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Multicriteria Based Decision Making of DevOps Data Quality Assessment Challenges Using Fuzzy TOPSIS

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ABSTRACT In current era, DevOps gain much interaction in software industry as it provides the flexible development environment. To meet the continuous development and operations, DevOps mainly focus, to integrate the data from heterogeneous source. While DevOps adoption, the quality assessment of data integrated from heterogeneous environment, is important and challenging at the same time. This study aims to identify the critical factors that could negatively impact the data quality assessment process in DevOps. We have used the systematic literature review (SLR) approach and identify a total of 13 critical challenging factors. The finding of SLR are further validated with industry experts via questionnaire survey. Finally, we have applied the Fuzzy TOPSIS approach to prioritize the investigated challenging factors with respect to their significance of DevOps data quality assessment process. The results show that analyzing data in real time, visualization of data and missing information and other invalid data are the highest ranked challenging factors which need to be addressed on priority basis, to successfully measure the quality of heterogeneous data in DevOps. We believe that the finding of this study will assist the practitioner to consider the most significant factors for measuring the quality of heterogeneous data in DevOps.

INDEX TERMS DevOps data quality assessment, fuzzy TOPSIS, empirical investigation.

I. INTRODUCTION

DevOps (development and operations) is now becoming an essential part of software industry over the last few years focusing on developers and operations to communicate well and deliver reliable and high-quality software services [2]. DevOps is the collaboration of responsibilities and sharing of tasks within a team, empowered with full accountability of their services, to support development and deployment process [3]. DevOps environment supports, cross functionality, task management, team responsibilities and trust. DevOps is an extended version of agile movement from continuous development to continuous integration and release of goals. To meet the criteria of continuous release, DevOps focuses on automation of change, configuration and released process [1].

In modern software development environment different tools and technologies are used, that produce a massive amount of information during development lifecycle, from requirements engineering to design, assessment and testing. Besides, the availability of variable tools and technologies, helps the software industry to avoid reliance on few vendor services and product reliability [5]. However, the information produced by different software tools is difficult to manage; as the producing tools are heterogeneous in nature [6].

The DevOps is considered as one of the effective approach to manage the heterogeneity of information by continuous integration between development and operations [13]. Despite this, DevOps activities are still facing problems while dealing with the information coming from heterogeneous

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environment. More importance is given to integration of data instead of assessing quality of data [8]. Josko and Ferreira [7] also states the importance of data quality assessment to ensure the useful outcomes of analytical processes. Therefore, the high-quality data enables analytical approaches that can improve key parameters, such as, performance, time and cost etc. Gürdür *et al.* [4] conducted a literature review study on data quality dimensions and developed a dashboard for quality assessment using systematic guidelines; but they ignore the DevOps environment. We further found a study conducted by Rubasinghe *et al.* [9] they work on software artifacts traceability in context of DevOps related software development environment using SAT- Analyzer V.1, ignoring concerns of data quality assessment.

Besides the importance of DevOps in software industry, limited attention has been given to address the problem of data quality assessment process. We did not find any study on data quality assessment challenges in DevOps environment. The challenges indicate the week areas that need to be addressed for the success and progression of software projects [10]. With the motivation of this research gap, we identified the data quality assessment challenges in DevOps environment. To meet the study objective, we have conducted systematic literature review and questionnaire survey to identify and validate the challenging factors of data quality assessment in DevOps. Finally, we apply the Fuzzy TOPSIS approach to priorities the investigated challenging factors with respect to their significance of data quality assessment in DevOps. The fuzzy approach is used to cater the human error, biasedness and to remove any uncertainty in decision making. Several existing studies adopted Fuzzy TOPSIS approach for estimating the exact numerical values, which are difficult to identify using simple TOPSIS. For example, Patil and Kant [20] applied Fuzzy AHP-TOPSIS approach to rank the solutions of knowledge management adoption that are useful to overcome the challenges of supply chain. Sun [21] also suggested a framework of performance evaluation using fuzzy AHP and fuzzy TOPSIS approach. We have adopted the same Fuzzy TOPSIS approach to prioritize the investigated challenging factors of data quality assessment in DevOps. This study will also provide future research directions, to develop a DevOps data visualization model for data quality assessment in heterogeneous environment. The following research questions have been developed to address given research gap.

RQ1: What are the most critical challenges investigated in literature related to data quality assessment that have negative impact on DevOps environment?

RQ2: Does identified challenges create hurdle in DevOps life cycle and are empirically validated by the industrial experts?

RQ3: How priorities can be assigned to identified challenges in order to measure their impact on DevOps environment?

RQ4: What would be the prioritization-based taxonomy of identified factors?

The remaining paper is organized as follow.

II. BACKGROUND AND MOTIVATION

Software development industry is showing a rapid standardization with un-predictable and fast growth rate. The intention behind the rapid change are customer requirements and request of change in positive manner. This problem has been addressed by agile development which targeted many companies to move towards agile in order to fulfill customer needs and frequent release [2]. Big companies like Facebook, IBM and Microsoft started their own bench mark in continuous deployment. Since, continuous deployment has a significant impact to the system stability it creates new business trends and challenges in software industry [11].

State of DevOps Report 2016 has figure out that DevOps contributed in performance, profitability and revenues in an organization. DevOps is growing with fast rate of 16% in 2014 to 19% in 2015 and 22% in 2016. The facts why companies moved toward DevOps is because their deployment time leads faster than before such as Amazon and Netflix have deployed changes thousands of times per day [14].

The concept of DevOps represents integration between development and operational environment that encourage to improve development scheme rather than software [15]. The DevOps provide a platform to project management team with better understandability, performance, integration and relationships among teams [12], [16].

Zaveri *et al.* [18] conducted a survey on linked data quality assessment and identified 16 dimensions. They classified the dimensions into four categories i) accessibility, ii) contextual, iii) intrinsic and iv) representational without considering DevOps activities. Gürdür *et al.* [4] also put forward their idea regarding data quality dimensions and merged them with empirical rules after identifying dimensions from literature. Their research focuses on merging empirical rules with data quality dimensions instead of finding challenges of data quality assessment in DevOps environment. Rubasinghe *et al.* [9] extend SAT- Analyzer V.1 tool that can establish traceability among the artifacts from the requirement gathering phase to software development life cycle in DevOps environment, instead of challenges to be resolved in data quality assessment.

Several studies have adopted Fuzzy AHP and Fuzzy TOPSIS method to solve different problems. Patil and Kant [20] applied Fuzzy AHP-TOPSIS to identify and rank the solutions of Knowledge management (KM) adoption in supply chain to manage the challenges, which can help the organizations to priorities the solutions and apply them in the work place according to the high ranked marked solution. Sun [21] also proposed a model of performance evaluation using Fuzzy AHP and Fuzzy TOPSIS approach. Awasthi *et al.* [22] used Fuzzy TOPSIS to produce aggregate scores for sustainability assessment of transportation and in selection of best alternative. Yang *et al.* [23] applied Fuzzy TOPSIS for vessel selection under uncertain environment. Wang and Lee [24] proposed a new approach of fuzzy TOPSIS for evaluating alternatives by integrating using objective and subjective weights. Krohling and Campanharo [25] adopted fuzzy TOPSIS to assess the ratings of response alternatives to a simulated oil spill. Kelemenis *et al.* [26] adopted fuzzy TOPSIS in order to support selection of managers in a large Greek IT firm. Mahdevari *et al.* [27] used fuzzy TOPSIS in underground coalmines to evaluate the safety risks and human health problems. Vinodh *et al.* [28] integrated fuzzy AHP–TOPSIS to classify the best approach for recycling plastics from all available plastic recycling techniques. Rostamzadeh and Sofian [29] applied fuzzy AHP and fuzzy TOPSIS multi criteria approach to improve performance of production system.

As DevOps is intended to be a cross-functional mode of working, industry has adopted many optimization techniques for continuous integration and deployment. Considering background and related research Avazpour *et al.* [19] motivated us to work on data quality assessment challenges considering DevOps working environment to contribute by identifying challenges in data quality assessment and try to resolve data integration problems during continuous integration and deployment. To achieve study objectives, we have conducted systematic literature review (SLR) to identify challenges of data quality assessment and validate them in real world industry by practitioners and prioritized the identified challenges using Fuzzy TOPSIS in order to check the weightage of challenges in DevOps environment and give suggestions to resolve these challenges.

III. METHODOLOGY

The purpose of this study is to identify the challenges that are critical for DevOps data quality assessment and to prioritize them for successful scaling of DevOps activities in software organizations. To meet the study aim, the three different research approaches are considered. In first phase, we have adopted systematic literature review, to identify the challenges of DevOps data quality assessment. The identified challenges were further validated with industry experts using questionnaire survey technique. Finally, we have applied the Fuzzy TOPSIS technique to prioritize the identified challenges with respect to their importance for success of DevOps data quality assessment. All the adopted research approaches are briefly discussed in the following section and graphically presented in Figure 1.

A. SYSTEMATIC LITERATURE REVIEW (SLR)

SLR approach was adopted to explore the existing available literature with the aim to identify the challenges of DevOps data quality assessment process. SLR is most widely used method to explore the literature according to a specific research area [30]. Kitchenham [30] reported that the outcomes of SLR are valid and comprehensive compared with informal literature study. Various studies adopted SLR approach to explore the existing literature on a specific topic [31]–[34], [41]–[43]. The phases adopted to conduct SLR are discussed in subsection.

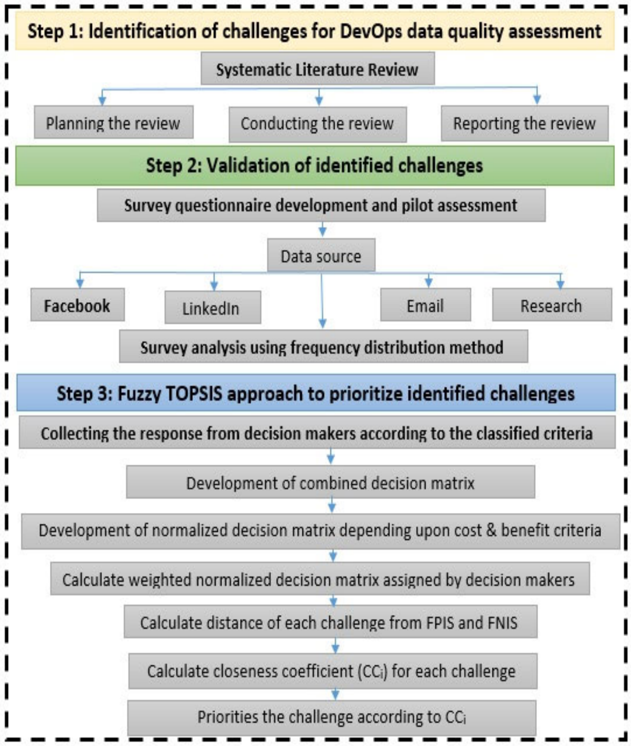

FIGURE 1. Proposed methodology flow.

TABLE 1. Links of data repositories used in this study.

Digital databases links	"http://ieeexplore.ieee.org" "http://dl.acm.org" "link.springer.com" "www.wiley.com" "www.sciencedirect.com" "scholar.google.com"
Searched items	Book chapter, Conferences, journal and workshop articles.
Language	English

1) PHASE1: PLANNING THE REVIEW

a: RESEARCH QUESTIONS

The aim of this study is to identify the challenges that could have negative impact on the DevOps data quality assessment process. The developed research questions of this study are presented in section 1.

Based on our understanding and by considering the recommendations of Chen *et al.* [35] and Khan and Keung [36], the six well-known digital repositories are selected (Table 1).

b: RESEARCH STRING

To explore the data from the selected digital repositories, we have developed a search string the keywords and their alternatives extracted for the primary studies i.e. [31], [32], [37]–[43]. The Boolean "AND" and "OR" are used to concatenate and formulate the research string. An example of adopted search strings is given below:

("barriers" OR "obstacles" OR "hurdles" OR "difficulties" OR "impediments" OR "hindrance" OR "challenges" OR "limitations") AND ("DevOps" OR "Development and Operation" OR "continuous deployment" OR "continuous delivery process" OR "continuous integration of teams" OR "Continuous development Unit" OR "SecDevOps" OR "DevSecOp") AND ("data quality assessment" OR "data heterogeneity" OR "data assessment" OR "data validation" OR "data visualization assessment").

c: INCLUSION CRITERIA

For inclusion criteria literature, the following criteria were considered:

- The selected article must be in conference, journal or book chapter.
- The study must describe about DevOps activities in software organization.
- The selected articles must report about the challenges of DevOps data quality assessment process.
- In the case of duplicate article of same project report, the latest version was considered.

d: EXCLUSION CRITERIA

To exclude the extracted literature, the following criteria were used. The same criteria have been adopted by Khan *et al.* [41] and Shameem *et al.* [44].

- Studies that do not describe DevOps challenges in software organization.
- Studies that do not pointed out data assessment related challenges in DevOps.
- Studies that were not written in English.

e: QUALITY EVALUATION (QE)

The quality evaluation of the selected studies was conducted during the study selection process. To determine effectiveness of the selected studies, we have created the QE checklist (Table 2). The instructions given by [35], [37] were followed in the format of this checklist. This technique was also used by [33], [35]–[37] in their studies to assess the quality of selected primary studies. The checklist consists of five QE questions:

2) PHASE 2: CONDUCTING THE REVIEW

a: STUDIES SELECTION

The selected primary studies were processed to refine using tollgate approach by Afzal *et al.* [46]. This approach consists of five phases (Figure 2, Table 3).

Initially, 110 studies were collected from online repositories by using search strings (section III) and by performing inclusion and exclusion criteria (section III.A phase-1). After carefully performing the (phase1 to phase5) of tollgate approach, the final 30 studies were selected (Table 3). Lastly the shortlist primary studies were assessed using selected QE criteria (Table 2). The list of total primary studies is given in Appendix A. Each selected primary study is labeled as (SP) to represent as SLR study.

TABLE 2. Evaluation checklist.

QE Questions	Checklist Questions
QE1	Does the selected primary study address the problems marked in research questions?
QE2	Does the selected study figure out data quality assessment challenges in DevOps?
QE3	Does the study explain DevOps environment in detail?
QE4	Does the selected primary study focus on DevOps data quality challenges in software organization?
QE5	Dose the selected study gives the answer to the constructed research question?

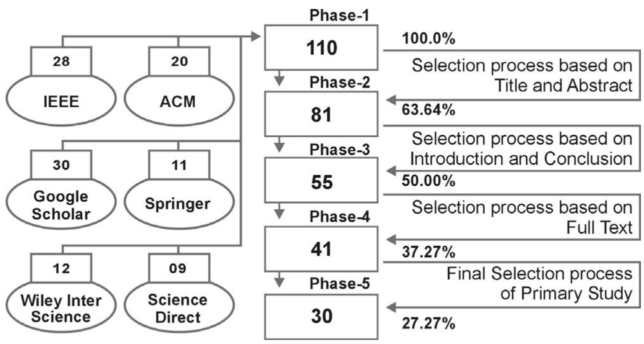

FIGURE 2. Phases of tollgate approach.

TABLE 3. Tollgate approach.

Research Directories	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Percentage of occurrence N=30
ACM	20	15	11	8	6	20%
IEEE	28	20	13	11	9	30%
Wiley	12	9	6	5	2	6.4%
Springer	11	8	5	4	3	10%
Science Direct	9	6	5	3	2	7%
Google Scholar	30	23	15	10	8	26.6%
Total	110	81	55	41	30	100%

b: DATA EXTRACTION AND SYNTHESIS

To address the research questions of this study, we extracted the data from the final selected primary studies (section III.A phase 2.a). The first two authors of this study continuously review the selected primary studies to extract the statements, ideas and themes; related to challenges of DevOps data quality assessment process. The extracted themes were firstly arranged in excel-sheet to record ideas, findings and concepts

TABLE 4. **Research approaches in selected primary studies.**

Approaches	Total score	Percentage N=30
Questionnaire survey	5	16%
Grounded theory	2	6%
Content analysis	2	6%
Action research	5	16%
Mixed Methods	10	33%
Case study	6	20%

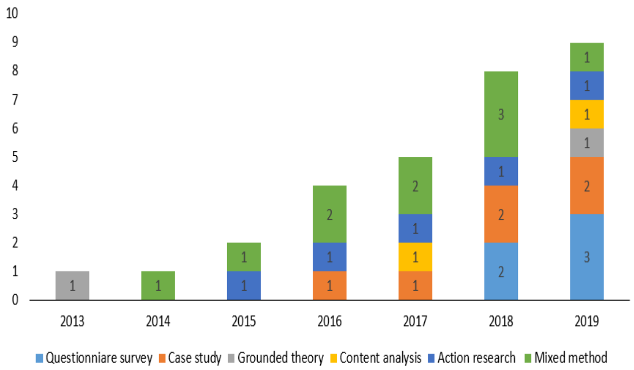

FIGURE 3. **Temporal distribution of primary studies.**

related to research problem. We further validate our data by involving external reviewers to remove inter-personal biasness. The external reviewer's selected 8 studies randomly from first phase of tollgate approach and carried out all phases of SLR approach. This approach has also been adopted by researchers in other branches of software engineering to remove biasness [31], [32], [35]–[37].

3) PHASE 3: REPORTING THE REVIEW

a: QUALITY ATTRIBUTES

The quality evaluation (QE) was evaluated based on five QE questions presented in section III.A (Table 2). The Appendix-A show all detail about selected primary studies including QE score. The analysis of QE indicates that more than 65% of primary studies score >70% which are quite reasonable results to answer the research questions of this study.

b: RESEARCH APPROACHES AND TEMPORAL DISTRIBUTION

The selected primary studies consist up of 5 (16% of questionnaire survey), 2 (6% of grounded theory analysis), 2 (6% of content analysis), 5 (16% of action research), 10 (33% of mixed method approach) and 6(20% of case study) as shown in Table 4.

The graph (Figure 3) shows that the significance of DevOps has increased in last few years which make this domain more impact full. During the selection of primary studies, the years were also identified showing the importance of DevOps data quality assessment in software companies.

TABLE 5. **Triangular fuzzy conversion scale [53].**

Linguistic Scale	Triangular Fuzzy Scale
Just Equal= JE	(1,1,1)
Equally Important = EI	(0.5,1,1.5)
Weakly Important = WI	(1,1.5,2)
Strongly More Important = SMI	(1.5,2,2.5)
Very Strongly More Important= VSMI	(2,2.5,3)
Absolutely more important= AMI	(2.5,3,3.5)

B. EMPIRICAL DATA COLLECTION

To validate the finding of SLR and to identify the additional challenges of DevOps data quality assessment, we have conducted questionnaire survey study. A survey questionnaire designed to collect the responses from the distributed experts (researchers and practitioners) [36]–[46]. The questionnaire sample consists of both closed and open-ended questions, enabling practitioners, to identify new DevOps data quality assessment challenges also. To collect the responses from the survey participants "agree", "strongly agree", "disagree" "strongly disagree" and "neutral" were used as Likert scale. According to Niazi *et al.* [10] response scale without neutral, bounds the respondent to provide either positive or negative response; however, providing neutral option will remove such biasness.

1) PILOT ASSESSMENT OF SURVEY QUESTIONNAIR

The designed questionnaire was sent to some industrial experts for evaluation including software engineering professors after their approval of invitation send to them for questionnaire assessment, in "King Fahad University of Petroleum and Minerals, Saudi Arabia" and "Indian Institute of Technology, India (IIT)." The respondent's responses were evaluated to check the consistency among them. The suggestions made by respondents are important to significantly improve survey questionnaire [47]. The respondents suggested to add questions regarding DevOps experience in an organization, and to use tabular format for second part of questionnaire. A final version of questionnaire was made after dealing with all corrections suggested by experts. A sample of final survey questionnaire is given in Appendix B.

2) DATA SOURCE

The goal of this study is to identify DevOps data quality assessment challenges in software organization. Hence, it was necessary to collect data from experts working in industry within DevOps environment. For this, after identification of DevOps data quality assessment challenges through SLR, we validate our findings of research with industrial experts to get real industry experience. The targeted population was contacted using LinkedIn, Facebook, Emails and ResearchGate. The data collection process was carried out during

TABLE 6. Identified challenges reported by SLR.

Sr.	Challenges	IDs of selected primary studies (Appendix A)
CCH-1	Data heterogeneity	[SP1], [SP2], [SP9], [SP15]
CCH-2	Data integration	[SP2], [SP24], [SP25], [SP30]
CCH-3	Error and inconsistent data	[SP10], [SP11], [SP25]
CCH-4	Misspelling in data entry	[SP3], [SP4], [SP9], [SP29]
CCH-5	Missing information and other invalid data	[SP5], [SP9], [SP12], [SP18], [SP19]
CCH-6	Traceability for data	[SP4], [SP7], [SP8], [SP13], [SP14]
CCH-7	Data harmonization	[SP6], [SP16], [SP23]
CCH-8	Visualization of data	[SP2], [SP4], [SP18], [SP20], [SP21], [SP26]
CCH-9	Data aggregation	[SP5], [SP10], [SP11]
CCH-10	Data provenance problem	[SP4], [SP7], [SP8], [SP17], [SP19]
CCH-11	Storage of transaction logs	[SP22], [SP24], [SP25]
CCH-12	Analyze data in real time	[SP3], [SP4], [SP10], [SP26], [SP28]
CCH-13	New visualization techniques and their assessment	[SP1], [SP3], [SP7], [SP18], [SP25], [SP27], [SP30]

TABLE 7. Response of respondents on identified challenges.

Sr #	Respondents N= 50							
	Positive Response			Negative Response			Neutral	
	S.A	A	%	S.D	D	%	N	%
CCH-1	30	10	80	2	5	14	3	6
CCH-2	21	9	60	5	8	26	7	14
CCH-3	15	15	60	3	10	26	7	14
CCH-4	24	11	70	5	5	20	10	20
CCH-5	35	10	90	-	-	-	5	10
CCH-6	36	8	88	-	2	4	4	8
CCH-7	11	20	62	1	3	8	15	30
CCH-8	25	19	88	-	1	2	5	10
CCH-9	16	8	48	3	3	12	20	40
CCH-10	12	15	54	-	5	10	18	36
CCH-11	9	23	64	4	2	12	12	38
CCH-12	25	21	92	-	1	2	3	6
CCH-13	13	11	48	2	2	8	22	44

October 2019 to November 2019. A total of 57 responses were received during the survey execution process and all the responses were manually checked to found the uncomplete entries. The seven responses were found uncomplete and the rest of the 50 complete responses were considered for further data analysis process. Table 6 and 7 in Section VI shows all finding of questionnaire survey.

3) DATA ANALYSIS

Frequency analysis method [33], [39], [42] is used to analyze the significance of identified challenges in selected studies. This approach is suitable to analyze ordinal and nominal data across variables and group of variables [10], [66].

C. FUZZY TOPSI

TOPSIS is one of the multi-criteria decision-making approach (MCDM), proposed by Hwang and Yoon in 1981 [48]. This approach is widely used to fix the multi-criteria decision-making problems. The attribute nominated should be at the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution [49], [50]. However, there are certain limitations while adopting TOPSIS, e.g. capturing vague data in fuzzy environment [51]. Yu [52] also identified fuzziness and vagueness as key characteristics, for many decision-making problems. Hence, TOPSIS may cause uncertainty under fuzzy decision-making environment. Therefore, to resolve such problem Fuzzy TOPSIS approach was proposed which is effective under such circumstances. This technique is effective for uncertainty in judgments and evaluations made by decision makers [49], [51].

The effectiveness of Fuzzy TOPSIS approach motivated us to adopt this technique for prioritization of DevOps data quality assessment challenges. We have considered the step by step protocols of fuzzy TOPSIS approach to prioritize the investigated challenges. Various other existing studies also used the same approach to fix the multicriteria decision making problems, e.g. [21], [49], [51].

Step 1: Calculate the rating value for linguistic data variables with respect to the fuzzy triangular scale (Table 5). The linguistic triangular fuzzy conversion scale developed by Bozbura *et al.* [53] was used in this study.

Step 2: Construct the Fuzzy performance/matrix for all alternatives by considering the group of q decision makers ($D1, D2 \ldots D_q$) containing p alternatives ($A1, A2 \ldots A_p$) and r criteria ($C1, C2 \ldots C_r$).

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_p \end{array} \begin{array}{c} \begin{array}{cccc} C_{11} & C_2 & \ldots & C_r \end{array} \\ \begin{pmatrix} R_{11} & R_{12} & \cdots & R_{1r} \\ R_{21} & R_{22} & \cdots & R_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ R_{p1} & R_{p2} & \cdots & R_{pr} \end{pmatrix} \end{array} \tag{1}$$

where R_{pr} is the rating of all alternatives A_p with respect to C_r.

Step 3: Aggregate fuzzy rating for solutions:

Fuzzy rating of $\tilde{K}$ decision makers $\tilde{X}_{ab} = (l_{abN}, p_{abN}, u_{abN})$, where $a = 1, 2, 3 \ldots$ m and $b = 1, 2, 3 \ldots$n and then the fuzzy aggregate fuzzy rating $\tilde{X}_{ab}$ of solutions with respect to each criteria, selected for alternatives is given by $\tilde{X}_{ab} = (l_{ab}, p_{ab}, u_{ab})$ where,

$$\mathrm{a} = N^{min}\{l_{abN}\}, \quad \mathrm{b} = \frac{1}{N}\sum_{n=1}^{N} p_{abN}, \quad \mathrm{c} = N^{max}\{u_{abN}\} \tag{2}$$

Step 4: Construct normalized fuzzy decision matrix.

The normalized fuzzy decision matrix is denoted by $\tilde{N}$ and is defined as follows:

$$\tilde{N} = [p_{ij}]_{\mathrm{m*n}}$$

where $i = 1, 2, 3 \ldots$, m and $j = 1, 2, 3 \ldots$ n

$$\tilde{p} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \text{ and } c_j^* = max c_{ij} \text{ (benefit criteria)} \tag{3}$$

$$\tilde{p} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \text{ and } a_j^- = \min a_{ij} \text{ (cost criteria)} \tag{4}$$

Step 5: Weighted Fuzzy normalized decision matrix is shown as follows:

$$\tilde{W} = [\tilde{v}_{ij}]_{\mathrm{m*n}} \, i = 1, 2, 3 \ldots, \quad \text{m and } j = 1, 2, 3 \ldots, \text{n} \tag{5}$$

where $\tilde{W} = \tilde{p}_{ij}^* w_j$

Step 6: Determine Fuzzy positive ideal solution (FPIS) and Fuzzy negative ideal solutions (FNIS) by using following formula:

$$\begin{aligned} A^+ &= \{v_1^+, \ldots, v_n^+\}, \text{ where} \\ v_j^+ &= \{\max(v_{ij}) \text{ if } j \in J; \min(v_{ij}) \text{ if } j \in \acute{J}\}, \end{aligned} \tag{6}$$

$$\begin{aligned} A^- &= \{v_1^-, \ldots, v_n^-\}, \text{ where} \\ v_j^+ &= \{\min(v_{ij}) \text{ if } j \in J; \max(v_{ij}) \text{ if } j \in \acute{J}\}, \\ J &= 1, 2, 3 \ldots, \text{n} \end{aligned} \tag{7}$$

Step 7: Calculate the distance of each alternative from FPIS and FNIS.

The calculated distance ($\tilde{d}_i^+$ and $\tilde{d}_i^-$) of each alternative from A^+ and A^- can be calculated by using following equation:

$$\tilde{d}_i^+ = \left\{\sum\nolimits_{j=1}^{n}\left((v_{ij} - v_{ij}^+)^2\right)\right\}^{1/2}, \quad i = 1, 2, 3 \ldots \text{m} \tag{8}$$

$$\tilde{d}_i^- = \left\{\sum\nolimits_{j=1}^{n}\left((v_{ij} - v_{ij}^-)^2\right)\right\}^{1/2}, \quad i = 1, 2, 3 \ldots \text{m} \tag{9}$$

Step 8: Calculate the closeness coefficient (CC_i) for each alternative by using the following equation:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}, \quad i = 1, 2, 3 \ldots \text{m}, \; C_i \in (0, 1) \tag{10}$$

Step 9: Find the ranks of alternatives by ranking them according to the CC_i of each alternative in descending order.

IV. RESULTS AND DISCUSSION

A. FINDINGS OF SLR (RQ1)

In phase-1, the challenges related to DevOps data quality assessment were identified through systematic literature study. All of the selected studies were related to DevOps data quality assessment and data visualization techniques considering software organizations. Total of 13 challenges were identified which were related to DevOps data quality assessment, from 30 selected primary studies. The identified challenging factors are enlisted in Table 6.

CCH1 (Data heterogeneity was considered in literature as a critical challenge in DevOps environment. As heterogeneity is a key problem for well-integrated and interoperable software processing environments to assess data quality [4]. One of the methods to resolve such issue is using linked data approach, which refers to link heterogeneous data on a single platform in such a way that it is machine readable [54]. Perera *et al.* [2] also highlighted that while considering various heterogeneous approaches, data heterogeneity often ignored, which effects quality of data [2].

CCH2 (Data integration) is a main key challenge marked in literature review, as integration is needed across various data sources [8]. This request of integration implies that, all the development artifacts in software processing are constantly accessible, even if they reside across different development tools. There are many adaptors and specialized tools where sharing of data is allowed, and where artifacts from different domains of engineering are made accessible throughout development process [6]. However, performing processing of data most of the time data integration lacks behind, as priority given to processing techniques. There should be continuous check-ins to predict the authentication of data integration during software development life cycle, for better data quality assessment [54].

CCH3 (Error and inconsistent data) was mentioned as key challenge in available literature, while working in DevOps environment. Since, continuous deployment leads all importance towards development of process, which cause error and inconsistency in data [4]. Data at each step must authenticated to remove error and inconsistency in continuous environment. Software development team must have knowledge about status of data before using it in deployment phase to make data more consistent. Therefore, to adopt DevOps activities in a scalable manner, one must deliver product on time without any inconsistency [55].

CCH4 (Misspelling in data entry) as development and operation team work together in DevOps environment, they should adopt best practices to resolve data entry issues, marked as major problem in literature studies. Focusing only on time span and product delivery may cause challenge of misspelling while entering data [4]. To validate the performance of product efficiency, data must counter checked, to resolve such issues. The links between different sites should be strong enough to find data entry source [19].

CCH5 (Missing information and other invalid data) due to integration of different sites in software organization, missing of information and other invalid data, is a critical challenge marked by literature in DevOps environment. There is no proper platform for development and operation teams to share their data, constraints and resources with each other, causing problems like missing information and other invalid data entry [19]. Although, not practicing lean terminology, which helps in the elimination of useless data from development environment, also create certain challenge of invalid data and missing of information [56]. This challenge can be resolved by automated data validation process or by practicing lean in development and operational environment [57].

CCH6 (Traceability of data) working in heterogeneous data environment traceability of data is a key issue identified during literature study, as source of data is missing to trace specific data [17]. Such challenge occurs only when proper data assessment pipeline is not defined and there is no proper backtracking path available through which data can be linked properly. The deviation paths of work products if not linked properly with multiple sites; causes challenge of traceability of data. Cito *et al.* [56] marking traceability as a major issue suggested that traceability can only be assessed by checking the quality and quantity of links among related data resources from different software tools.

CCH7 (Data Harmonization) in literature is suggested to be a common issue while working in DevOps environment. During continuous deploying life cycle, integration of multiple source of information to leverage the combined information outcomes, is an expensive task [11], [56], [57]. Once the system is ready, to change the format of data is critical due to change impact on other sources of data. Many companies are doing research on building a data mapping software technique, in order to make transition from one format to another in user friendly way [58]. However, due to the availability of large and open data sets this problem has become challenging. The increasing demand to integrate such open data sets, ongoing updates, visualization and analysis while addressing privacy and security concerns is a common problem. To support data harmonization, developing end-to-end automated process will result in data product with low quality [19]. Therefore, there should be addressable data mapping techniques to resolve such challenge.

CCH8 (Visualization of Data) it can be claimed from literature study that, without suitable visualization and understanding of large integrated data sets in heterogeneous data environment, it is critical day by day to understand purpose of data [19]. Although many users are not familiar with low presentation of data that is targeted to specific group or site. To overcome such problems sub- systems must be integrated for example applications like healthcare, smart city, traffic control systems, land usage and agriculture data must have visualization platform to measure relevant flow of data on heterogeneous sites. Proper data visualization tools must be developed for resolving such challenges [59].

CCH9 (Data Aggregation) is one of the key challenges in mining process, determined from literature studies. A data searched, reported and presented from different source is important, to gain specific business objectives [2]. Consistent approach is required to present and aggregate data, which is a challenging factor in DevOps environment [11].

CCH10 (Data Provenance Problem) data provenance means location of particular data when and where that data was generated [60]. Data provenance is one of the biggest challenges identified from literature to authenticate data. Since data is coming from multiple source, causing challenge of trustworthiness in heterogeneous data environment. Integrity and authenticity must be valuated while analyzing data. There must be some machine learning algorithms to address any particular change [57]. However, measuring provenance of data is challenging as too many checks sometimes create difficulty for developers and operators to work in friendly environment of software development [56].

CCH11 (Storage of transition logs) while considering data validity and security, storage of transition logs is also main challenge determined by literature study in DevOps environment. Nowadays world is generating data in zeta bytes causing issue of storage logs [57]. New engineers must be aware of big data concerns in industry, to manage storage concerns of transition logs [61].

CCH12 (Analyze Data in Real Time) DevOps data quality assessment can be achieved if challenge like analyzing data in real time is been performed smoothly, as discussed in literature [62]. All security measures and automated monitoring frameworks are the major challenges; proper tools are required to maintain such scalability. Data generated in real time i.e., online development systems must keep check on data assessment while sharing data in a continuous environment of DevOps during production [9].

CCH13 (New visualization techniques and their assessments) in order to implement new visualization techniques or integration of new techniques with the existing system is determined as a challenging factor in literature. As all security and privacy, protocols have to update according to new data visualization techniques [19]. There are no proper assessment criteria to assess new techniques and avoid uncertainty issues. The new visualization tools must follow all privacy guidelines suggested by developers. Such tools if implemented properly with whole team discussion may help to reduce time and cost [56]. However, still assessment of such visualization techniques for DevOps data quality assessment might not be possible due to lack of knowledge and training sessions conducted to discuss and promote such techniques [57].

Since, less attention has been paid in past on DevOps data quality assessment challenges. The results of SLR findings also validating our facts by showing, the percentage ratio of existence of DevOps data quality assessment challenges discussed in literature. There are only few reports highlighting the issue of DevOps data quality assessment, as mentioned in section II. The most critical challenges according to SLR findings are CCH 6 (Traceability for data 43%), CCH 12 (Analyze data in real time 35%) and CCH 5 (Missing information and other invalid data).

B. FINDINGS OF EMPIRICAL STUDY (RQ2)

In phase 2, the identified challenges were empirically validated using empirical study. For this technique, a questionnaire was designed to validate challenges of DevOps data quality assessment in software organizations. Fifty respondents responded an online questionnaire completely to validate 13 identified challenges. To find missing and incomplete responses all the collected data was manually reviewed by first and second author. The role of respondents in their organizations ranged from developers to project managers, testers and data analyzers having experience in DevOps.

The designed questionnaire consists of additional open-ended questions to enable the respondents to identify some additional challenges, which were not mentioned in a questionnaire. The scale use to collect possible responses is a Laker scale with 5 points as, ''strongly disagree'', ''disagree'', ''neutral'', ''agree'' and ''strongly agree''. The addition of neutral according to Niazi *et al.* [10], is to show neutral behavior towards the statement does not present any significant disadvantage. Although it helps responded to behave neutral in any condition instead of imposing them to answer positive or negative, which would be a biased decision.

The questionnaire sample is provided in Appendix B which consist of two parts i.e. part I contains personal data and part II contains questions regarding DevOps data quality assessment challenges in software organizations. The results provided in Table 7 shows that the wide range of respondents behave positively agreeing the identified challenges of DevOps data quality assessment in software organizations. We have noticed that *CCH 12 (Analyze data in real time)* is the most critical challenge with percentage of 92% in empirical study, and 35% in SLR findings. There should be proper tools to analyze data in real environment. As data is coming from different sources like IoT devices and online web portals etc. [9].

The second most important critical challenge validated in empirical study is *CCH 5 (Missing information and other invalid data)* with percentage of 90%. Suggesting that there should be proper linkage between data coming from different sites in order to manage such challenge. Adequate platform is required to allow daily check-ins which is quite challenging factor while dealing with DevOps activities [57].

Other most critical challenges validated in this empirical approach are *CCH 6 (Traceability for data)* and *CCH 8 (Visualization of data)* having percentage of 88%. Therefore, organization must consider to resolve such issues on first preference as data is increasing day by day leaving behind gap of how to back track and trace the data origin source. There should be a proper lookup for such challenges and organization should measure them with their continuous deployment activities. Assessing of data quality before its further processing will helps the organization to use data with full assurance which save time and cost [9].

Furthermore, *CCH 1 (Data heterogeneity)* with percentage of 80% and *CCH 4 (Misspelling of data entry)* with percentage of 70% are also significant challenges for data quality assessment in DevOps environment. In addition, none of the identified challenge have percentage below 40%, showing that respondent have knowledge about the identified challenges and consider them important in DevOps environment.

C. METHODOLOGY OF FUZZY TOPSIS TO PRIORITIZE CHALLENGES (RQ3)

In this section, the identified and validated challenges (section IV.A, section IV.B) are prioritized based on their significance to DevOps using Fuzzy TOPSIS approach. This approach has been used by many researchers in other field of engineering [23]–[29], [63]–[65]; and is suitable while dealing with multi criteria data source environment. The 50 respondents of first survey, to validate the challenges of DevOps data quality assessment responds well. Therefore, we shortlisted five of them as decision makers after their approval to give opinions on second survey. The profiles of decision makers are shown in Table 8. After approval from research experts and three external reviewers, a questionnaire sample of second study is provided in Appendix C.

However, the sample size of our second survey is small, might limit the generalization of our study but Fuzzy TOPSIS method is a subjective approach, that can acknowledge the data collected from small sample [10], [66], [67]. The reason of selecting small sample size is that we just want to get response of experts according to the scaled categories. The similar sample size for scaling has been considered in different other research domains. For example, Cheng and Li [68] has collected data from nine experts for comparison of success factors, for construction partnering. Ramasubbu [69] conducted a survey for intelligent building systems, and results were based on nine responses. Shameem *et al.* [65] used seven experts to identify important human error factors

TABLE 8. Profiles of decision makers.

Decision Makers	Experience in DevOps	Years of service
1	DevOps activity management, Quality check, dealing with back end quarries development	5 years
2	Data visualization techniques, Quality assurance, managing DevOps activities, coordination between different sites for better performance and security	4 years
3	DevOps security, data assessment task management, dealing with real time quarries	6 years
4	DevOps team management, works with data assessment tools, customer requirement dealings for quality product	3 years
5	DevOps tools management, interlinking global sites for continuous deployment	4 years

TABLE 9. Outcomes of decision maker 1.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	2	2.5	3	1.5	2	2.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5
	Decision Maker 1														
CCH-1	1.5	2	2.5	2.5	3	3.5	1	1	1	1	1	1	0.5	1	1.5
CCH-2	0.5	1	1.5	2	2.5	3	1	1	1	1.5	2	2.5	1	1.5	2
CCH-3	1	1.5	2	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1	1	1
CCH-4	1	1.5	2	0.5	1	1.5	1	1.5	2	1	1	1	1	1.5	2
CCH-5	1	1	1	2.5	3	3.5	1	1	1	0.5	1	1.5	0.5	1	1.5
CCH-6	0.5	1	1.5	2	2.5	3	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
CCH-7	1.5	2	2.5	0.5	1	1.5	2	2.5	3	0.5	1	1.5	2.5	3	3.5
CCH-8	1.5	2	2.5	2	2.5	3	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
CCH-9	0.5	1	1.5	2.5	3	3.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5
CCH-10	1.5	2	2.5	1.5	2	2.5	1	1.5	2	0.5	1	1.5	1	1	1
CCH-11	0.5	1	1.5	0.5	1	1.5	1	1	1	0.5	1	1.5	1	1	1
CCH-12	2.5	3	3.5	2	2.5	3	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5
CCH-13	2	2.5	3	1.5	2	2.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5

in health care emergency centers in Taiwan using fuzzy TOPSIS. Shameem *et al.* [66] used five expert's opinion to prioritized challenges of agile in distributed software development environment. Niazi *et al.* [10] has introduced the taxonomy of challenges in software project management using three experts to scale their factors. Considering the related study our results are relatively significant enough to measure the research gap. The reported challenges were categorized according to the framework proposed by Cheng and Li [68]. He classified process improvement activities into five categories i.e. project administration, coordination, software methodology, human resource management and technology. Khan *et al.* [67] also used the same category division for software process improvement success factors. Due to similar nature of study, to improve DevOps data quality assessment environment, we categories the challenges into mentioned categories.

Step 1: Five decision makers were selected by consulting academic experts and research team. Based on identified challenges (alternatives) and selected attributes i.e. (project administration, coordination, software methodology, human resource management, technology) we prioritize the challenges of data quality assessment in DevOps.

Step 2: Performance matrix is constructed for each response of decision makers as shown in "(1)". Decision makers evaluate criteria by considering all alternatives.

Tables 9, 10, 11, 12 and 13 shows the outcomes collected from five decision makers after assigning linguistic variables to all alternatives.

Step 3: Aggregate Fuzzy rating for solution by using formula in "(2)" is shown in Table 14.

Step 4: Normalized fuzzy decision matrix was constructed by evaluating the benefit and cost criteria as shown in Eq 3 and Eq 4. The "project administration, coordination, software methodology and human resource management" were considered to be a significant criterion whereas "technology" to use is considered as cost criteria in this study. The Table 15 shows the results after applying formula.

TABLE 10. Outcomes of decision maker 2.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	2.5	3	3.5	1.5	2	2.5	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5
	Decision Maker 2														
CCH-1	1	1.5	2	2	2.5	3	1	1	1	0.5	1	1.5	1	1	1
CCH-2	1	1	1	0.5	1	1.5	0.5	1	1.5	2	2.5	3	1	1.5	2
CCH-3	1	1.5	2	2	2.5	3	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5
CCH-4	1	1.5	2	1	1	1	1	1	1	0.5	1	1.5	1	1.5	2
CCH-5	1	1	1	1.5	2	2.5	1	1.5	2	0.5	1	1.5	1	1.5	2
CCH-6	1	1	1	2	2.5	3	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5
CCH-7	2	2.5	3	0.5	1	1.5	1.5	2	2.5	1.5	2	2.5	1.5	2	2.5
CCH-8	2	2.5	3	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
CCH-9	1.5	2	2.5	2	2.5	3	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5
CCH-10	2	2.5	3	2.5	3	3.5	1	1.5	2	1	1	1	1	1	1
CCH-11	1	1	1	0.5	1	1.5	1	1.5	2	0.5	1	1.5	1	1.5	2
CCH-12	1.5	2	2.5	2.5	3	3.5	0.5	1	1.5	1.5	2	2.5	1	1	1
CCH-13	2	2.5	3	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	2	2.5	3

TABLE 11. Outcomes of decision maker 3.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
	Decision Maker 3														
CCH-1	1	1.5	2	1.5	2	2.5	1	1	1	0.5	1	1.5	0.5	1	1.5
CCH-2	1	1	1	2.5	3	3.5	0.5	1	1.5	2	2.5	3	1	1.5	2
CCH-3	1	1.5	2	2	2.5	3	1	1	1	0.5	1	1.5	1	1.5	2
CCH-4	1	1.5	2	1.5	2	2.5	1	1.5	2	1.5	2	2.5	1	1.5	2
CCH-5	1	1	1	2	2.5	3	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
CCH-6	1.5	2	2.5	2.5	3	3.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
CCH-7	2	2.5	3	1.5	2	2.5	1.5	2	2.5	0.5	1	1.5	2.5	3	3.5
CCH-8	2	2.5	3	2	2.5	3	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5
CCH-9	0.5	1	1.5	2.5	2	3.5	2	2.5	3	0.5	1	1.5	1	1	1
CCH-10	0.1	1	1.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1	1	1
CCH-11	1	1	1	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5
CCH-12	1.5	2	2.5	2.5	3	3.5	2	2.5	3	1.5	2	2.5	0.5	1	1.5
CCH-13	1.5	2	2.5	2	2.5	3	1.5	2	2.5	0.5	1	1.5	1	1	1

Step 5: Weighted normalized Fuzzy decision matrix is calculated by multiplying weight of each criterion with alternatives. Equation 5 shows how to calculate the weighted normalized decision matrix; results are shown in Table 16.

Step 6: To determine Fuzzy positive ideal solution (FPIS) and Fuzzy Negative Ideal solution (FNIS) the selected cost criteria is "Technology" while the remaining criteria "Project Administration", "Coordination", "Software Management" and "Human Resource Management" were considered as benefit criteria. This decision has been taken by having discussion with decision makers and research team. The value of benefit criteria will be better if value is quite near to the FPIS and far away from FNIS "(6)" & "(7)". The Table 17 below shows calculation regarding FPIS and FNIS.

Step 7: Distance of each alternative from FPIS and FNIS was calculated by using Formula mentioned in "(8)" and

"(9)". For example, for alternative CCH1 and criteria Project Management, the calculation results of distance from FPIS and FNIS are as follow.

- **Fuzzy positive ideal solution**

  $\tilde{d} = \{1/3(0.2-0.6)^2+(0.9-1.6)^2+(2.5-3.5)^2\}^{1/2} = 0.7$

- **Fuzzy negative ideal solution**

  $\tilde{d} = \{1/3(0.2-0.0)^2+(0.9-0.7)^2+(2.5-1.5)^2\}^{1/2} = 0.6$

TABLE 12. Outcomes of decision maker 4.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	1.5	2	2.5	2	2.5	3	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5
	Decision Maker 4														
CCH-1	1	1	1	2	2.5	3	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5
CCH-2	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5	1	1	1
CCH-3	1	1.5	2	2	2.5	3	1.5	2	2.5	0.5	1	1.5	1	1.5	2
CCH-4	1	1.5	2	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
CCH-5	1	1	1	0.5	1	1.5	1	1	1	2.5	3	3.5	0.5	1	1.5
CCH-6	0.5	1	1.5	1.5	2	2.5	2	2.5	3	0.5	1	1.5	0.5	1	1.5
CCH-7	1	1	1	0.5	1	1.5	1.5	2	2.5	1.5	2	2.5	2.5	3	3.5
CCH-8	0.5	1	1.5	1.5	2	2.5	2	2.5	3	2	2.5	3	1.5	2	2.5
CCH-9	0.5	1	1.5	2	2.5	3	2	2.5	3	0.5	1	1.5	1	1	1
CCH-10	2	2.5	3	1.5	2	2.5	0.5	1	1.5	1	1	1	1	1	1
CCH-11	0.5	1	1.5	1	1	1	1	1	1	0.5	1	1.5	0.5	1	1.5
CCH-12	1.5	2	2.5	1.5	2	2.5	2	2.5	3	0.5	1	1.5	0.5	1	1.5
CCH-13	1.5	2	2.5	0.5	1	1.5	2.5	3	3.5	0.5	1	1.5	1.5	2	2.5

TABLE 13. Outcomes of decision maker 5.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5
	Decision Maker 5														
CCH-1	0.5	1	1.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1	1	1
CCH-2	1	1	1	2.5	3	3.5	1.5	2	2.5	0.5	1	1.5	1	1	1
CCH-3	0.5	1	1.5	1.5	2	2.5	1	1	1	0.5	1	1.5	1	1.5	2
CCH-4	1	1	1	0.5	1	1.5	0.5	1	1.5	1	1	1	0.5	1	1.5
CCH-5	1.5	2	2.5	2.5	3	3.5	2	2.5	3	0.5	1	1.5	1	1	1
CCH-6	2	2.5	3	0.5	1	1.5	0.5	1	1.5	1	1	1	1.5	2	2.5
CCH-7	1.5	2	2.5	2	2.5	3	1.5	2	2.5	0.5	1	1.5	1.5	2	2.5
CCH-8	2	2.5	3	2.5	3	3.5	1	1	1	1.5	2	2.5	0.5	1	1.5
CCH-9	1	1	1	1.5	2	2.5	0.5	1	1.5	1.5	2	2.5	1	1	1
CCH-10	0.5	1	1.5	2	2.5	3	1	1.5	2	0.5	1	1.5	0.5	1	1.5
CCH-11	1	1	1	1	1	1	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5
CCH-12	2.5	3	3.5	1.5	2	2.5	0.5	1	1.5	0.5	1	1.5	1	1	1
CCH-13	2	2.5	3	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5	1.5	2	2.5

Using same formulas, we have calculated distance points for each alternative from FPIS and FNIS, and after adding them get values for $\tilde{d}_i^+$ *and* $\tilde{d}_i^-$ where i= 1, 2, 3…n. Table 18 and 19 shows all calculated values and Figure 3 shows the graphical distribution of each factor from FPIS and FNIS.

Step 8: Considering formula in eq. 10 we calculated the closeness coefficient CCi for each alternative. For example, CCi of CCH13 is calculated below. Table 20 shows CCi for all 13 alternatives.

$CCi = 2.57/(2.57 + 2.63) = 0.49$

Step 9: After calculating the CCi we ranked the alternatives using CCi value in descending order (Figure 5).

According to ranking of alternatives (Figure 5) by Fuzzy TOPSIS approach CCH12 (Analyze data in real time) marked as most critical challenge while working in DevOps environment. Therefore, there should be proper visualization tools to monitor data in real time. All the sites must have detailed information about their relevant running programs for real time authentication [9], [62]. CCH 8 (Visualization of data) is considered to be the challenging factor as development of data visualization tools in order to work in running environment and to merge more artifacts for smooth assessment is quite difficult [11]. Another challenge CCH 5 (missing information and invalid data) is difficult to manage as development and operation team of DevOps focus more on coordination

TABLE 14. Combined decision matrix of all decision makers.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	1.5	2.3	3.5	0.5	1.7	3	0.5	1.2	2.5	0.5	1.4	2.5	0.5	1.4	2.5
	COMBINED DECISION MATRIX														
CCH-1	0.5	1.4	2.5	1.5	2.4	3.5	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5
CCH-2	0.5	1.2	2.5	0.5	2.1	3.5	0.5	1.2	2.5	0.5	2	3	1	1.3	2
CCH-3	0.5	1.4	2	1.5	2.3	3	0.5	1.4	2.5	0.5	1	1.5	0.5	1.3	2
CCH-4	1	1.4	2	0.5	1.4	2.5	0.5	1.2	2	0.5	1.2	2.5	0.5	1.5	2.5
CCH-5	1	1.2	2.5	0.5	2.3	3.5	0.5	1.4	3	0.5	1.4	3.5	0.5	1.3	2.5
CCH-6	0.5	1.5	3	0.5	2.2	3.5	0.5	1.3	3	0.5	1.2	2.5	0.5	1.6	2.5
CCH-7	1	2	3	0.5	1.5	3	1.5	2.1	3	0.5	1.4	2.5	1.5	2.6	3.5
CCH-8	0.5	2.1	3	1.5	2.4	3.5	0.5	1.3	3	0.5	1.7	3	0.5	1.6	2.5
CCH-9	0.5	1.2	2.5	1.5	2.4	3.5	0.5	2	3	0.5	1.2	2.5	0.5	1	1.5
CCH-10	0.1	1.8	3	1.5	2.3	3.5	0.5	1.3	2	0.5	1	1.5	0.5	1	1.5
CCH-11	0.5	1	1.5	0.5	1	1.5	0.5	1.3	2.5	0.5	1	1.5	0.5	1.1	2
CCH-12	1.5	2.4	3.5	1.5	2.5	3.5	0.5	1.6	3	0.5	1.6	2.5	0.5	1	1.5
CCH-13	1.5	2.3	3	0.5	1.7	3	0.5	1.8	3.5	0.5	1	1.5	0.5	1.7	3

TABLE 15. Normalized fuzzy decision matrix.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	1.5	2.3	3.5	0.5	1.7	3	0.5	1.2	2.5	0.5	1.4	2.5	0.5	1.4	2.5
	NORMALIZED FUZZY DECISION MATRIX														
CCH-1	0.1	0.4	0.7	0.4	0.7	1.0	0.1	0.3	0.4	0.1	0.3	0.4	0.3	0.5	1.0
CCH-2	0.1	0.3	0.7	0.1	0.6	1.0	0.1	0.3	0.7	0.1	0.6	0.9	0.3	0.4	0.5
CCH-3	0.1	0.4	0.6	0.4	0.7	0.9	0.1	0.4	0.7	0.1	0.3	0.4	0.3	0.4	1.0
CCH-4	0.3	0.4	0.6	0.1	0.4	0.7	0.1	0.3	0.6	0.1	0.3	0.7	0.2	0.3	1.0
CCH-5	0.3	0.3	0.7	0.1	0.7	1.0	0.1	0.4	0.9	0.1	0.4	1.0	0.2	0.4	1.0
CCH-6	0.1	0.4	0.9	0.1	0.6	1.0	0.1	0.4	0.9	0.1	0.3	0.7	0.2	0.3	1.0
CCH-7	0.3	0.6	0.9	0.1	0.4	0.9	0.4	0.6	0.9	0.1	0.4	0.7	0.1	0.2	0.3
CCH-8	0.1	0.6	0.9	0.4	0.7	1.0	0.1	0.4	0.9	0.1	0.5	0.9	0.2	0.3	1.0
CCH-9	0.1	0.3	0.7	0.4	0.7	1.0	0.1	0.6	0.9	0.1	0.3	0.7	0.3	0.5	1.0
CCH-10	0.0	0.5	0.9	0.4	0.7	1.0	0.1	0.4	0.6	0.1	0.3	0.4	0.3	0.5	1.0
CCH-11	0.1	0.3	0.4	0.1	0.3	0.4	0.1	0.4	0.7	0.1	0.3	0.4	0.3	0.5	1.0
CCH-12	0.4	0.7	1.0	0.4	0.7	1.0	0.1	0.5	0.9	0.1	0.5	0.7	0.3	0.5	1.0
CCH-13	0.4	0.7	0.9	0.1	0.5	0.9	0.1	0.5	1.0	0.1	0.3	0.4	0.2	0.3	1.0

and continuous delivery product rather than assessing data quality. There should be proper training sessions to skilled team properly about their role in a team. Proper weekly meeting sessions should be conducted to check the results and to authenticate data for further tasks. All the above marked challenges are critical in DevOps environment and proper scheduling must be performed to manage them properly. This will help DevOps activities to function smoothly.

D. MAPPING OF INVESTIGATED CHALLENGES IN SPI MANIFESTO (RQ4)

The SPI manifesto was developed by experts working in domain of software engineering, to assist in the effective initiation of a software process improvement activities. DevOps is also a software process improvement approach therefore, mapping of DevOps data quality assessment challenges in the SPI manifesto, will clear the category of these challenges. There are three core categories of SPI manifesto i.e. people, business and change. These core categories consist of further 10 principles that provide decision-based knowledge for experts dealing with SPI challenges (Figure 6).

In this research the mapping was conducted by two authors who collected data from literature and empirical study on DevOps data quality assessment challenges in software organizations. The classification of identified challenges was based on three core categories of SPI i.e. (people, business

TABLE 16. Weighted normalized decision matrix.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
WEIGHT	1.5	2.3	3.5	0.5	1.7	3	0.5	1.2	2.5	0.5	1.4	2.5	0.5	1.4	2.5
WEIGHTED NORMALIZED DECISION MATRIX															
CCH-1	0.2	0.9	2.5	0.2	1.2	3.0	0.1	0.3	1.1	0.1	0.4	1.1	0.2	0.7	2.5
CCH-2	0.2	0.8	2.5	0.1	1.0	3.0	0.1	0.4	1.8	0.1	0.8	2.1	0.1	0.5	1.3
CCH-3	0.2	0.9	2.0	0.2	1.1	2.6	0.1	0.5	1.8	0.1	0.4	1.1	0.1	0.5	2.5
CCH-4	0.4	0.9	2.0	0.1	0.7	2.1	0.1	0.4	1.4	0.1	0.5	1.8	0.1	0.5	2.5
CCH-5	0.4	0.8	2.5	0.1	1.1	3.0	0.1	0.5	2.1	0.1	0.6	2.5	0.1	0.5	2.5
CCH-6	0.2	1.0	3.0	0.1	1.1	3.0	0.1	0.4	2.1	0.1	0.5	1.8	0.1	0.4	2.5
CCH-7	0.4	1.3	3.0	0.1	0.7	2.6	0.2	0.7	2.1	0.1	0.6	1.8	0.1	0.3	0.8
CCH-8	0.2	1.4	3.0	0.2	1.2	3.0	0.1	0.4	2.1	0.1	0.7	2.1	0.1	0.4	2.5
CCH-9	0.2	0.8	2.5	0.2	1.2	3.0	0.1	0.7	2.1	0.1	0.5	1.8	0.2	0.7	2.5
CCH-10	0.0	1.2	3.0	0.2	1.1	3.0	0.1	0.4	1.4	0.1	0.4	1.1	0.2	0.7	2.5
CCH-11	0.2	0.7	1.5	0.1	0.5	1.3	0.1	0.4	1.8	0.1	0.4	1.1	0.1	0.6	2.5
CCH-12	0.6	1.6	3.5	0.2	1.2	3.0	0.1	0.5	2.1	0.1	0.6	1.8	0.2	0.7	2.5
CCH-13	0.6	1.5	3.0	0.1	0.8	2.6	0.1	0.6	2.5	0.1	0.4	1.1	0.1	0.4	2.5

TABLE 17. FPIS and FNIS results.

	Project Administration			Coordination			Software Methodology			Human Resource Management			Technology		
W	1.5	2.3	3.5	0.5	1.7	3	0.5	1.2	2.5	0.5	1.4	2.5	0.5	1.4	2.5
A+	0.6	1.6	3.5	0.2	1.2	3.0	0.2	0.7	2.5	0.1	0.8	2.5	0.2	0.7	2.5
A-	0.0	0.7	1.5	0.1	0.5	1.3	0.1	0.3	1.1	0.1	0.4	1.1	0.1	0.3	0.8
A+ = FPIS , A- = FNIS W= Normalized weights															

TABLE 18. Distance from FPIS.

Distance from FPIS						
Sr#	Project Administration	Coordination	Software Methodology	Human Resource Management	Techn ology	di^+
CCH-1	0.7	0.0	0.9	0.9	0.0	2.48
CCH-2	0.8	0.1	0.5	0.2	0.7	2.31
CCH-3	1.0	0.3	0.4	0.9	0.1	2.63
CCH-4	1.0	0.6	0.6	0.5	0.1	2.78
CCH-5	0.7	0.1	0.3	0.1	0.1	1.35
CCH-6	0.5	0.1	0.3	0.5	0.2	1.51
CCH-7	0.3	0.4	0.2	0.4	1.0	2.37
CCH-8	0.4	0.0	0.3	0.2	0.2	1.07
CCH-9	0.8	0.0	0.2	0.5	0.0	1.48
CCH-10	0.5	0.1	0.6	0.9	0.0	2.06
CCH-11	1.3	1.1	0.4	0.9	0.0	3.72
CCH-12	0.0	0.0	0.2	0.4	0.0	0.67
CCH-13	0.3	0.3	0.1	0.9	0.2	1.77

and change) to portray the conceptual mapping framework based on literature study discussed in section IV.A. The challenges belong to different dimensions of DevOps practices. The results were verified for further assessment and were sent to two DevOps experts in ''King Fahad University of Petroleum and Minerals, Saudi Arabia'' and ''Indian Institute

TABLE 19. Distance from FNIS.

	Distance from FNIS					
SR#	Project Administration	Coordination	Software Methodology	Human Resource Management	Technology	di-
CCH-1	0.6	1.1	0.0	0.0	1.0	2.67
CCH-2	0.6	1.0	0.4	0.7	0.3	2.99
CCH-3	0.3	0.8	0.4	0.0	1.0	2.57
CCH-4	0.4	0.5	0.2	0.4	1.0	2.50
CCH-5	0.6	1.1	0.6	0.8	1.0	4.11
CCH-6	0.9	1.0	0.6	0.4	1.0	3.94
CCH-7	1.0	0.8	0.7	0.4	0.0	2.81
CCH-8	1.0	1.1	0.6	0.6	1.0	4.26
CCH-9	0.6	1.1	0.6	0.4	1.0	3.72
CCH-10	0.9	1.1	0.2	0.0	1.0	3.19
CCH-11	0.1	0.0	0.4	0.0	1.0	1.50
CCH-12	1.3	1.1	0.6	0.4	1.0	4.46
CCH-13	1.1	0.8	0.8	0.0	1.0	3.63

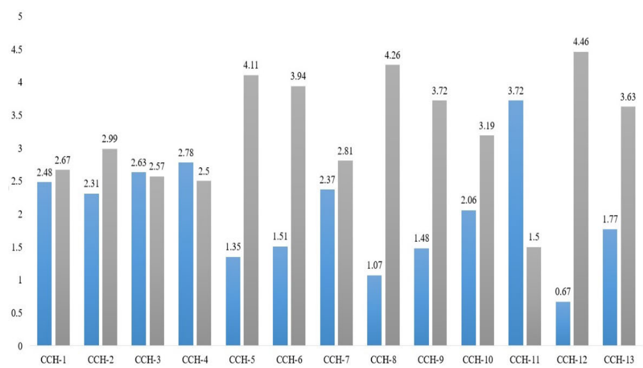

FIGURE 4. Graphical distribution of CCHs from FPIS and FNIS.

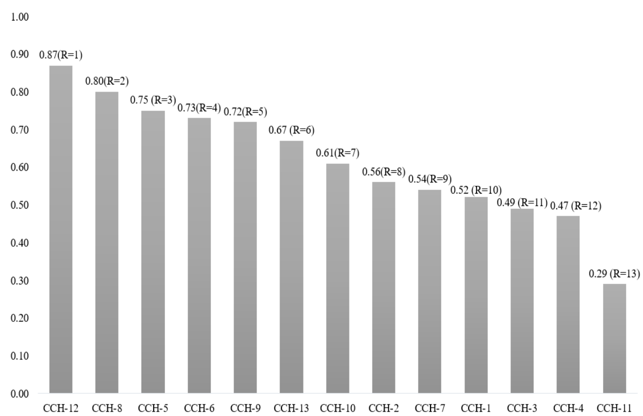

FIGURE 5. Ranking of CCHs.

of Technology, India (IIT)''. Based on their recommendations, we re-arranged the position of some factors, the final version of mapping is shown in Figure 7.

We have ranked the identified success factors based on the CC_i (Table 20), with the aim to check the significance of a particulate factors within the specific process area. For example, Figure 6 shows that while comparing with all

TABLE 20. CCi values and ranking.

Challenges	CCi	Rank
Data heterogeneity (CCH1)	0.52	10
Data integration (CCH2)	0.56	8
Error and inconsistent data (CCH3)	0.49	11
Misspelling in data entry (CCH4)	0.47	12
Missing information and other invalid data (CCH5)	0.75	3
Traceability for data (CCH6)	0.73	4
Data harmonization (CCH7)	0.54	9
Visualization of data (CCH8)	0.80	2
Data aggregation (CCH9)	0.72	5
Data provenance problem (CCH10)	0.61	7
Storage of transaction logs (CCH11)	0.29	13
Analyze data in real time (CCH12)	0.87	1
New visualization techniques and their assessment (CCH13)	0.67	6

the identified factors, the CCH8 (Visualization of data) is ranked as 2nd but within its specific process area (business), CCH8 ranked as the most important factor. This shows the significance of CCH8 within certain process areas and also for overall study objective. Consequently, Figure 5, shows the ranked order of all the identified factors within their category and for overall study objective. This prioritization-based taxonomy (Figure 6), assists the practitioners and researchers to consider the most important challenges, by considering their significance within the process area and for overall study objective.

V. SUMMARY AND DISCUSSION

The key objective of this study is to identify the challenges that hinders the data quality assessment in DevOps

TABLE 21. Results according to proposed research questions.

Sr		Results
RQ1:	What are the most critical challenges investigated in literature related to data quality assessment in DevOps environment?	CCH-1 Data heterogeneity CCH2- Data integration CCH3- Error and inconsistent data CCH4- Misspelling in data entry CCH5- Missing information and other invalid data CCH6- Traceability for data CCH7- Data harmonization CCH8- Visualization of data CCH9- Data aggregation CCH10- Data provenance problem CCH11- Storage of transaction logs CCH12- Analyze data in real time CCH13- New visualization techniques and their assessment
RQ2:	Does identified challenges create hurdle in DevOps continuous deployment life cycle and are empirically validated by the experts?	According to the outcomes calculated above from empirical study shows positive response towards the impact of such challenges in DevOps environment. A survey was conducted and we collected 50 responses form respondents working in DevOps environment showing their knowledge and experience about the identified challenges.
RQ3:	How priorities can be assigned to the identified challenges in order to measure their impact on DevOps environment?	The sensitivity level of data quality assessment challenges in DevOps environment was calculated by applying fuzzy TOPSIS technique by selecting five decision makers. A process development framework was adopted consisting of five criteria to measure the priority of data quality assessment challenges for better manageable structure of DevOps. This leads us to focus on new area of research not discussed in detail before as second importance is given to data quality assessment as shown in (Figure 5).
RQ4:	What would be the prioritization-based taxonomy of identified factors?	The prioritization-based taxonomy (Figure 6) will assist the practitioners to consider the most significant challenges, by considering their importance within the process area and for overall study objectives.

environment. Using the step by step protocols of systematic literature review, we have identified the 13 factor that could negatively influence the DevOps data quality assessment process. A questionnaire survey study was conducted to validate the finding of literature review with experts. The identified challenges were further analyzed concerning to their impact on DevOps data quality assessment, applying the fuzzy TOPSIS. Besides, this study explores the new research area in the domain of DevOps (i.e. data quality assessment) as it has an important value towards the success and progression of DevOps. As most of existing studies ignored the assessment of data quality that comes from heterogeneous environment, as they previously more focused on continuous deployment, delivery and integration process. The brief summary of study results against each research question is given in Table 21.

VI. THREATS AND VALIDITY

The literature review process was conducted by the first author of the paper and it might be threat to the findings of the study as the data collected by a single author could be biased. However, the first and third authors continuously examine the extracted data to find any issues and limitation that were ignored by the second author.

One possible threat towards the validity of this study is that, due to the limited time and resources, the sample size of survey questionnaire (n=52) might not be strong enough to justify the validity of the reported challenging factors. However, based on the different other existing studies [11], [14], this is a representative sample to justify the understanding and assessment of the challenging factors.

Construct validity refers that whether or not the selected measurement scale precisely measured the given variables. The DevOps challenging factors were extracted from the available state of the art literature and validated by conducting the empirical study with the industrial experts. The feedback of the survey participants revealed that the reported challenging factors related to their work.

Internal validity represents the assessment of the reported results and analysis. We have conducted a pilot study

TABLE 22. Selected primary studies.

ID	Description	QE1	QE2	QE3	QE4	QE5	Total
SP1	P. Perera, R. Silva, and I. Perera, "Improve software quality through practicing DevOps," in 2017 Seventeenth International Conference on Advances in ICT for Emerging Regions (ICTer), IEEE, Sep. 2017, pp. 1-6.	0.5	1	1	1	1	4
SP2	Gürdür, D., El-khoury, J. and Nyberg, M., 2019. Methodology for linked enterprise data quality assessment through information visualizations. *Journal of Industrial Information Integration*, *15*, pp.191-200.	0.5	0.5	1	1	1	3
SP3	Heath, T. and Berners-Lee, T., 2009. Linked Data-The Story So Far. *International Journal on Semantic Web and Information Systems (IJSWIS)*.	1	1	0.5	1	1	4.5
SP4	Hyland, B. and Wood, D., 2011. The joy of data-a cookbook for publishing linked government data on the web. In *Linking government data* (pp. 3-26). Springer, New York, NY.	1	1	1	0.5	1	4.5
SP5	Rahm, E. and Do, H.H., 2000. Data cleaning: Problems and current approaches. *IEEE Data Eng. Bull.*, *23*(4), pp.3-13.	1	1	1	0.5	1	4.5
SP6	Borovina Josko, J.M. and Ferreira, J.E., 2017. Visualization properties for data quality visual assessment: An exploratory case study. *Information Visualization*, *16*(2), pp.93-112.	1	1	1	1	0.5	4.5
SP7	Rubasinghe, I., Meedeniya, D. and Perera, I., 2018, September. Traceability Management with Impact Analysis in DevOps based Software Development. In *2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (pp. 1956-1962). IEEE.	1	1	0	0	1	3
SP8	Claps, G.G., Svensson, R.B. and Aurum, A., 2015. On the journey to continuous deployment: Technical and social challenges along the way. Information and Software technology, 57, pp.21-31.	1	1	0.5	1	0	3.5
SP9	Farroha, B.S. and Farroha, D.L., 2014, October. A framework for managing mission needs, compliance, and trust in the DevOps environment. In 2014 IEEE Military Communications Conference (pp. 288-293). IEEE.	1	1	1	0	0.5	3.5
SP10	Kim, G., Behr, K. and Spafford, K., 2014. The phoenix project: A novel about IT, DevOps, and helping your business win. IT Revolution.	0.5	1	1	1	1	4.5
SP11	Callanan, M. and Spillane, A., 2016. DevOps: making it easy to do the right thing. Ieee Software, 33(3), pp.53-59.	1	1	1	1	0	4
SP12	Meyer, M., 2014. Continuous integration and its tools. IEEE software, 31(3), pp.14-16.	1	0	1	1	0.5	3.5
SP13	Avazpour, I., Grundy, J. and Zhu, L., 2019. Engineering complex data integration, harmonization and visualization systems. Journal of Industrial Information Integration, p.100103.	1	0	0	0.5	1	2.5
SP14	D. Marijan, M. Liaaen, and S. Sen, "DevOps Improvements for Reduced Cycle Times with Integrated Test Optimizations for Continuous Integration," in *2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC),* 2018, pp. 22-27.	1	0	0	1	1	3
SP15	B. Snyder, and B. Curtis, "Using Analytics to Guide Improvement during an Agile–DevOps Transformation," *IEEE Software*, *35*(1), 2018, pp.78-83.	1	1	1	0	1	4
SP16	L. E. Lwakatare, P. Kuvaja, and M. Oivo, "Relationship of DevOps to agile, lean and continuous deployment," in *International Conference on Product-Focused Software Process Improvement, Springer, Cham*, Nov. 2016, pp. 399-415.	1	0.5	1	1	0	3.5
SP17	J. Cito, J. Wettinger, L. E. Lwakatare, M. Borg, and F. Li, "Feedback from Operations to Software Development—A DevOps Perspective on Runtime Metrics and Logs" in *International Workshop on Software Engineering Aspects of Continuous Development and New Paradigms of Software Production and Deployment,* Springer, Cham, 2018, pp. 184-195.	1	1	1	0	0	3
SP18	W. Gottesheim, "Challenges, benefits and best practices of performance focused DevOps," in *Proceedings of the 4th International Workshop on Large-Scale Testing,* Feb. 2015, pp. 3-3. ACM.	1	1	1	1	0	4
SP19	N. Beigi-Mohammadi, M. Litoiu, M. Emami-Taba, L. Tahvildari, M. Fokaefs, E. Merlo, and I. V. Onut, "A DevOps framework for quality-driven self-protection in web software systems," in *Proceedings of the 28th Annual International Conference on Computer Science and Software Engineering, IBM Corp*, Oct. 2018, pp. 270-274.	0	1	1	1	0.5	3.5
SP20	W. Hasselbring, S. Henning, B. Latte, A. Möbius, T. Richter, S. Schalk, and M. Wojcieszak, "Industrial DevOps," in *2019 IEEE International Conference on Software Architecture Companion (ICSA-C*), IEEE, Mar. 2019, pp. 123-126.	1	1	1	0	1	4
SP21	Nogueira, A.F., Ribeiro, J.C., M. Zenha-Rela, and A. Craske, "Improving La Redoute's CI/CD Pipeline and DevOps Processes by Applying Machine Learning Techniques," in *2018 11th International Conference on the Quality of Information and Communications Technology (QUATIC),IEEE,* 2018, pp. 282-286.	1	1	1	0.5	1	4.5

TABLE 22. *(Continued.)*

SP22	M. Rajkumar, A. K. Pole, V. S. Adige, and P. Mahanta, "DevOps culture and its impact on cloud delivery and software development," in *2016 International Conference on Advances in Computing, Communication, & Automation (ICACCA)(Spring), IEEE,* 2016, pp. 1-6.	1	1	1	0.5	0	3.5
SP23	K. Kuusinen, V. Balakumar, S. C. Jepsen, S. H. Larsen, T. A. Lemqvist, A. Muric, A. O. Nielsen, and O. Vestergaard, "A Large Agile Organization on Its Journey Towards DevOps," in *2018 44th Euromicro Conference on Software Engineering and Advanced Applications (SEAA), IEEE,* AUG. 2018, pp. 60-63.	1	1	0.5	1	1	4.5
SP24	C. A. Cois, J. Yankel, and A. Connell, "Modern DevOps: Optimizing software development through effective system interactions," in *2014 IEEE International Professional Communication Conference (IPCC), IEEE,* 2014, pp. 1-7.	1	1	0	0	1	3
SP25	W. John, G. Marchetto, F. Németh, P. Skoldstrom, R. Steinert, C. Meirosu, I. Papafili, and K. Pentikousis, "Service provider devops. *IEEE Communications Magazine*," *55*(1), 2017, pp.204-211.	1	1	1	0	1	4
SP26	S. S. Samarawickrama, and I. Perera, "Continuous scrum: A framework to enhance scrum with DevOps," in *2017 Seventeenth International Conference on Advances in ICT for Emerging Regions (ICTer), IEEE,* 2017, pp. 1-7.	0.5	1	0	1	1	3.5
SP27	Ebert, C., Gallardo, G., Hernantes, J. and Serrano, N., "DevOps. *Ieee Software*," *33*(3), 2016, pp. 94-100.	1	1	0	0	0.5	2.5
SP28	V. Gupta, P. K. Kapur, and D. Kumar, "Modeling and measuring attributes influencing DevOps implementation in an enterprise using structural equation modeling," *Information and Software Technology*, *92*, 2017, pp. 75-91.	1	1	1	0	1	4
SP29	B. Fitzgerald, and K. J. Stol, "Continuous software engineering: A roadmap and agenda," *Journal of Systems and Software*, *123*, 2017, pp. 176-189.	1	1	0	1	1	4
SP30	L. Chen, "Continuous delivery: overcoming adoption challenges." *Journal of Systems and Software*, *128*, 2017. pp.72-86.	1	1	0.5	1	0	3.5

Scoring Points
- "An article giving answers to the checklist questions was assigned 1 point".
- "An article partially answer to the checklist questions was assigned 0.5 points".
- "An article not giving any answer to the checklist questions was assigned 0 points".

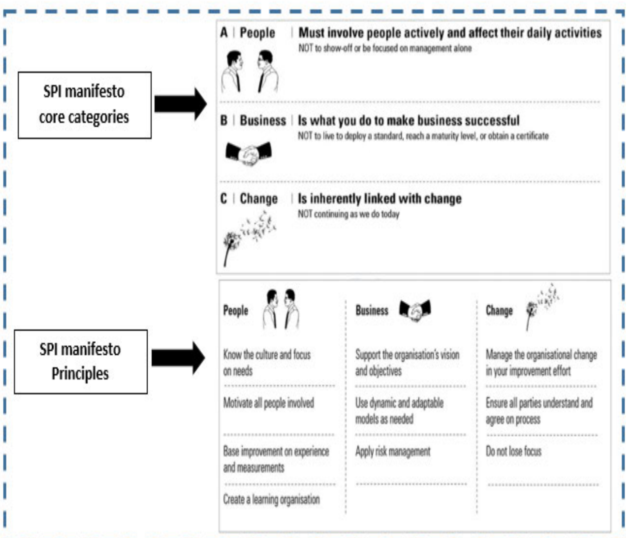

FIGURE 6. Core categories and principles of SPI manifesto values.

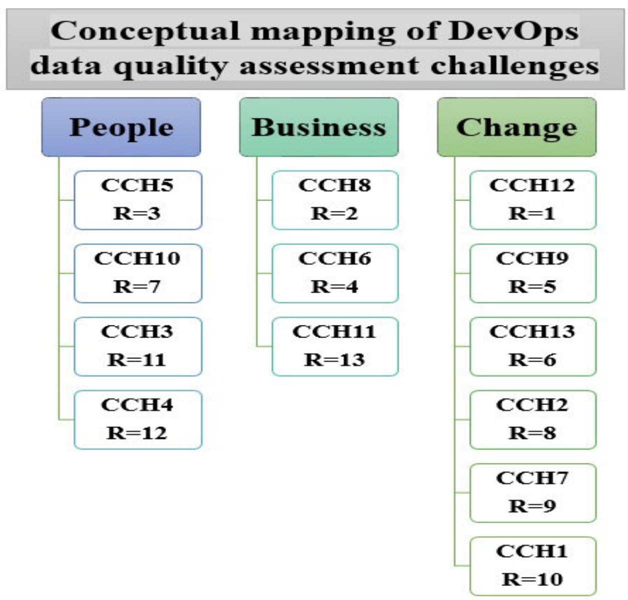

FIGURE 7. Conceptual framework of DevOps data quality assessment challenges.

(section III. B.1) with the research experts that provides an acceptable internal validity level. External validity related to generalize the results of the study. In this research study, most of the survey respondents were from Asian countries and we were unable to generalize the results with respect to other regions. However, the data sample of this study also consists of responses from different other continents and we believe that this data sample was sufficiently representative.

TABLE 23. Empirical study survey questionnaire.

Section 1(Respondents information)					
Full Name			Position		
Working experience in DevOps environment?			Years:		
Company Name					
Email Address					
Address of company and country name					
Total academic and industrial experience?	Years:				
Have you ever participated in DevOps related international activities?	Yes ☐		NO ☐		
Total number of employees in an organization?	Less than 20 ☐		More than 20 ☐		
Please specify your organization type?	Small ☐	Medium ☐	Large ☐		
How many years ago this organization adopted DevOps activities in real practice?	Less then five ☐		More than five ☐		
Dose organization improving DevOps practices according to their standards?	Yes ☐		NO ☐		
Dose organization working on data quality while adopting DevOps?	Yes ☐		NO ☐		
Section B Challenges of data quality assessment while working in DevOps heterogeneous environment					
The key objective of this section is to validate the identified challenges in real world industry. The reported challenges were identified by using systematic literature review. Please rank the challenges according to your own understanding and experience.					
Using 5 points as “strongly disagree SD”, “disagree D”, “neutral N”, “agree A” and “strongly agree SA”.					
Identified Challenges	**SD**	**D**	**SA**	**A**	**N**
Data heterogeneity (CCH1)	☐	☐	☐	☐	☐
Data integration (CCH2)	☐	☐	☐	☐	☐
Error and inconsistent data (CCH3)	☐	☐	☐	☐	☐
Misspelling in data entry (CCH4)	☐	☐	☐	☐	☐
Missing information and other invalid data (CCH5)	☐	☐	☐	☐	☐
Traceability for data (CCH6)	☐	☐	☐	☐	☐
Data harmonization (CCH7)	☐	☐	☐	☐	☐
Visualization of data (CCH8)	☐	☐	☐	☐	☐
Data aggregation (CCH9)	☐	☐	☐	☐	☐
Data provenance problem (CCH10)	☐	☐	☐	☐	☐
Storage of transaction logs (CCH11)	☐	☐	☐	☐	☐
Analyze data in real time (CCH12)	☐	☐	☐	☐	☐
New visualization techniques and their assessment (CCH13)	☐	☐	☐	☐	☐
Add challenge apart from reported ones					

Moreover, the prioritization of challenges (Fuzzy TOPSIS approach) was based on the opinions of decision makers, it’s a hasty approach, which may affect the study results.

However, we have calculated distance of each alternative from FPIS and FNIS which indicates the acceptable validity for prioritization of challenges depending upon selected criteria. Same approach has been used in other studies to identify challenges in fuzzy environment to get ideal solution [63]–[65].

VII. IMPLICATIONS

This study has both research and practical implications to simplify DevOps continuous deployment activities by pointing out the challenges previously being ignored in DevOps data quality assessment. Since, priority was attained by continuous deployment and delivery process keeping behind DevOps data quality assessment activities which causes various hurdles while adopting DevOps. The identification DevOps data quality assessment challenges, and suggestion to give first priority to data assessment rather than linking different deployment units is an important contribution for academia. It would help developers and other concern departments to resolve problems hindering in DevOps data quality assessment before further processing of data. The prioritization and taxonomy of identified challenges is important from managerial point of view to assist DevOps team to evaluate and revise their practices and management approaches in specific area, for better scalability of DevOps environment.

TABLE 24. Fuzzy Topsis survey sample template.

Section 1(Respondents information)				
Full Name	Phone#:		Position	
Working experience in DevOps environment?			Years:	
Company Name				
Email Address				
Address of company and country name				
Total academic and industrial experience?	Years:			
Have you ever participated in DevOps related international activities?	Yes ☐	NO ☐		
Total number of employees in an organization?	Less than 20 ☐	More than 20 ☐		
Please specify your organization type?	Small ☐	Medium ☐	Large ☐	
How many years ago this organization adopted DevOps activities in real practice?	Less then five ☐	More than five ☐		
Dose organization improving DevOps practices according to their standards?	Yes ☐	NO ☐		
Dose organization working on data quality while adopting DevOps?	Yes ☐	NO ☐		

Section B (Part 1):Criteria wise Comparison of challenges to measure impact

The key objective of this section is to validate criteria wise comparison of challenges. The reported challenges were identified by using systematic literature review and validated by empirical study.
Please rank the challenges according to your own understanding and experience using **linguistic scale** given bellow.

Linguistic values

Linguistic Scale	***Triangular Fuzzy Scale***
Just Equal= JE	(1,1,1)
Equally Important = EI	(0.5,1,1.5)
Weakly Important = WI	(1,1.5,2)
Strongly More Important = SMI	(1.5,2,2.5)
Very Strongly More Important= VSMI	(2,2.5,3)
Absolutely more important= AMI	(2.5,3,3.5)

Project Administration "PA", Coordination "C", Software methodology "SM", Human resource management "HRM", Technology "T"

Identified Challenges	**PA**	**C**	**SM**	**HRM**	**T**
	Linguistic values				
Data heterogeneity (CCH1)					
Data integration (CCH2)					
Error and inconsistent data (CCH3)					
Misspelling in data entry (CCH4)					
Missing information and other invalid data (CCH5)					
Traceability for data (CCH6)					
Data harmonization (CCH7)					
Visualization of data (CCH8)					
Data aggregation (CCH9)					
Data provenance problem (CCH10)					
Storage of transaction logs (CCH11)					
Analyze data in real time (CCH12)					
New visualization techniques and their assessment (CCH13)					

The purpose of this questionnaire is to determine the weight of each criteria and compare the challeges according to the selected weighted criterias.

Section B (Part 2) Also Weight importance of all five criteria using same linguistic Scale values.
Purpose of getting each criteria weight is to check the significance of criteria in DevOps Development.

Selected Criteria for DevOps Development Process	**Linguistic values**
Project Administration (PA)	
Coordination (C)	
Software Methodology (SM)	
Human Resource Management (HRM)	
Technology (T)	

Note: Mark the identified challenges with criteria using linguistic values for example if criteria "project administration PA" is the main cause of challenge "Data heterogeneity (CCH1)" then mark it as "Absolutely more important= AMI" and wise versa if criteria have low weightage.

VIII. CONCLUSION AND FUTURE WORK

The increasing trend of using DevOps activities in organizations motivated us to identify the factors that have negative impact on DevOps data quality assessment, as the data is coming from different sources e.g. (IoT and online web centers etc.) and its size is increasing day by day [9]. It is significant to address the challenging factors of DevOps data quality for the successful implementation of DevOps activities in software industry. In this study, we have conducted a systematic literature review and a total of 13 challenging factors were identified. The literature findings were further validated with experts using questionnaire survey study. The results of questionnaire survey study releveled that the identified challenging factors could negative the impact the practices of DevOps data quality assessment process. We have mapped the identified challenging factors in the criteria of software process development framework and finally, the Fuzzy TOPSIS approach was applied to prioritize the challenges, based on selected criteria. The results show that missing information and other invalid data (CCH5), visualization of data (CCH8) and analyze data in real time (CCH12) are declared the highest ranked challenging factors for DevOps data quality assessment process. We believe the results of this study will provide the knowledge base for practitioners and researchers to develop the effective techniques for the success and progression of DevOps data quality assessment process.

In future, we will conduct multivocal literature study to identify the additional challenging factors of DevOps data quality assessment process. We also plan to conducted industrial empirical study to identify the best practices which are important to adopt for the successful implementation of DevOps data quality assessment process. Finally, we will conduct case study with real-world industry experts and design a readiness model for DevOps implementation in software industry.

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APPENDIXES

APPENDIX-A: SELECTED PRIMARY STUDIES

See Table 22.

APPENDIX B: (EMPIRICAL STUDY SURVEY QUESTIONNAIRE)

See Table 23.

APPENDIX C: (FUZZY TOPSIS SURVEY SAMPLE)

See Table 24.

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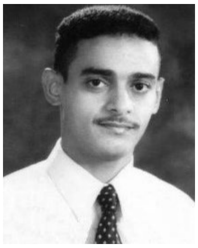

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