

Proposed Data Quality Evaluation Method for a Transportation Agency

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Abstract

The data quality evaluation is essential towards designing a data assessment method for any company because data is an important asset. Therefore, the purpose of this study is to develop the data quality evaluation method for a transportation agency in Malaysia in order to quantify the quality of data in the SIKAP licensing system. This can benefit the transportation agency to improve the quality of data for the use of reporting, forecasting business operations and data integration with other agency's systems. The relevant data evaluation dimensions have been identified from literature study and relative data evaluation framework which are necessarily required by the transportation agency to maintain high data quality in the SIKAP system. The process design for the proposed method involves data dimension identification, capturing the relevant database structure, subjective evaluation with a questionnaire and objective evaluation with data profiling. From the design process, the result shows that data evaluation method for a transportation agency must have a minimum of six data quality dimensions. SIKAP, the legacy system is in the process to revamp into a new system. Thus, this research contributes to enhance the current system's data quality during revamping process and data migration into the new system.

Keywords: Data Quality; Data Dimension; Data Profiling; Evaluation; Transportation System

1. Introduction

Data is an important asset to any agency. It is defined as "stored representations of objects and events that have meaning and importance in the users' environment". It is also called as information, that is, "data that have been processed in such a way as to increase the knowledge of the person who uses the data" [1]. However, data is meaningless when there is no quality. One of the most widespread definitions of data quality states that data are of high quality "if they are fit for their intended uses in operations, decision making and planning" [2]. There is an excessive concern about the quality of corporate data. Poor data have many impacts, for example on operations (i.e., causing customer and employee dissatisfaction and increased costs); tactical (i.e., affecting decision making and causing mistrust), and strategic (i.e., affecting the overall organization's strategy) [3]. Thus, it is important to identify the degree of data quality for the purpose of successful business in any agency.

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According to [4], three main attributes from a total of 49 are frequently used to describe data quality; completeness, accuracy and timeliness. The other criteria of these attributes are consistency, accessibility, relevance, up-datedness, validity, periodicity, reliability, precision, integrity and confidentiality [4]. No matter how efficient the process of data entry, errors will still occur, for example, data redundancy, misspelling and others. Gartner survey in 2015 on the usage and adoption of data quality tools revealed that the respondents estimated a loss of \$8.8 million in average annually due to the data quality issues. Nevertheless, IBM estimated that the annual cost of poor quality data to business is 3.1 trillion dollars in the US for 2016. Poor data definitely have many impacts towards an organization, such as incoherent management and operational reporting [3]. Thus, all agencies need to adopt data quality evaluation method to ensure the data is accurate and fit their use.

In a transportation agency, high-quality data is crucial for accessing the latest information, better decision-making and policy planning. SPAD (Suruhanjaya Pengangkutan Awam Darat) that is the Land Public Transport Commission is a transportation agency in Malaysia that owns commercial data of vehicles such as taxis, buses, lorries, licenses, operators and enforcement. SIKAP (Sistem Perlesenan Kenderaan Perdagangan), the Driver Safety Practice System is the main operational function in SPAD that process and stores data of vehicles, licenses, permits and enforcement cases. These data are used for dashboard reporting by the operation and management team and other agencies that are integrated into this transportation organization. Research shows that data quality issues in transportation utilize three attributes of data quality that are related to data archiving; suspect or erroneous data, missing data, and data accuracy [5]. In another study, from the analysis of TransGuide data, missing data has accounted for about 25 percent of the overall data quality records [5]. The availability and integrity of data also have important implications for decision making for transportation planning models, infrastructure maintenance, the asset management and to develop models for service regulation [6]. We found that there are data quality issues such as data redundancy, data misspelling and missing value occurs in the SIKAP system. Therefore, there is a need to build data quality evaluation method that is suitable and meets the transportation agency's requirements. The aim of this research is to propose data quality evaluation method for SIKAP system in a transportation agency. This paper is organized into four sections. The next section describes the previous studies related to this research. Section 3 describes the proposed data quality evaluation method and followed by conclusion in section 4.

2. Literature Review

2.1 Data Quality

Data quality is an assessment of data's fitness and its purpose to serve in a given context. Data with high quality should represent the real-world entities accurately in the structure, and fit for their intended use in operations, planning and decision making [7]. According to quality management, data quality is important to meet users' or customers' needs [3, 8]. Data quality is aimed to be measured quantitatively [7]. The attributes of data quality can be classified into two types; high data quality and poor data quality [4]. In business, data quality is measured to determine whether data can be used as a basis for reliable business intelligence and for organizational decisions. Thus, the organization should measure their data whether data is fit for use for business purposes. Based on our study [2, 3, 7] the attributes that define high and poor data quality is as shown in Table 1.

Table 1: Attributes of data quality

Item	Attributes
High data quality	Completeness, accuracy or positional accuracy, timeliness or up-datedness or currency, validity, periodicity, relevance, reliability, precision, integrity, confidentiality or data security, comparability, consistency or internal consistency or external consistency, concordance, granularity, repeatability, readily useable or usability or utility, objectivity, ease with understanding, importance, reflecting actual sample, meeting data standards, use of standards, accessibility, transparency, representativeness, disaggregation.
Poor data quality	Missing data, under-reporting, inconsistencies, data errors or calculation errors or errors in report forms or errors resulted from data entry, invalid data, illegible handwriting, non-standardization of vocabulary, and inappropriate fields.

2.2 Data Quality Dimension

In order to achieve data quality that suits users, customers and business needs, the data should follow a dimension or combination of multiple dimensions. A dimension is a measurable data quality property that can be used to guide the process of valuing the quality [3]. Moreover, dimensions are sometimes referred to as attributes or characteristics. The four major data quality dimension components that are critical to the data improvement process are accuracy, completeness, consistency and timeliness [9]. Based on seminal work that has been gathered from data consumers, data quality dimensions are classified into four categories that are intrinsic (accuracy, believability, objectivity and reputation), contextual (appropriate amount, completeness, relevancy, value-added and timeliness), representational (concise, understandable, interpretability, consistency) and accessibility (access security). According to [10], Redman classifies data quality dimensions into data values and data format. Data value dimensions refer specifically to values and the independent ability of the internal representation of data such as accuracy, completeness, currency and consistency. As for data format, information that meets certain criteria, for example, ability to interpret correctly, format that can be applied in various situation and also that can be changed easily are categorized as appropriateness, interpretability, portability, format precision, format flexibility, ability to represent null values, efficient use of memory and representation consistency.

There are a lot of data quality dimensions that have been defined by the researchers. Chen et al. [7] proposed five important metrics of qualities for transportation field. They are accuracy, thematic accuracy, logical consistency, completeness and lineage. A. Barbero [6] proposed to promote data quality that focuses on verification of data accuracy, precision, completeness, timeliness, and integrity for transportation sectors. Ahn *et al.* [5] proposed fundamental measures that should be universally considered for measuring data quality of traffic sensor data such as accuracy, completeness, validity, timeliness, coverage and accessibility. There are other data quality measures that could be appropriate such as relevancy, consistency of presentation, reliability for traveller information services. Staron & Scandariato [11] define data quality dimensions for the intelligent transportation system. The dimension requires characteristics such as precision, completeness, provenance, free from error and objectivity and freshness. Data that are required for sustainable transportation indicators can be collected using some statistics; consistent definitions and meet the minimum data quality standards which refer to accuracy, transparency, comprehensiveness, frequency, consistency and availability [12]. Since data quality dimension is subject to the need and

requirement of the organization, they have to choose the suitable dimensions accordingly to define the metrics for data quality evaluation.

2.3 Data Quality Problems in Transportation

The transport sector encompasses the movements of people and goods through different modes (e.g. road, rail, or air,) at the urban, intercity and international scale. The availability and quality of transport-related data are important for decision making in the public sector. Data also a prerequisite for private-sector firms making strategic and operational decisions about production, marketing or shipment of goods, or the movement of passengers, as well as by their respective chains of suppliers. The common data problems in transportation that have been identified by the study comprise of three attributes of data quality that are relevant to Intelligent Transportation System (ITS) data archiving; suspect or erroneous data, missing data, and data accuracy [5]. Intelligent Transportation Systems rely on the availability of high-quality data to make correct decisions in diverse traffic situations [11]. The data quality problem that happened in intelligent transportation is an erroneous addressing of data in the databases thus the faulty output of decision algorithms. Data quality problems that faced by the transportation such erroneous data, missing data and data accuracy are serious problems that will affect the operation and cause customer dissatisfaction.

Data managed at the local-level creates another problem for the organization to maintain data. Information silos are one of the problems produced by managing data at the local level [13]. Lee *et al.*[13] have mentioned that information silos occur in many organizations, which produces a problem like inconsistency of the data definition, format and data values. Besides, operational cost such as excess labour costs, assessment costs, data re-input costs and process failure costs might rise due to poor data detection and correction[14]. These tasks must be conducted by organization especially when the daily business involves crucial data that needs to be used by decision-makers and top management to choose the best path for their company future growth. In order to build trust, poor data should be avoided or treated otherwise an organization will receive bad perception from their customers, partners and difficult to build trust for the future business dealings.

2.4 Data Quality Assessment

The data should be assessed to evaluate the quality and importance of information in an organization. Data quality assessment is the scientific process and statistical evaluation of data to determine whether they possess the quality for business purposes and are usable[15]. According to[10], data assessment follows measures that quantify relevant data quality dimensions. Andreescu *et al.*[16], mentioned data quality assessment is highly context and application dependent whereby it is difficult to formulate a general solution that will work in all situations. According to [17], data quality methodologies have been defined and developed to measure and improve data quality in organizations. A methodology can be referred as a set of procedures that are designed to measure and enhance the data quality of a specific application.

2.5 Data Quality Assessment Methodologies

There are various methodologies for data quality assessment and improvement that have been developed by the researchers. Here we discuss 4 main methodologies that we focus to derive a suitable quality assessment methodology for SIKAP transportation system.

2.5.1 Total Data Quality Management (TDQM)

The TDQM methodology was the general methodology which is the outcome of academic research at Massachusetts Institute of Technology. TDQM that is the Total Data Quality Management consist 4 phases: (1) Definition, (2) Measurement, (3) Analysis and (4) Improvement. Phase 1 definition involves Data Analysis, Data Quality Requirement Analysis and Process Modeling. Data Analysis is to define characteristics at 2 levels; high level: description of functionalities for information consumers and low level: description of the basic units and components of the information product and their relationship. Data quality requirement analysis is to define information quality requirements from the perspective of suppliers, manufacturers, consumers and managers. Process Modeling is to define the Information Manufacturing System. Phase 2 refers to measurement where its input is information quality dimensions and the IQ metrics and the output of this phase is information quality problems. Phase 3 is data analysis and used to identify the causes of errors and to determine root causes of the discrepancy. The output of this phase is the list of actions for improving data quality. The last phase is the improvement part. The selection of strategies and techniques is to identify key areas for improvement. The output of this phase is IQ improvement techniques. TDQM is widely accepted as a methodology to ensure data quality. However, TDQM is hard to adapt for larger firms which own large databases [18] because in large organizations many people have responsibilities for data and may have different data user needs.

2.5.2 Data Quality Assessment (DQA)

Data quality assessment in practice involves subjective and objective assessment[19]. Subjective data quality assessments can use a questionnaire to measure the stakeholder perceptions of data quality dimensions. Objective assessments can be task-independent or task-dependent. Task-independent metrics do not depend on the task which just gives a general view of the data status without the related knowledge of the application and can be applied to any data set, regardless of the tasks at hand. Task-dependent metrics include the organization's business rules, company and government regulations, and constraints provided by the database administrator that developed in specific application contexts. The analysis begins with subjective and objective assessments of a specific dimension where both are compared. The outcome of the analysis will fall into one of four quadrants. The goal is to achieve a data quality state that falls into Quadrant IV. If the analysis indicates Quadrants I, II, or III, the company must investigate the root causes and take corrective actions. At a minimum level, it will assist to ensure the development of multi-level and multi-tasked metrics so as to measure the quality of data.

2.5.3 AIMQ (A Methodology for Information Quality Assessment) Methodology

The AIMQ methodology is the information quality methodology focusing on benchmarking which is an objective and domain independent technique for quality evaluation[10]. There are three main components in AIMQ methodology. The first that is the PSP/IQ model is a 2 rows X 2 column model. The two rows can be considered either as a product or a service and the two columns demonstrate the data quality that is measured by predefined specifications or the user expectation criteria that reflects explicit data quality dimensions. The second component refers to a questionnaire that is designed to identify data quality measurement. The list of measurement identified in a single quadrant creates the data quality measures for that quadrant. Then a gap analysis technique is applied to compare the standard and the data quality practice of the organization. This is called benchmarking. Besides, ideas are collected from different roles such as IQ collectors, consumers, or professional to

compare the data quality measurement proposed by them. The AIMQ methodology is very comprehensive and functions better if it addresses specific needs of the organization by creating the questionnaire that comprises well-defined specifications.

2.5.4 Information Quality (IQ) Assessment Framework by Six Sigma Approach

Information Quality (IQ) Assessment Framework by Six Sigma Approach [20] was developed by adopting Six Sigma approach that reflects four phases; (1) Establish IQ Requirements, (2) Identifying IQ Dimensions, (3) Implementing Six Sigma and (4) Assessing IQ. The proposed framework can provide critical factors for data quality, the current and improved quality (sigma) level, the insufficiencies in information systems and the root causes of poor information. This framework implements House of Quality (HOQ) for information quality assessment at phase 3. This is a matrix that composes to sub-matrices that are related to each other whereby customer requirements matrix is created using the customer responses collected from phase 1. Information Quality (IQ) Assessment Framework by Six Sigma Approach is a comprehensive framework. However, much effort such as time and resources are needed to ensure the successful implementation.

2.6 Comparison of Data Quality Evaluation Methodologies

These four data quality methodologies have been studied. The strength and weaknesses comparison of four data quality methodologies are shown in Table 2.

Table 2: Comparison data quality evaluation methodologies

Methodology	Strengths	Weaknesses
TDQM	The TDQM has been extensively used as a guide to organizational data re-engineering initiatives [10].	TDQM is difficult to adapt to larger firms which own large databases [18].
DQA	The DQA methodology combines the subjective and objective assessment of data quality that aids in developing data quality metrics in practice [19].	Need to conduct a subjective and objective assessment in parallel.
AIMQ	The AIMQ methodology is very comprehensive[17].	Uses a pre-defined list of dimensions which may not address the specific needs of the organization [17].
IQ Assessment Framework by Six Sigma Approach	Accurate, systematic and pragmatic assessment results[20].	Much effort such as time and resources are needed to ensure the successful implementation of the method in the organization.

The main data quality dimensions to be adopted in the transportation agencies are found to be accuracy, completeness, validity, timeliness and accessibility. Data problems in transportation that have been identified from the literature are erroneous data, missing data, and data accuracy.

An organization might consider many data dimensions and attributes that are suitable and meet the organization's requirements before identifying the right measure to improve data quality.

3.0 The Proposed Data Quality Evaluation Method

Data quality dimensions are identified to choose the relevant dimensions to evaluate the data quality of the SIKAP system. The observation result by SIKAP's admin indicates data problems such as duplicated data or data redundancy, missing value, incorrect data and misspellings. Through the literature review and the nature of the system, it has been found that accuracy, completeness, consistency, timeliness, relevance and accessibility are important data quality dimensions for the SIKAP system. The proposed method is based on the past literature review and deep understanding of the SIKAP system. Following to that, each dimension will be mapped to a specific data profiling.

Completeness refers to the absence of the essential data, for example, the available data is missing. In the SIKAP system, "missing data" occurred, for example, the user did not key in a field because it is not a mandatory field. Meanwhile, accuracy is defined as the extent to which data are correct, reliable and certified. The data that have been the key in SIKAP should be acceptable and accurate since it is important for business operation. Data accuracy and completeness focus on data stored in corporate databases. On the other hand, consistency is the extent to which data is presented in the same format and compatible with previous data. For example, a vehicle's date of permit validity has the same value and format in the dashboard reporting as that stored in the database. Relevance refers to an extent for which information is applicable and helpful for the task at hand. The data that contain in SIKAP should suitable for dashboard reporting which will help the operation and management team for analysis and decision making. Accessibility refers to data availability, or easy and fast retrievable. For example, data sets should be available in the database to be accessible for dashboard reporting or to be retrieved by the user when needed. Timeliness reflects how up-to-date the data is with respect to the task it used for. Timeliness is the longevity of data that is used for the task at hand. The data that contain in SIKAP should be up to date and should aid the operation and management team for analysis and decision making. Based on the review in depth, the proposed data quality evaluation method is shown in Figure 1. In the proposed evaluation method, subjective evaluation refers to questionnaire while objective evaluation used data profiling.

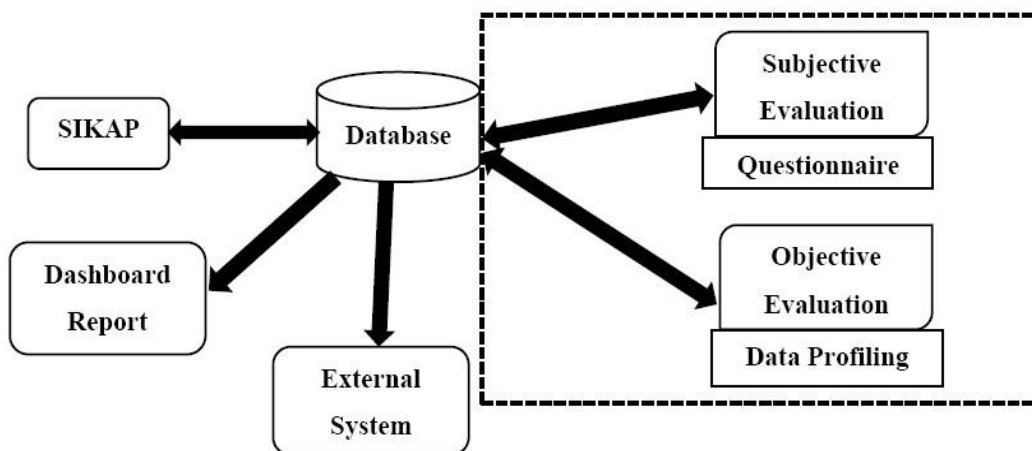


Figure 1: Proposed data quality evaluation method

According to [21], subjective assessment depends on the user experience, the task at hand, and the use of questionnaires. A survey questionnaire is designed to gather users' perspective on data quality of SIKAP and also to specify of those data quality dimensions priorities for evaluating data quality. In the objective assessment, we used the task-dependent metrics that include the organization's business rules, regulations, and constraints provided by the database administrator, to be applied to the dataset. Data profiling is the process of examining the data available in an existing data source and collecting statistics and information about that data [22]. Data profiling helps to find data quality rules and requirements that will support further thorough data quality evaluation. Data quality dimensions such as accuracy, completeness, consistency, relevance, timeliness and accessibility can be measured from the database through SQL-queries. SQL Server Management Studio software is used to run the SQL-queries. The data quality dimensions identified for SIKAP system is mapped into suitable data profiling and it is shown in Figure 2.

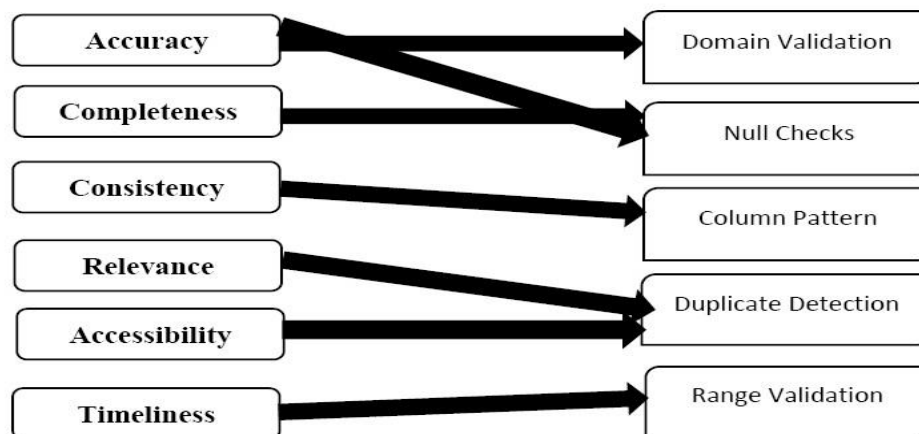


Figure 2: Proposed data profiling for each data quality dimension

Four tables that are involved in this research are a bus, taxi, lorry and master license table. Figure 3 shows the diagram of the SIKAP database structure. Bus vehicle table contains 66235 records, taxi vehicle table contains 167645 records, lorry vehicle table contains 307298 records and master license table contains 563215 records.

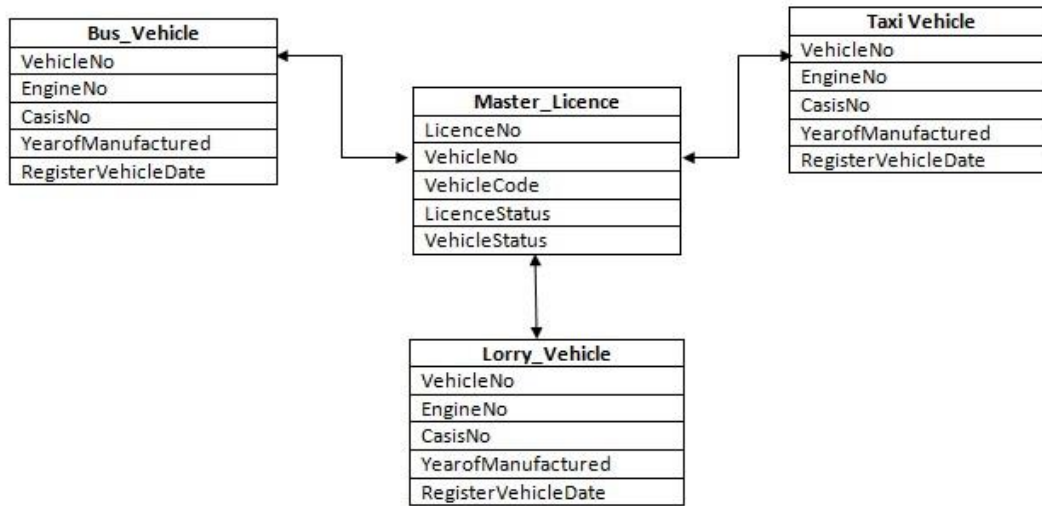


Figure 3: SIKAP database structure

Based on Figure 2, accuracy can be measured by data profiling using domain validation to ensure the data is correct or no misspelling and wrong data entry occur. Accuracy also can be measured by null check to identify missing values in a column of a table in the database. Completeness can be measured by null check to identify missing values in the SIKAP database table. Consistency can be measured by data pattern whether the data is present in the same format as the previous data. Then, relevance and accessibility can be measured to identify duplicated data or data redundancy in the database. The last is timeliness which can be measured whether the data in the database is up to date by querying the minimum or maximum for date time column. By matching the list of data profiling with the SIKAP database structure we show the evaluation format for each data quality dimensions in Table 3.

Table 3: Evaluation format for each data quality dimension

Data Quality Dimension	Data Profiling	Data Check Description
Accuracy	Domain Validation	Vehicle Status; Y, T, null
Accuracy Completeness	Null Value Checks	Null value e.g. column VehicleNumber
Consistency	Column Pattern	VehicleNumber format
Relevance Accessibility	Duplicate Detection	VehicleNumber data across three tables of the vehicle; lorry, taxi and bus.
Timeliness	Range Validation	Minimum or maximum date of data entry or recorded. E.g. Modified date of vehicle tables.

3.1 Data Quality Evaluation in the SIKAP system workflow

The proposed data quality evaluation method in the workflow of the SIKAP system is shown in Figure 4. There is no data quality evaluation exist in the normal workflow of the SIKAP system. By using the proposed data quality evaluation method, the data that have been

entered in the SIKAP system will be evaluated using each data quality dimensions proposed; accuracy, completeness, consistency, relevance, accessibility and timeliness. First, the data will be evaluated with the accuracy dimension. The data quality report will be produced as the output of the data quality evaluation method. The data quality report contains the data quality evaluation results of six main data quality dimensions.

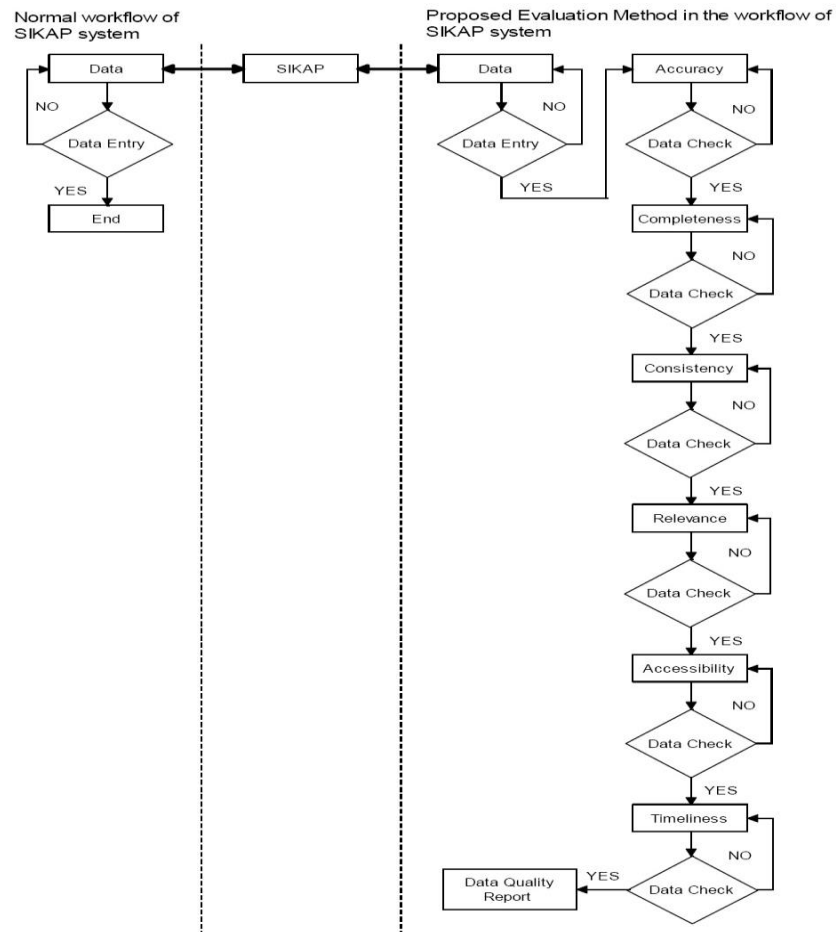


Figure 4: Proposed data quality evaluation method in the SIKAP's workflow

4.0 Conclusion

Data is the asset of the agency. High-quality data will add value to the agency. Poor data can cause customer and employee dissatisfaction, affect decision making and disturb the overall organization's business strategy. The common data quality issues are data duplication, redundancy, missing value, incorrect data and misspellings. Thus, an agency needs to adopt data quality evaluation method to ensure the data is accurate and fit the use of agency. This research concluded that there are six data quality dimensions for data quality evaluation in the transportation agency, SPAD. The dimensions include accuracy, completeness, consistency, relevance, accessibility and timeliness. We also created a data quality evaluation method for the transportation agency and it consists of subjective evaluation with a questionnaire and objective evaluation with data profiling.

The proposed data quality evaluation method will help the transportation agency to quantify the quality of data in the existing SIKAP licensing system.

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