($N = 1$, 4%, $N = 2$, 3%), respectively.

Table 7 presents a summary of the results of the reliability tests conducted on the validated model, including the Cronbach's alpha for each construct, the corrected item-total correlation, and the Cronbach's alpha coefficients if an item was removed. The results of the reliability analysis showed that the internal consistency of the model was satisfactory. The values of Cronbach's alpha computed for the following constructs: Historical data revision ($N = 7$), Architectural bad smell ($N = 9$), Architectural dependency coupling ($N = 10$), Architectural complexity ($N = 7$), Architecture modularization ($N = 5$), Architectural change ($N = 8$), Architectural technical debt ($N = 5$), Architectural cohesion ($N = 4$), and Software architecture size ($N = 5$), as well as architectural erosion ($N = 6$), were 0.874, 0.922, 0.887, 0.854, 0.870, 0.859, 0.942, 0.834, 0.941, and 0.840, respectively. The corrected item-total correlation coefficients for Historical data revision items ranged from 0.532 (HDR1) to 0.805 (HDR7); Architectural bad smell items ranged from 0.443 (ABS1) to 0.892 (ABS8); Architectural dependency coupling items ranged from 0.467 (ADC 10) to 0.690 (ADC7); Architectural complexity items ranged from 0.427 (APC7) to 0.779 (ACP 3); Architecture

TABLE 5 | CVR and Mean results for the content validity.

Construct	Item	CVR	Mean	Status	Construct	Item	CVR	Mean	Status
Historical data revision (HDR)	HDR1	1.00	2.00	Accept	Architecture modularization (AM)	AM1	−0.25	1.38	Reject
	HDR2	1.00	2.00	Accept		AM2	0.75	1.88	Accept
	HDR3	−0.25	1.13	Reject		AM3	0.50	1.75	Accept
	HDR4	0.50	1.63	Accept		AM4	0.25	1.63	Accept
	HDR5	0.75	1.88	Accept		AM5	0.25	1.63	Accept
	HDR6	1.00	2.00	Accept		AM6	−0.50	1.00	Reject
	HDR7	0.25	1.50	Accept		AM7	−0.25	1.13	Reject
	HDR8	0.75	1.88	Accept		AM8	−0.25	1.25	Reject
	HDR9	1.00	2.00	Accept		AM9	0.00	1.38	Reject
	HDR10	−1.00	0.63	Reject		AM10	0.25	1.63	Accept
Architectural bad smell (ABS)	ABS1	0.75	1.88	Accept	Architectural change (ACH)	ACH1	0.75	1.88	Accept
	ABS2	0.75	1.88	Accept		ACH2	0.25	1.50	Accept
	ABS3	0.75	1.75	Accept		ACH3	0.75	1.88	Accept
	ABS4	1.00	2.00	Accept		ACH4	0.50	1.75	Accept
	ABS5	0.75	1.88	Accept		ACH5	0.25	1.63	Accept
	ABS6	0.75	1.75	Accept		ACH6	0.50	1.75	Accept
	ABS7	0.25	1.50	Accept		ACH7	−0.25	1.25	Reject
	ABS8	−0.50	1.00	Reject		ACH8	0.00	1.38	Reject
	ABS9	0.50	1.75	Accept		ACH9	0.00	1.38	Reject
	ABS10	−0.25	1.25	Reject		ACH10	0.00	1.38	Reject
	ABS11	0.25	1.63	Accept		ACH11	−0.25	1.13	Reject
Architectural dependency coupling (ADC)	ADC1	0.50	1.75	Accept		ACH12	0.75	1.88	Accept
	ADC2	0.50	1.75	Accept		ACH13	0.25	1.63	Accept
	ADC3	1.00	2.00	Accept	Architectural technical debt (ATD)	ATD1	0.75	1.88	Accept
	ADC4	1.00	2.00	Accept		ATD2	0.75	1.88	Accept
	ADC5	0.25	1.63	Accept		ATD3	0.50	1.63	Accept
	ADC6	1.00	2.00	Accept		ATD4	0.75	1.88	Accept
	ADC7	0.50	1.63	Accept		ATD5	1.00	2.00	Accept
	ADC8	0.25	1.63	Accept	Architectural cohesion (ACO)	ACO1	0.25	1.50	Accept
	ADC9	−0.25	1.25	Reject		ACO2	1.00	2.00	Accept
	ADC10	−0.25	1.25	Reject		ACO3	0.25	1.50	Accept
	ADC11	0.75	1.88	Accept		ACO4	−0.25	1.00	Reject
	ADC12	−0.25	1.25	Reject		ACO5	0.25	1.63	Accept
	ADC13	−0.25	1.25	Reject	Software architecture size (SAZ)	SAZ1	1.00	2.00	Accept
	ADC14	−0.25	1.25	Reject		SAZ2	0.50	1.63	Accept
	ADC15	0.25	1.63	Accept		SAZ3	1.00	2.00	Accept
	ADC16	0.25	1.63	Accept		SAZ4	0.75	1.88	Accept
	ADC17	0.50	1.75	Accept		SAZ5	−0.50	0.75	Reject
	ADC18	0.50	1.75	Accept		SAZ6	−0.50	1.00	Reject
	ADC19	0.25	1.38	Reject		SAZ7	0.50	1.63	Accept
	ADC20	−0.50	1.13	Reject		SAZ8	−0.25	1.00	Reject
	ADC21	0.50	1.75	Accept		SAZ9	−0.50	0.75	Reject
	ADC22	−0.50	1.00	Reject	Architectural erosion (AE)	AE1	0.75	1.88	Accept
Architectural complexity (ACP)	ACP1	0.75	1.88	Accept		AE2	0.75	1.88	Accept
	ACP2	0.25	1.63	Accept		AE3	0.50	1.63	Accept
	ACP3	0.50	1.63	Accept		AE4	0.50	1.63	Accept
	ACP4	0.25	1.50	Accept		AE5	0.25	1.50	Accept
	ACP5	0.25	1.63	Accept		AE6	1.00	2.00	Accept
	ACP6	1.00	2.00	Accept		AE7	0.75	1.88	Accept
	ACP7	0.50	1.63	Accept		AE8	1.00	2.00	Accept
						AE9	1.00	2.00	Accept
						AE10	1.00	2.00	Accept

TABLE 6 | Outlines adopted items of the final version for the content validity model.

Construct	Original items	Deleted/ merged items	Final version
Historical data revision	10	3	7
Architectural bad smell	11	2	9
Architectural dependency coupling	22	12	10
Architectural complexity	7	—	7
Architecture modularization	10	5	5
Architectural change	13	5	8
Architectural technical debt	5	—	5
Architectural cohesion	5	1	4
Software architecture size	9	4	5
Architectural erosion	10	4	6

modularization items ranged from 0.665 (AM2) to 0.699 (AM4); Architectural change items ranged from 0.440 (ACH5) to 0.742 (ACH1); Architectural technical debt items ranged from 0.780 (ATD4) to 0.897 (ATD3); Architectural cohesion items ranged from 0.586 (ACO4) to 0.753 (ACO3); Software architecture size items ranged from 0.788 (SAZ3) to 0.940 (SAZ4); Architectural erosion items ranged from 0.513 (AE6) to 0.688 (AE1).

5.3 | Measurement Model Assessment

The measurement model is the starting point for evaluating a research model because it determines whether each construct being measured is measured correctly.

Before examining the measurement model, we considered ruling out the common method bias (CMB). VIF values greater than 5 indicate not only severe collinearity but also model contamination with common method bias [93]. The maximum VIF value for any predictor construct was 3.402, as reported in Table 9, ruling out the CMB in our data. As a result, collinearity among predictor constructs is not a critical issue in the measurement model, and we can proceed with the analysis of the findings report.

The measure is said to be reliable when its factor loadings (FL) are above 0.50 [93, 108]. provided a range of factor loadings quality, i.e., excellent (0.71), very good (0.63), good (0.55), fair (0.45) to poor (< 0.32). It was feasible to either remove one of the factor loadings or put a limit on both [109, 110]. In order to improve construct definition in relation to high factor loadings and uncorrelated items, the deletion procedure was chosen as the recommended option [110]. Most of our scale factor' loadings were above 0.53 (see Table 8 and Figure 2), so base for the reliability of our measures was established.

All the constructs' internal consistency reliability was calculated using composite reliability (CR) and Cronbach's alpha (CA). As can be observed in Table 8, the threshold for reliability of the measure is > 0.7 scores of CA for each of the construct [93], thereby estimations met the criteria very well. However, owing to the underestimation problem with CA there is a need of greater estimation of true reliability [93]. Therefore, CR was measured to evaluate the reliability. As shown in Table 8, the model met adequately the acceptable values of CR, i.e., > 0.7 for confirmatory purposes.

In terms of calculating construct convergent validity, average variance explained (AVE) values are used using the previous formula. The AVE results were found to range from 0.507 to 0.707, as summarized in Table 8. The AVE results for each individual indicate that all AVE values are greater than the minimum threshold value (> 0.5). In addition, all constructs satisfy the AVE criteria, indicating convergent validity.

We reached the conclusion that discriminant validity is based on < 0.85, which is a threshold that is used in most studies. Table 9 demonstrates that most of the HTMT values are below 0.85, with a few exceptions that are still below 0.90, such as the value for AE, which is 0.889. This value is considered acceptable, although it is on the higher side of the liberal threshold [93]. With regards to computing the quality of the measurement model by employing the values of communality (H2), all those values were positive for all blocks (as shown in Table 8), ensuring the predictive validity quality of the measurement model.

5.4 | Structural Model Assessment

The assessment of the structural model was critical in continuation with the first step of the research model evaluation. A structural model shows the relationship between constructs and related theories based on existing literature. According to study [93] a large number of characteristics were necessary to evaluate the structural model. This model has only direct effect hypotheses to be tested, i.e., direct effect relationships.

5.4.1 | Hypothesis Testing

The hypothesis on the direct effect was tested using bias-corrected 95% confidence intervals, and the impact of the independent constructs on AE was determined using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. The results of the hypothesis testing and their accompanying interpretations can be viewed in Table 10.

Hypothesis 1 proposed that ACH significantly identifies an occurrence of the AE, results revealed that ACH had a statistically significant impact on AE ($B = 0.172$, $t = 2.866$, $p = 0.004$), hence H1 was supported; Hypothesis 2 postulated that ACO significantly identifies an occurrence of the AE, results showed that ACO had a statistically significant impact on AE ($B = 0.119$,

TABLE 7 | Shows the reliability test results for the validated model.

Construct	Item	Cronbach's alpha if item deleted	Corrected item-total correlation	Construct	Item	Cronbach's alpha if item deleted	Corrected item-total correlation
Historical data revision (HDR) (**0.874**)	HDR1	0.876	0.532	Architecture modularization (AM) (**0.870**)	AM1	0.850	0.667
	HDR2	0.874	0.540		AM2	0.852	0.665
	HDR3	0.857	0.651		AM3	0.843	0.690
	HDR4	0.851	0.689		AM4	0.843	0.699
	HDR5	0.849	0.725		AM5	0.824	0.782
	HDR6	0.846	0.754	Architectural change (ACH) (**0.859**)	ACH1	0.825	0.742
	HDR7	0.842	0.805		ACH2	0.842	0.609
Architectural bad smell (ABS) (**0.922**)	ABS1	0.928	0.443		ACH3	0.836	0.655
	ABS2	0.921	0.626		ACH4	0.854	0.492
	ABS3	0.908	0.799		ACH5	0.859	0.440
	ABS4	0.911	0.749		ACH6	0.836	0.658
	ABS5	0.912	0.740		ACH7	0.839	0.633
	ABS6	0.914	0.697		ACH8	0.843	0.604
	ABS7	0.912	0.740	Architectural technical debt (ATD) (**0.942**)	ATD1	0.928	0.849
	ABS8	0.902	0.892		ATD2	0.924	0.870
	ABS9	0.905	0.834		ATD3	0.919	0.897
Architectural dependency coupling (ADC) (**0.887**)	ADC1	0.884	0.515		ATD4	0.940	0.780
	ADC2	0.881	0.556		ATD5	0.932	0.826
	ADC3	0.877	0.603	Architectural cohesion (ACO) (**0.834**)	ACO1	0.775	0.696
	ADC4	0.880	0.559		ACO2	0.789	0.671
	ADC5	0.879	0.585		ACO3	0.748	0.753
	ADC6	0.874	0.656		ACO4	0.832	0.586
	ADC7	0.872	0.690	Software architecture size (SAZ) (**0.941**)	SAZ1	0.925	0.855
	ADC8	0.872	0.679		SAZ2	0.935	0.800
	ADC9	0.873	0.677		SAZ3	0.938	0.788
	ADC10	0.885	0.467		SAZ4	0.910	0.940
Architectural complexity (ACP) (**0.854**)	ACP1	0.808	0.781		SAZ5	0.930	0.830
	ACP2	0.832	0.638	Architectural erosion (AE) (**0.840**)	AE1	0.800	0.688
	ACP3	0.809	0.779		AE2	0.827	0.549
	ACP4	0.828	0.677		AE3	0.800	0.686
	ACP5	0.853	0.499		AE4	0.817	0.604
	ACP6	0.843	0.552		AE5	0.803	0.672
	ACP7	0.858	0.427		AE6	0.835	0.513

Note: Bold values indicates the items and constructs meet validity and reliability thresholds.

$t = 2.142$, $p = 0.033$), so H2 was supported; Hypothesis 3 anticipated that ADC significantly identifies an occurrence of the AE, analysis findings showed that ADC had also a statistically significant impact on AE ($B = 0.229$, $t = 4.23$, $p < 0.001$), so H3 was also supported; Hypothesis 4 predicted that ACP significantly identifies an occurrence of the AE, results of the analysis revealed that ACP had not a statistically significant impact on AE ($B = 0$ 0.063, $t = 1.067$, $p = 0.286$), therefore H4 was not supported; Hypothesis 5 forecasted that ATD significantly identifies an occurrence of the AE, results exhibited that ATD had not a statistically significant impact AE ($B = 0.05$, $t = 0.869$, $p = 0.385$), so H5 was also not supported; Hypothesis 6 proposed that AM significantly identifies an occurrence of the AE, findings revealed that AM had a statistically significant impact on AE ($B = 0.379$, $t = 6.263$, $p < 0.001$), so H6 was approved; Hypothesis 7 projected that ABS significantly identifies an occurrence of the AE, findings showed that ABS had a statistically significant impact on AE ($B = 0.215$, $t = 3.356$, $p = 0.001$), so H7 was supported; Hypothesis 8 anticipated that HDR significantly identifies an occurrence of the AE, data analysis revealed that HDR a statistically significant impact on AE ($B = 0.152$, $t = 3.313$, $p = 0.001$), so H8 was also supported; Hypothesis 9 estimated that SAZ significantly identifies an occurrence of the AE, findings exhibited that

TABLE 8 | Presents the results of the reliability, validity, and quality of measurement assessment for the model.

Construct	Item	Factor loading (FL)	Cronbach's alpha (CA)	Composite reliability (CR)	AVE	VIF	H2
HDR	HDR1	0.71	0.855	0.888	0.533	1.680	0.371
	HDR2	0.60					
	HDR3	0.69					
	HDR4	0.73					
	HDR5	0.78					
	HDR6	0.76					
	HDR7	0.81					
ABS	ABS1	0.58	0.876	0.901	0.507	3.396	0.381
	ABS2	0.69					
	ABS3	0.70					
	ABS4	0.76					
	ABS5	0.59					
	ABS6	0.73					
	ABS7	0.78					
	ABS8	0.74					
	ABS9	0.81					
ADC	ADC1	0.53	0.891	0.911	0.512	1.530	0.393
	ADC2	0.76					
	ADC3	0.74					
	ADC4	0.72					
	ADC5	0.58					
	ADC6	0.71					
	ADC7	0.70					
	ADC8	0.80					
	ADC9	0.90					
	ADC10	0.66					
ACP	ACP1	0.81	0.859	0.887	0.531	1.621	0.378
	ACP2	0.69					
	ACP3	0.76					
	ACP4	0.75					
	ACP5	0.72					
	ACP6	0.74					
	ACP7	0.61					
AM	AM1	0.74	0.804	0.864	0.560	3.307	0.337
	AM2	0.75					
	AM3	0.76					
	AM4	0.74					
	AM5	0.76					

(Continues)

SAZ a statistically significant impact on AE ($B = -0.196$, $t = 4.11$, $p < 0.001$), so H9 was approved.

Based on the empirical evidence, it can be concluded that ACH, ACO, ADC, AM, ABS, HDR, and SAZ have the most significant influence on the identification of the AE construct, as shown in Figure 3. However, the effect of ACP and ATD is not statistically significant, as indicated by the non-significant p-value. Therefore, it is recommended to remove ACP and ATD from the structural model.

TABLE 8 | (Continued)

Construct	Item	Factor loading (FL)	Cronbach's alpha (CA)	Composite reliability (CR)	AVE	VIF	H2
ACH	ACH1	0.71	0.862	0.892	0.509	3.402	0.362
	ACH2	0.70					
	ACH3	0.74					
	ACH4	0.67					
	ACH5	0.66					
	ACH6	0.74					
	ACH7	0.76					
	ACH8	0.72					
ATD	ATD1	0.90	0.882	0.893	0.627	1.109	0.434
	ATD2	0.81					
	ATD3	0.75					
	ATD4	0.73					
	ATD5	0.77					
ACO	ACO1	0.76	0.798	0.868	0.623	2.301	0.375
	ACO2	0.83					
	ACO3	0.83					
	ACO4	0.72					
SAZ	SAZ1	0.85	0.896	0.923	0.707	1.808	0.555
	SAZ2	0.84					
	SAZ3	0.83					
	SAZ4	0.79					
	SAZ5	0.89					
AE	AE1	0.75	0.859	0.895	0.587	1.000	0.419
	AE2	0.73					
	AE3	0.75					
	AE4	0.76					
	AE5	0.81					
	AE6	0.78					

5.4.2 | Coefficient of Determination (R^2)

Model accuracy is measured by R^2. This metric illustrates how much endogenous (dependent) variance is accounted for by exogenous constructs. In order to calculate the value of R2 that is associated with the dependent constructions, Smart PLS was utilized. According to the findings, the total R^2 predicted for CCCU was 0.819, which indicates that approximately 81.9% of the variance in identifying AE is explained by its independent components (i.e., ACH, ACO, ADC, AM, HDR, ABS, ACP, ATD, and SAZ). As a result, the value of R^2 is regarded to be high because it is greater than 0.67, as suggested by [100].

5.4.3 | Assessment of Effect Size (F^2)

In accordance with the classification approach proposed by [101] and the approach proposed by [93], Table 11 shows that, in the context of the constructs impacting the identification of AE, ADC and AM were ascertained to have a medium effect size. Concurrently, it was determined that the effect sizes for ACH, ACO, ABS, HDR, and SAZ were all small, while the remaining constructs, which are ACP and ATD, had a no effect size.

5.4.4 | Assessment of Predictive Relevance (Q^2)

If the value of Q^2 is more than zero, the model is said to have the potential to have predictive relevance for a certain endogenous component, as stated by [93]. The value of Q^2 corresponding to the endogenous constructs (i.e., AE) is 0.446; thus, this demonstrates that the model possesses the required predictive relevance.

5.4.5 | Goodness of Fit of the Model–GoF

Combining effect size and convergent validity is how the GOF is measured [104] and the allowable range for this measurement is 0 to 1. GOF value was well-accepted, whereas the obtained value is 0.693. This value is considered to be large, as stated by [107]

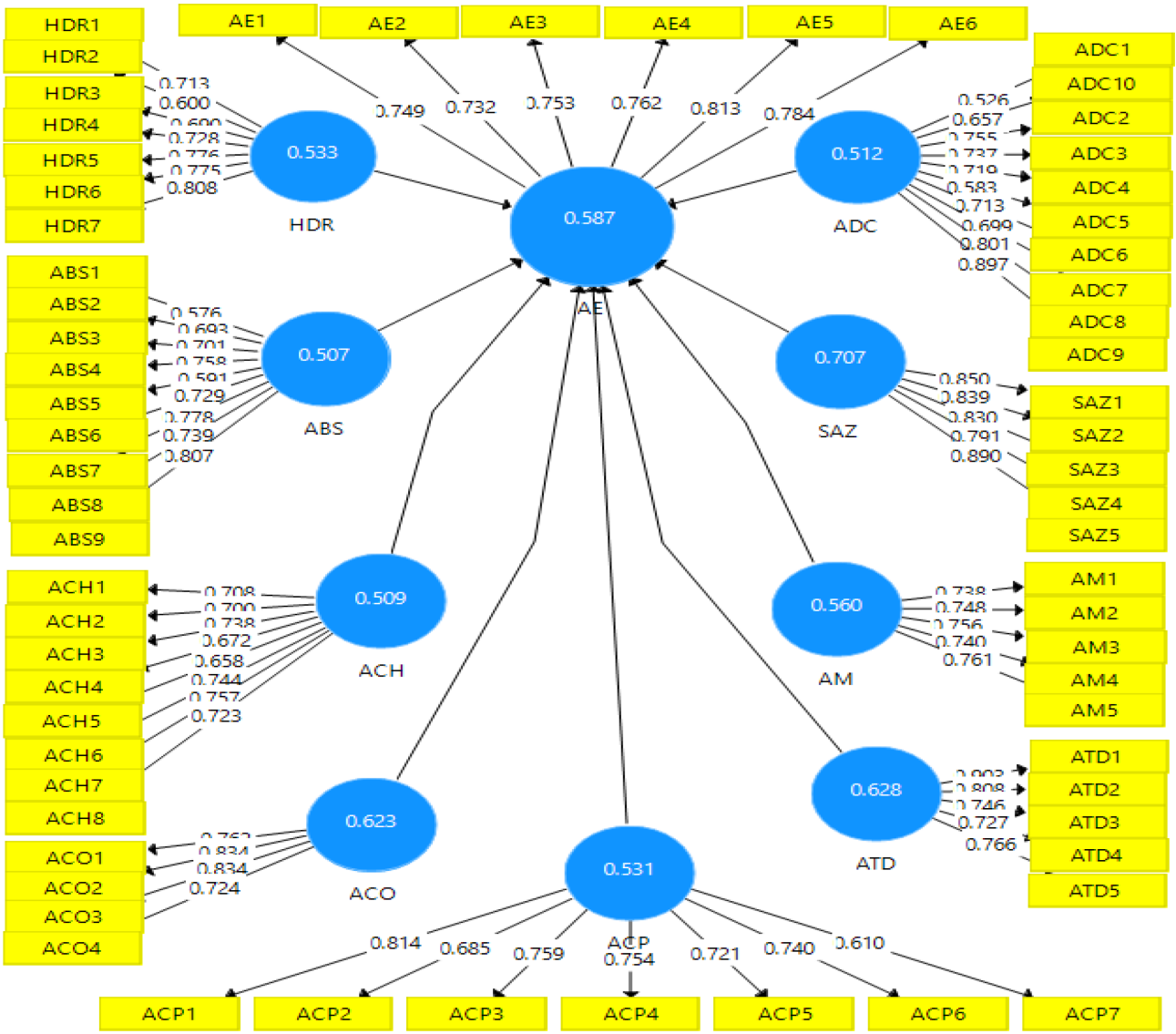

FIGURE 2 | Measurement model of architectural erosion.

TABLE 9 | Shows the results of the discriminant validity analysis using HTMT ratios.

Item	ABS	ACH	ACO	ACP	ADC	AE	AM	ATD	HDR	SAZ
ABS										
ACH	0.812									
ACO	0.588	0.832								
ACP	0.528	0.417	0.377							
ADC	0.204	0.308	0.128	0.274						
AE	0.872	0.843	0.758	0.352	0.34					
AM	0.868	0.664	0.631	0.511	0.179	0.889				
ATD	0.139	0.184	0.285	0.19	0.108	0.157	0.136			
HDR	0.567	0.575	0.405	0.588	0.141	0.402	0.522	0.177		
SAZ	0.504	0.519	0.553	0.182	0.246	0.739	0.659	0.099	0.382	

TABLE 10 | Findings of the hypothesis tests.

Hypo	Path	Std. beta	Std. error	*T*-value	*p*-value	Decision
H1	ACH → AE	0.172	0.065	2.866	0.004	Supported**
H2	ACO → AE	0.119	0.057	2.142	0.033	Supported*
H3	ADC → AE	0.229	0.054	4.23	0.000	Supported**
H4	ACP → AE	0.063	0.060	1.067	0.286	Not Supported
H5	ATD → AE	0.05	0.058	0.869	0.385	Not Supported
H6	AM → AE	0.379	0.068	6.263	0.000	Supported**
H7	ABS → AE	0.215	0.066	3.356	0.001	Supported**
H8	HDR → AE	0.152	0.050	3.313	0.001	Supported**
H9	SAZ → AE	−0.196	0.047	4.11	0.000	Supported**

Note: Significant level at $p^{**} < 0.01$, $p^{*} < 0.05$.

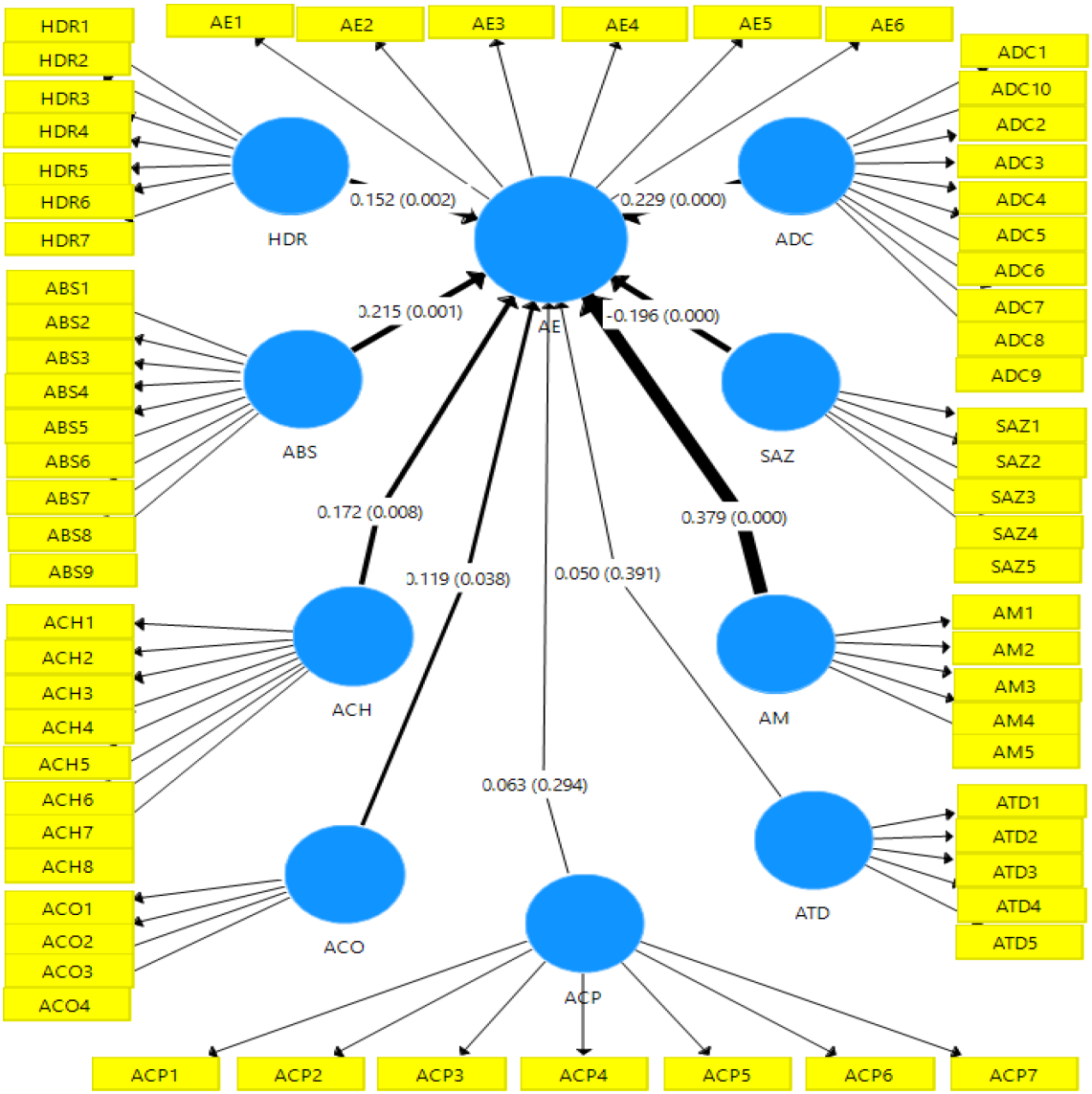

FIGURE 3 | The findings of the structural model's evaluation for architectural erosion.

when above 0.36. Consequently, the overall fitness of the structural model was demonstrated to be confirmed by the findings of this investigation. Moreover, multicollinearity for the structural model was also assessed. VIF values beyond 5 are an indication of collinearity [93]; the inner VIF value, which is 3.402, showed that the structural model was well fitted. Figures in the

TABLE 11 | The results of effect (F^2).

Construct	F^2	Effect size status
ACH	0.048	Small
ACO	0.034	Small
ADC	0.189	Medium
ACP	0.013	No effect
ATD	0.012	No effect
AM	0.240	Medium
ABS	0.075	Small
HDR	0.076	Small
SAZ	0.117	Small

Supporting Information provide a detailed structural model with or without architectural technical debt and complexity constructs.

6 | Discussion

In this section, the most important results obtained will be dealt with, analyzed, and discussed, and the implications of the importance of the results will be clarified in terms of their division. In addition, some recommendations will be presented in order to identify future research directions in relation to this domain.

6.1 | Instrument Validity and Reliability

After the preliminary work on the software metrics model for architectural erosion that was published in [13]. This idea was originally created using a set of 92 metrics representing 10 quality factors for monitoring architectural erosion. Each metric practice was assigned to one of the metric approaches (10, 11, 22, 7, 10, 13, 5, 5, and 9) items for Historical data revision, Architectural bad smell, Architectural dependency coupling, Architectural complexity, Architecture modularization, Architectural change, Architectural technical Debt, Architectural cohesion, and Software architecture size, respectively.

Following a strict methodology, including a content validity evaluation process and a reliability analysis, the model was fine-tuned. Experts provided feedback during the content validity round, suggesting answers and comments that would help refine the language used and explicitly declare the convergence of some metrics and their refinement into a single concept that explains the extent of its strong significance through the various definitions of some items. This is what provides a considerable explanation for the integration of many convergent items in an abstract idea to recognize a concept that aims for the coherence of a unified definition. It should be noted that many of the metrics items were proposed by several researchers. These same items are used in more than one study, each time with a concept that is quite different from the one used in the other study. As a consequence of this, a large number of metrics were commonly used among the researchers based on the unified understanding of the study's authors. Thus, this model provides an initial contributory perception that can be utilized to establish and refine the metrics of unified significance under the classification or appropriate approach for identifying architectural erosion.

In historical data revision construct, HDR1 and HDR4 items were combined to form one coherent concept, while the HDR3 and HDR10 items were deleted because the required criteria were not met. It is also noticeable in architectural dependence coupling construct that it has the most items of any of the others. However, six of these items are so similar in definition—each one converges with another in the same concept—that they could be reduced to only three. On the other hand, eight other items of this construct were eliminated since they did not fulfill the requirements. A similar observation holds true when we examined the architectural erosion construct; we found five items—AE6, AE7, AE8, AE9, and AE10—present a convergent concept that is essentially one. This is probably because past research and expert judgement have concluded that all of these things represent only a single concept. This led to their consolidation into a single concept, which satisfies all the necessary criteria. The rest of the other constructs are only included in the removal of some items due to the failure to meet these criteria. Notably, the content validation was adopted in the first round and subsequently passed to the same experts, with no changes made to the path taken in the adopted round. It would be inappropriate to proceed with another round using the same items and evaluation criteria [111].

As soon as the agreement was established on the model's content validity, an additional round was included to investigate the items' and construct's internal consistency reliability. Researchers with backgrounds in software engineering were asked to evaluate items on the constructs again, using a 5-point Likert scale. In this context, the reliability, as determined by Cronbach's alpha, is evidence that the items represent the constructs in a consistent manner. All the items per each construct indicate none of them significantly reduced the value of the alpha coefficient if they were removed from the construct, except for HDR1, ABS1, and ACP7 items; their values increased from 0.874 to 0.876, 0.922 to 0.928, and 0.854 to 0.858, respectively. However, increasing the value of these items is a minor change that will have no effect on the items and their constructs, especially since these values represent the study's initial sample. Furthermore, even though these are the least closely related items, their corrected item-total correlation is high, and these values are greater than the specified value of 0.2. Therefore, the resulting value indicates that the model has high reliability.

6.2 | Measurement Model Assessment

When conducting an analysis of a research model, the first thing that has to be done is to take into consideration the measurement model assessment. This is because the measurement model is the one that decides whether or not each construct being tested is being correctly assessed. In this respect, the findings indicated that the quality of the predictive validity of the measurement model was ensured, which was based on the criteria that were decided to be investigated in order to evaluate this model. This explains that examining the content in terms of formulating items and categorizing them within the appropriate construct and reconsidering the concepts in a comprehensive and investigative manner, in addition to the consistency of reliability, has

provided a strong indication of the coherence and ensuring the predictive power of the model in terms of constructs and their items.

In connection with the results obtained, the model was passed on the criteria, as the measuring factor loading should be at least 0.50 as stated by [93, 108] in order to be reliable. Most of our scale factor loadings were above 0.53; thereby, every item must have at least this value to be considered for preservation. Hence, it's important that this number be as high as possible. Composite reliability (CR) revealed that internal consistency reliability the threshold for the reliability of the measure is > 0.7 which is a greater estimation of true reliability than Cronbach's alpha (CA). Whether the values are Composite reliability (CR) or for Cronbach's alpha (CA), they all achieve the required value; thereby, it could be that the concept of reliability presents as an indication that has a significant impact when two terms work with each other to produce the same results with high consideration. Furthermore, all constructs and items that meet AVE criteria and HTMT values for predictability in the measurement model were shown to have evidence of convergent and discriminant validity.

6.3 | Structural Model Assessment

In this perspective, hypotheses were established to test the possibility of a relationship between classifications of various metrics approaches and architectural erosion. The hypotheses were empirically tested to determine whether the categorization of metrics approaches significantly identifies architectural erosion. The results of the evaluation of the structural model show that all classifications of various metrics approaches significantly identify architectural erosion except for architectural complexity (ACP) and architectural technical debt (ATD).

We observed empirical evidence for ACH significantly identifying an occurrence of the AE based on the obtained result ($B = 0.172$, $t = 2.866$, $p < 0.004$, $F2 = 0.048$); hypothesis H1 can be accepted. This demonstrates that ACH is considered to be a crucial stage in the process of architectural tactics and knowledge analysis [112], which aims to predict problems in a software system using metrics that can identify architectural deterioration [19, 113]. In addition to this, assessing architectural change can provide clues as to the presence of flaws [32], as well as information regarding the connection between architecture change, deterioration, and the manifestation of vulnerabilities [27]. In the same context, as a consequence of the fact that the ACO and ADC significantly detect an occurrence of the AE ($B = 0.119$, $t = 2.142$, $p < 0.033$, $F2 = 0.034$; $B = 0.229$, $t = 4.23$, $p < 0.001$, F [2] = 0.189, respectively), Hypotheses 2 and 3 were able to be accepted as valid hypotheses. This agrees with the findings of the architectural cohesion and coupling analysis [15, 31], and it is a major approach to identifying architectural inconsistency by analyzing system releases based on the degree of coherence and dependency coupling between the modules, packages, or classes. Focusing on Hypothesis 6, the introduced satisfied results in terms of identifying an occurrence of the AE ($B = 0.379$, $t = 6.263$, $p < 001$, $F2 = 0.238$). Therefore, the findings of the correlation between AM and the emergence of AE are consistent with the observations by [114]; besides, modularization metrics provide a better representation picture for fault prediction, design flaw detection, identifying source code anomalies, and architectural degradation [115], as well as improving architecture [116] with regard to the analysis of faults and changes that could be isolated and separated. Moreover, the results regarding the relationship between ABS and the occurrence of AE ($B = 0.215$, $t = 3.356$, $p = 0.001$, $F2 = 0.075$) are consistent with the analysis and examination of the various studies on architectural smells and their relationship to determine the presence of architectural erosion [55, 56, 59, 60, 117] and instability in order to identify hidden defects in software architecture [118]. Concerning Hypothesis 8, it was determined that it statistically indicates an occurrence of the AE ($B = 0.152$, $t = 3.313$, $p < 0.001$, $F2 = 0.074$). This provides significant evidence supporting the hypothesis, which is in line with research showing that historical metrics may automatically discover violations of design principles [34], high-performance forecasting of low architectural quality (i.e., architectural erosion) in architectural modules, and even in the case of rapid decay [19]; estimation of severity based on the analysis of change over time [37], as well as historical metrics for assessing and forecasting architecture quality condition [36].

Specifically, Hypothesis 9 exhibited SAZ findings in terms of identification of AE ($B = -0.196$, $t = 4.11$, $p < 0.00$, $F2 = 0.117$) which significantly impacts. Mostly since the hypotheses were looking at both sides in terms of determining the erosion, rather than the effect. The appearance of size metrics with a negative determination does not necessarily imply that using such metrics would be useless. As a result, many studies [15, 31, 47, 50] have pointed out the significance of studying the metrics of architecture size from this perspective, suggesting that these metrics may be reached in the study of the size of architecture with other measurements of another classification (e.g., cohesion or coupling metrics) or analysis of the negative side of erosion in terms of effect.

According to the empirical results of Hypotheses 4 and 5, the findings showed no significant identification on AE ($B = 0.063$, $t = 1.067$, $p < 0.286$, $F2 = 0.013$; $B = 0.05$, $t = 0.869$, $p < 0.385$, $F2 = 0.012$), respectively. Hence, the Hypothesis 5 which is ATD, was not supported [15]. indicated that ATD metrics are not appropriate to identify architectural inconsistencies. In contrast [119], indicated that bad code smells contribute to technical debt. Code smell correlates more with technical debt than architectural degradation. Few studies include architectural degradation and code smell, suggesting it is linked to technical debt. Therefore, this observation demands further investigation and consideration.

The quality of the output of the structural model suggests that the predictive quality, which was measured by Q2, R2, and goodness of fit (GOF), is well-accepted. Furthermore, the values of Q2, R2, and GOF are regarded as high, which confirms the overall fitness of our structural model. This reveals a general observation of these results that all classifications of metrics approaches have a statistically significant relationship for identifying architectural erosion, except for the ATD and ACP approaches, which were not statistically supported. In the same line, it would be wonderful to see an initiative taken to empirically analyze this relation within the context of an independent study. This would be a terrific step forward. As a consequence of this, the study model can be utilized for the purpose of recognizing the context of architectural erosion.

7 | Practical Implications

The research provides a range of practical implications, which are extensively elaborated upon in the following sections.

7.1 | Implications for Researchers

The empirical findings of this study provide valuable assistance to researchers by providing a deeper understanding of the relationship between architectural erosion and approaches of software metrics. Moreover, the model contributes to a structured analysis of different metrics approaches (e.g., architectural change, dependency coupling, bad smells), providing researchers with a comprehensive basis for further empirical studies. By providing validated metrics and a clear taxonomy of approaches, this work facilitates reproducible and comparative research in detecting and addressing architectural erosion.

The study highlights the importance of architectural smells as diagnostic tools for assessing software design quality and detecting potential issues early. By focusing on architectural smells independently, researchers gain a clearer understanding of their impact without conflating them with broader concepts such as architectural technical debt. Despite variations in definitions, the findings enable researchers to systematically investigate architectural smells as early indicators of architectural erosion. This separation allows for more targeted studies that can uncover relationships between architectural issues and the long-term health of software systems.

7.2 | Implications for Practitioners

For practitioners, the findings serve as actionable guidance for prioritizing mitigation strategies in software systems and help to understand the relationship between architectural erosion and approaches to software metrics. In the same context, architectural smells, as identified in this study, can act as early warning signs for potential architectural erosion. By addressing these smells proactively, practitioners can mitigate their evolution into significant technical debt, thereby reducing long-term maintenance costs and ensuring system stability. The results offer practical insights into the relative importance of various metrics-based approaches. Practitioners can utilize the validated model to:

- Identify and prioritize architectural smells most likely to degrade system performance.
- Focus efforts on metrics approaches (e.g., dependency coupling, modularization) with significant impacts on architectural erosion.
- Implement targeted strategies to improve architectural design quality and prevent long-term erosion.

Moreover, instead of assessing all the adopted approaches of measures and all quality attributes, the developed model prioritizes crucial measure approaches and quality attributes linked to architectural erosion, making it easier for these stakeholders to identify erosion points and conduct effective control assessments.

8 | Threats to Validity of the Study

This section discusses the four key threats to the validity, which are described [120, 121] in this study, and the mitigation proposed to deal with them is below.

8.1 | Threats to External Validity

The ability of the researchers to generalize the findings of academic research to applications in the industry is one of the factors that contribute to the study's external validity [120]. The number of respondents in this study should be deemed a sufficient sample size for the SEM analysis [122]. Although this number of people that participated in the survey could lead to potential criticism of this study for having limited generalizability, the model is simple and the sample of the target population is restricted to specific experts around the world, as well as target respondents have a variety of academic and industrial backgrounds and experiences from different countries.

8.2 | Threats to Internal Validity

Internal validity lies in the extent to which the independent factors that influence or cause a change in the dependent factors are determined [121]. One of the most important limitations in this study is the extent to which different metrics approaches (independent variables) are selected within an appropriate classification and the extent to which they are able to determine architectural erosion. It is acknowledged that there may be alternative approaches for assessing architectural erosion; however, this study is limited to metric-based approaches that have been demonstrated to be the most popular solutions in the field. The findings of relevant studies were analyzed to categorize these approaches into relevant classifications and provide a clear understanding of architectural erosion.

8.3 | Threats to Construct Validity

The concept of construct validity is concerned with the degree to which there exists a gap between the theoretical depiction of a concept and its practical use [123]. One of the most significant limitations that poses a threat to the construct's validity and reliability is the self-selection bias for respondents chosen. In the current investigation, the potential for concerns was addressed by identifying the most suitable experts and engaging with them through a comprehensive mapping study process. The goal was to present the actual picture of the concepts in a manner that was correct and accurate based on the knowledge and experience that the experts possess in the relevant field of work. Another threat to this validity is the collection of metrics and their association within specific approaches categories. To mitigate this threat, the metrics used in the study are widely used and well established in the literature. Thus, they accurately represent the concepts they propose to measure. Furthermore, the specified metrics represent all the concepts and approaches to these categories, as well as experts agreed these categories at the stage of the content validity and reliability.

8.4 | Threats to Conclusion Validity

The ability to draw a correct and legitimate conclusion about a connection between independent variables provided by the experiment (dependent variable) resulting from it is what is being evaluated by the concept of conclusion validity [121]. According to [93], VIF values should be less than 5, so we excluded common method bias (CMB) by ensuring that no predictor variable had a VIF of more than 3.402, as shown in Table 8. Another limitation of this study is the use of immature subjects, which may represent a significant threat to conclusion validity. However, our study's representative sample was comprised of professionals working on this topic, whether they belong to academic or industry fields.

9 | Conclusions and Future Research

The comprehension of the significant metrics approaches and practices in the identification of architectural erosion context and the identification of the key quality attributes associated with architecture degradation is an opportunity to deepen knowledge of erosion and generate additional discussions on the topic. Since the primary objective of the study is to develop a model with the aim of assessing and classifying the metrics within the earlier approaches that have been used in studies to recognize architectural degradation. Furthermore, it is possible to consider this work to be the first one of its kind, to the best of the authors' knowledge, to build a theoretical model of metric approaches classification for architectural erosion that has been validated and is reliable. To evaluate this model from an initial conceptualization perspective, instrument content validity and reliability testing were used. A questionnaire-based survey was used to collect data from 130 software engineering professionals with experience in architecture erosion and software metrics. After several steps are achieved in terms of measurement and structural mode, the needed model fit, reliability, and validity were attained. The findings revealed that there is a significant relationship between all the classifications of metrics approaches and architectural erosion, with the exception of architectural complexity and architectural technical debt.

During this research, various concepts and improvements were considered as potential directions for future work. Specifically, the focus was on established metrics and quality attributes for monitoring architectural erosion, based on systematic mapping studies. This study was limited to the investigation of these approaches. The authors of this work do not intend to imply, however, that these approaches of established metrics and quality attributes of monitoring degradation associated with architectural erosion are unique. As a result, further study is needed to fully broaden the model's scope to include many different perspectives. Second, although this study introduced an empirical report on each classification of metrics approaches on the identification of the architectural erosion, it did not consider the identification of each classification of metrics approaches on each quality attribute of architectural erosion. In subsequent research, it may be possible to investigate these relationships, for instance, the measures of architectural complexity approach for the identification of usability (e.g., understandability attribute) (as one of the indicators of monitoring architecture degradation) In addition, despite the fact that the measures of architectural complexity approach (external change) for determining architectural erosion was not statistically supported in this study, it would be interesting to see if there was an initiative to empirically investigate the relationships between the measures of architectural complexity approach and the identification of architectural erosion independently. Third, on the other hand, according to an analysis of the systems utilized in the previous studies, monolithic architecture is one of these measures that is most frequently used. This demonstrates to developers and architects that this model is appropriate for systems based on monolithic architecture; however, applying this model to another architecture may result in inconsistent outputs (e.g., the microservice architecture). From this point, researchers have a great opportunity to do an additional empirical study based on a combination of system contexts with different architectural patterns, with the goal of finding a solution to this issue. A case study will be conducted to empirically validate our model in practical settings, providing evidence of its effectiveness in future planning.

Author Contributions

Ahmed Baabad Conceived the study idea, conducted literature review, developed the research model, designed the methodology, collected and analyzed the data, and wrote the initial draft. **Hazura Binti Zulzalil** Supervised the research, contributed to model refinement, provided critical review of the methodology, and guided data analysis and result interpretation. **Sa'adah Hassan** Assisted in refining the research instrument, contributed to data collection strategy, participated in reviewing the final manuscript. **Salmi Binti Baharom** Supported statistical analysis validation, helped in interpreting results, and contributed to finalizing the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.