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Review Article

Advantages and Challenges of Information Fusion Technique for Big Data Analysis: Proposed Framework

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ABSTRACT

Introduction: Recently, with the surge in the availability of relevant data in various industries, the use of Information Fusion technique for data analysis is increasing. This method has several advantages, such as increased accuracy, and the use of meaningful information. In addition, there are certain challenges, including the impact of data type and analytical method on results. The goal of this study is to propose a framework for introducing the advantages and classifying the challenges of this technique.
Method: We conducted a review of articles published between January 1960 and December 2017 for the design stage and from January 2018 to December 2018 for the evaluation stage. Articles were identified from various databases such as Science Direct, IEEE, Scopus, Web of Science, and Google Scholar, using the keywords decision fusion, information fusion, and symbolic fusion. We report the advantages and challenges of the methodologies described in these articles. Analysis was conducted in accordance with PRISMA guidelines.
Results: A total of 132 articles were identified in the design stage and 90 articles were identified in the evaluation stage. Categories within the framework for challenges include "hardware and software requirements for processing and maintaining the process", "data" and "data analysis method". The categories for advantages include "value modeling", "preferable management of uncertainty and variability", "excellent decision making", "comprehensive interpretation and representation", "data management" and "simplicity of infrastructure". Our results indicate using these two frameworks with 95% Confidence interval.
Conclusion: An overall understanding of the advantages and challenges of the information fusion technique could act as a guide for the researcher for the correct usage of this technique.

Introduction

Today, the amount of data that is digitally collected and stored in large volumes is increasing exponentially due to the advent of technology. It is predicted that the collective sum of world's data will be as high as 175 ZB by the year 2025 (1-3). Such massive data

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sets are termed as 'Big Data', which has become a topic of interest in all industries. However, this huge amount of data is largely unstructured (4, 5). This unstructured data can be translated into meaningful information using data management techniques such as the information fusion technique (6-8). Analyzing such data to identify hidden patterns within the data is called Big Data analysis. The data that is generated from online transactions, (emails, videos, audio, images, click streams, logs, posts, search queries, health records, social networking interactions, science data, sensors, mobile phones and applications) have characteristics such as diversity, scalability, uncertainty, speed in production and complexity, where analysis using conventional data mining methods is not possible (2, 9, 10). In such cases, information fusion technique offers a potential solution to derive valuable outcomes from complex systems (11). In fact, this technique is a method associated with data mining, which uses the concepts of knowledge representation, arithmetic and mathematics that can be used in constructing a model, extracting information, pre-processing and increasing the quality of data for better understanding of information (12, 13). This can play an important role for decision-making in a variety of domains, such as sensor and image processing (13, 14).

Classical data mining techniques frequently do not work when problems get increasingly complicated (15). To solve complex problems, a classifier cannot be used on its own to categorize data. Simple data mining techniques prove ineffective since they do not offer the needed performance. In such instances, more robust techniques such as the fusion techniques are used where classifiers are combined and often use selected sets of appropriate and useful features to perform tasks. The use and application of these techniques is increasing in various fields including healthcare and medicine. For example, the fusion techniques are used to analyze a variety of data such as diverse and high-volume gene data, image segmentation and signal analysis (11).

The overarching goal of the information fusion technique is to reduce complexity to a manageable level for a human analyst or operator and is used to optimize and summarize the information (16). Further, it utilizes multiple information sources to achieve objectivity and increased awareness of the goal (17). It is an effective method for the automatic or semi-automatic conversion of information from various sources and different time points. However, there are certain advantages and challenges presented with this technique. Some of the advantages are noise reduction, increased accuracy and delivering high quality unbiased results (11) The key challenges of this technique are associated with system processing, data storage, data representation and the type of method to be used (18).

A general understanding of the advantages of this technique will help capitalize its full potential and recognizing the challenges may assist in designing and delivering robust solutions. However, at present the advantages, challenges and functions of the technique are discussed separately in various studies. To our knowledge, there is only one framework that categorizes the challenges of this technique (16), while a framework that classifies the advantages of this technique currently does not exist in the literature. Availability of a framework serves as a useful guide for researchers by summarizing complicated information all in one place. The framework can be reused for similar fields of study, thereby reducing the efforts of the researchers. Therefore, the objective of this study is twofold (i) to introduce a framework that describe the advantages of the technique and (ii) update the framework of challenges by comparing it with a previously proposed framework.

Method

Source of Data

To design the framework a comprehensive search was conducted on five bibliographic electronic databases (Science Direct, IEEE, Web of Science, Scopus and Google Scholar) using the keywords decision fusion, information fusion and symbolic fusion. We included articles published in the English language between January 1960 and December 2017 for the design stage and from January 2018 to December 2018 for the evaluation stage in accordance with the PRISMA guidelines (19).

Search Strategy

We followed a 2-stage process to identify a list of comprehensive literature for the study-stage 1, design and stage 2, evaluation (20, 21). We included all relevant literature (i.e., books, surveys, review papers and original research papers) for the design stage and only original research papers for the evaluation stage. We included literature (i) written in English language, (ii) discusses the advantages and/or challenges of the information fusion technique. The electronic search resulted in a total of 18,889 articles in the design stage (see Figure 1) and 2,429 articles in the evaluation stage (see Figure 2). After removing duplicates, the titles of 9,993 articles (design) and 1,482 articles (evaluation) were screened for relevance. Next, we reviewed the abstracts of 4,653 articles (design) and 150 articles (evaluation) and this process resulted in 166 articles (design) and 118 articles (evaluation) for full-text review. From this a total of 34 articles and 28 articles were excluded from the design and evaluation stages respectively, since the full text of these articles were not available, or they did not meet the inclusion criteria. This resulted in 132 articles and 90 articles in the design and evaluation stages that were included in the final analysis. Overall, two reviewers (EN and HT) independently evaluated the records for inclusion.

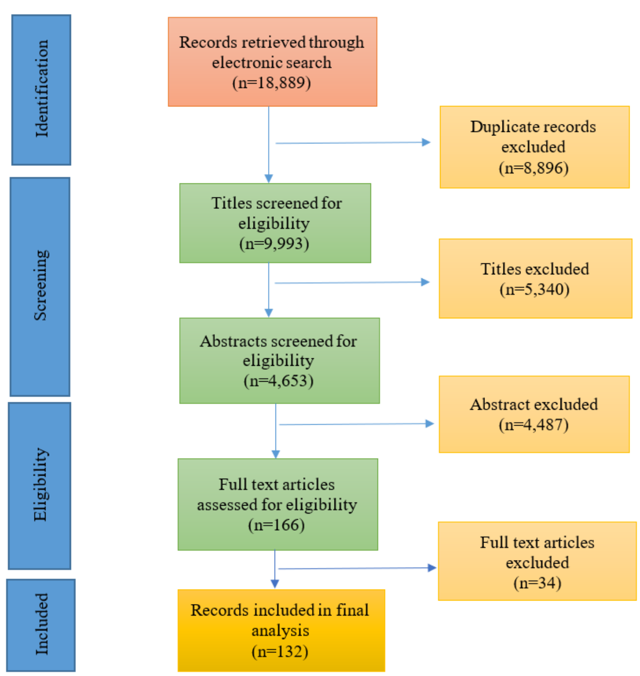

Figure1: Summary of the research process in the design step

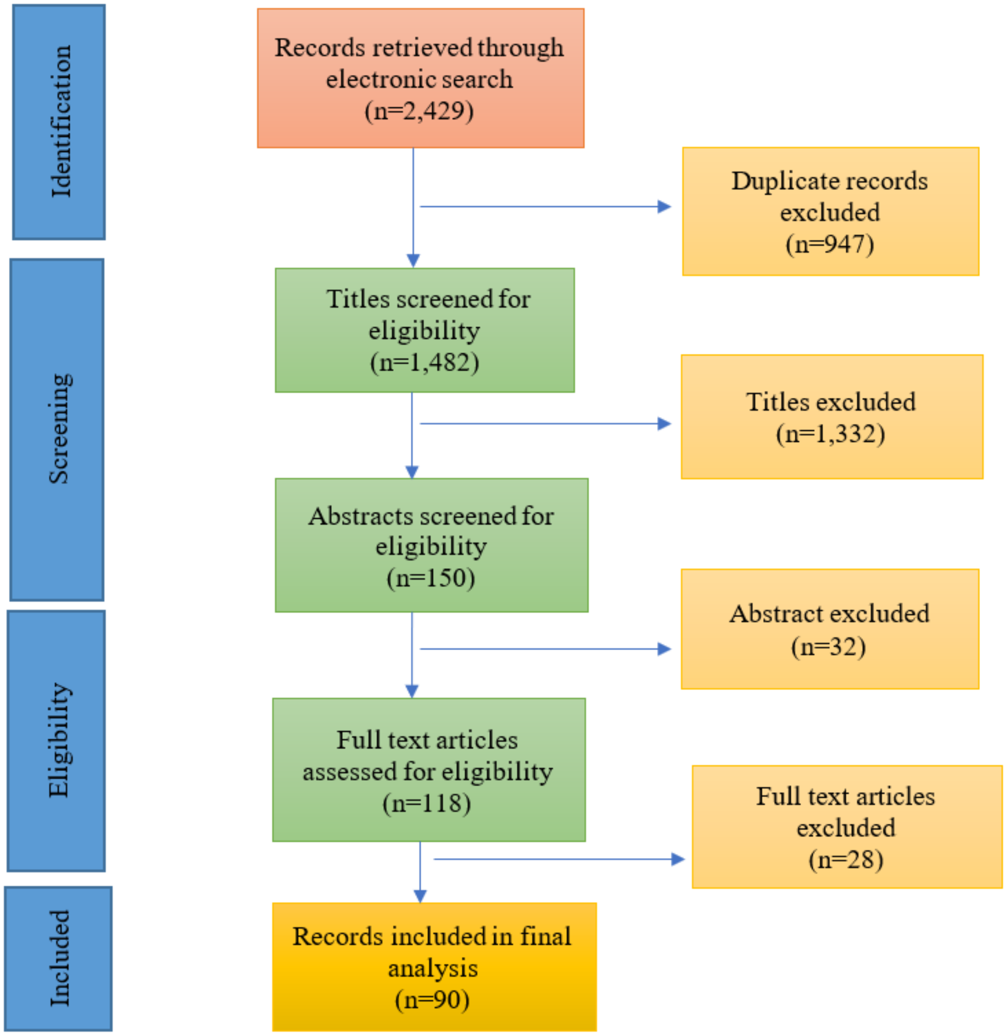

Figure 2: Summary of the research process in the evaluation step

Framework Development

We categorized the data based on the frequency of occurrence within the text to create the intended framework. Next, we tested the proposed framework by evaluating the challenges and advantages against 2018 papers by their confidence interval (evaluation stage). To check the compliance rate of the categories in the evaluation stage with that in the design stage, we used a confidence interval of 95%.

Results

Designing the Framework

After an extensive review of the texts and extracting the advantages and challenges, the related texts were categorized. The classification of the advantages and challenges are presented in Table1, Figure 3 and Table 2, Figure 4 respectively.

Table 1. Classification of advantages of Information Fusion technique in the design stage

Category	Subcategory	Description	Reference
Value modeling	Classification	It is used to categorize information and provides results with high accuracy, sensitivity, specificity, precision and consistency. It leads to improved modeling metrics such as the MCC (Matthews correlation coefficient), that is reliable, robust and effective. Also, the rating error rate is reduced.	(17, 22-79)
	Extract and display of best information	It extracts better, more important, useful, rich, valuable, relevant and meaningful information, and improves the signal-to-noise ratio (relative to unrelated information) and provides promising, better and reasonable results and consequently, makes a better decision.	(6, 30, 37, 51, 80-96)
	Segmentation	It provides partitioning, especially in high-performance images and low error rates and also allows automatic segmentation.	(37, 56, 88, 97-100)
	Disclose detail and summarized information	It summarizes the information and acts as a filter. In this way, it focuses on more important information by reducing information overload and occasionally provides relevant details for better discovery, for example, the discovery of tumor location.	(87, 101, 102)
	Tracking	It improves the tracking device or apps effectively and manages their changes. For this purpose, it uses indicators such as accuracy, latency, and robustness.	(103-105)
	Estimate	It provides the possibility of estimation with less error and high accuracy.	(51, 81, 106-108)
	Better understanding of complexity	It performs complex tasks by dividing them into components and discovering their relationships. In this way, it simplifies system perception and provides useful information about the underlying system.	(58, 91, 101, 109, 110)
	Detection	It identifies the region of interest with high accuracy for feature extraction, particularly in abnormality detection, it is useful for delivering reliable and robust results. It helps in discovering the boundaries/borders and identifying lesions in images, for example, in mammographic images, which can reduce false positive. It can also help in identifying surgical instruments and predicting protein subcellular location.	(14, 17, 26, 27, 34, 49, 50, 52, 57, 68, 79, 84, 85, 88, 92-94, 102, 110-124)

Preferable management of uncertainty and variability	----	It can handle the technique of disturbing the data analysis process. For example, it reduces uncertainty, eliminates noise in data, manipulates nonuniformities, reduces ambiguity, eliminates outliers, and is robust against variability by overcoming it.	(22-24, 28, 36, 42, 80, 91, 103, 125-130)
Excellent decision making	----	Where it is necessary to make a final decision from various decisions, it manages nonuniformity in individual decisions. The most informative benefits are extracted from individual decisions and duplicates are eliminated. Some individual decision challenges are resolved, and decisions are made more accurate, reliable, robust and relevant; and real-time decision making is provided.	(23, 80, 81, 131, 132)
Comprehensive interpretation and representation	Representation	It is capable to display important features and it provides the obtained knowledge especially on the basis of illustrating polymer emergence, which helps the protein feature representation.	(29, 49, 133, 134)
	Interpretation	It helps on the basis of results' interpretation. It helps the provider to interpret medical images and reduce misdiagnosis.	(29, 135)
Data management	Quality	It improves data quality in the fused environment. For example, it improves the accuracy of information or provides access to high-availability information.	(23, 51, 56, 86, 136)
	Retrieval	It improves the recovery function, which means it displays related items by improving indicators such as accuracy, precision and recall.	(68, 71, 90, 137)
	Conflict management	It automatically manages the coincidence of events, manages evidence interference in a data-driven approach and is able to clean up similar objects. It improves overlaps and minimizes duplication.	(28, 56, 80, 120)
Simplicity of infrastructure	System	It minimizes the amount of data transmission between resources and reduces the communication load. It is capable of performing parallel processing that saves time and memory.	(29, 93, 128, 138)
	Security	This method improves security in the biometric system by employing multimodal fusion and can effectively reduce the spoof attack.	(22)

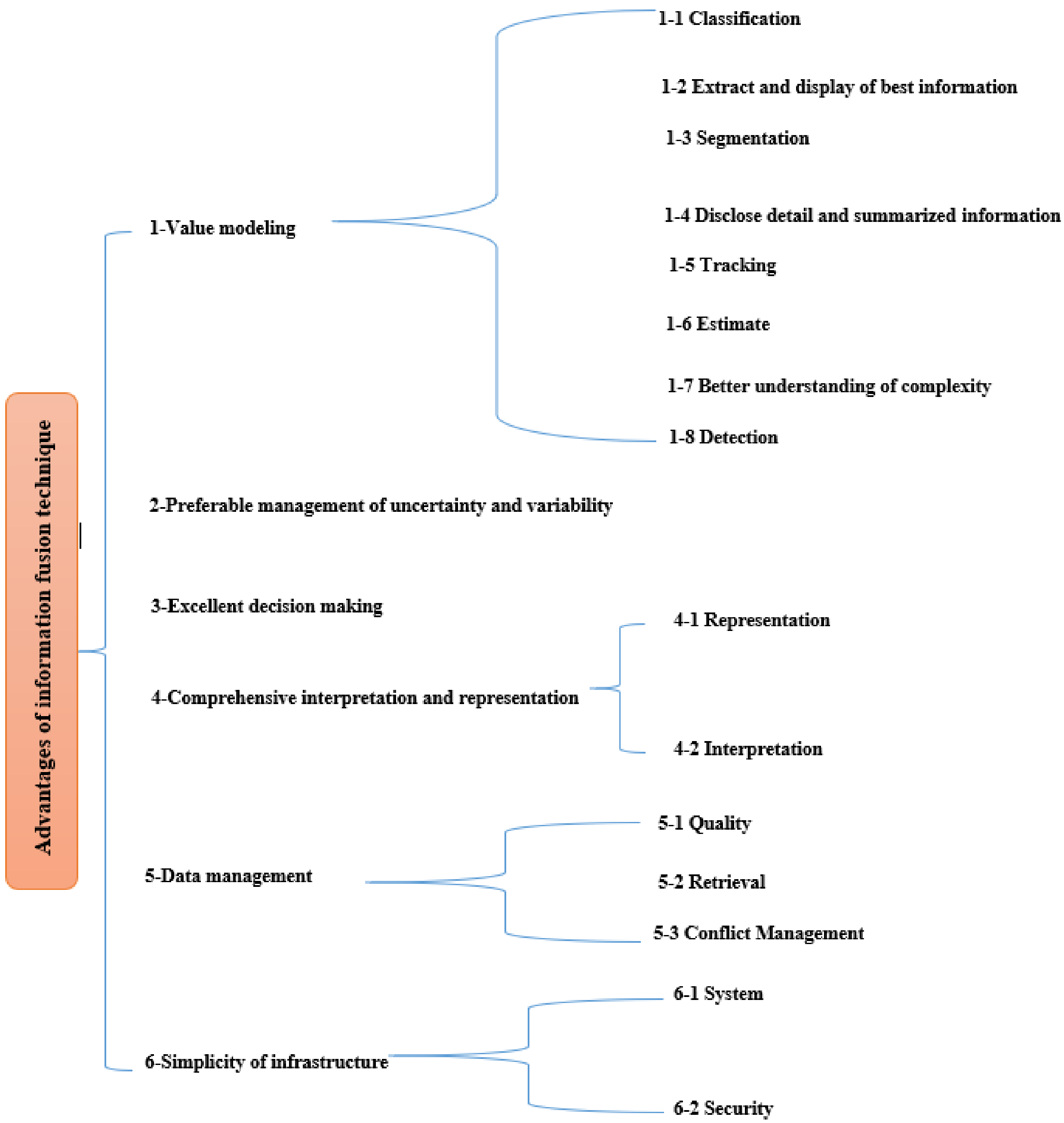

Figure 3: Advantages and applications of information fusion technique

Table 2. Classification of challenges of Information Fusion technique in the design stage

Category	Subcategory	Description	Reference
Hardware and software requirements for processing and maintaining the process	Hardware and software	For using this technique, system memory, CPU system and other requirements are needed to carry out heavy calculations and to process large volumes of data.	(18, 22, 23, 103, 139)
	Security	In social networks, security is a challenge that makes it difficult to process the technique and should be considered. Also, privacy and ownership are challenges in the field.	(18, 22)
	Visualization	To display fused information, the appropriate method should be considered such as the use of charts, or graphs, which is a challenge, especially in different fields.	(18, 24, 136)
Data	Lack of data quality	Data quality is an important factor that, if not considered, will cause difficulty in the result of the analysis. Data quality involves the use of appropriate information for demand (goal), complete and comprehensive information, transparency and consistency.	(25, 26, 80, 111, 133, 136, 140-142)
	Data with unclear and varied structures	The structure and type of data are important in the analysis process. For example, non-structured data will affect the results of the analysis. Also, dynamicity, uncertainty, noise, missing data, and complexity create problems. Additionally, different data formats and heterogeneity or diversity will affect the result of the analysis. Sometimes data measurements are faced with errors, which will not be effective.	(12, 17, 18, 22, 27-30, 106, 109, 140, 143-149)
	Streaming data	A quick change in the amount of data over time or in producing high-speed data is another challenge.	(18, 81, 140, 145)
	Unstructured correlated data	Data dependencies and multiple correlations of variables sometimes increase the effect of an error and influence the results.	(109, 125, 142, 143, 145)
Data analysis method	-----	The type of method used to process and analyze data with the goal of obtaining valuable information is very important, that includes: Choosing the right sources of data, choosing appropriate methods of extraction, and choosing the appropriate classifying method- especially in rare cases or in a high dimensional area, with a low sample size and selecting the appropriate analysis method.	(18, 31-34, 112, 145, 150)

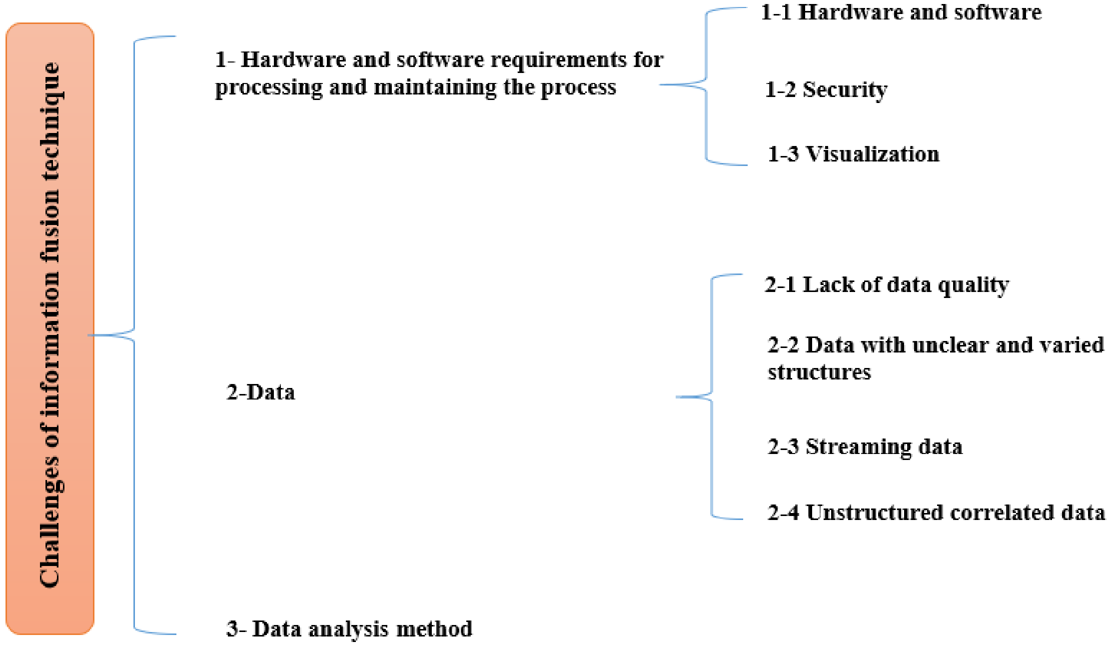

Figure 4: Challenges of information Fusion technique

Evaluating the Framework

In this step, we reviewed the papers from January 2018 to December 2018 that described the advantages and challenges of the information fusion technique within the text. Two reviewers (EN and HT) independently screened the articles and upon mutual consensus decided on the categories for the evaluation stage, which are presented in tables 3 and 4. Further, the prototype of the framework for advantages and challenges were calculated with 95% confidence interval, and the results are shown in Tables 5 and 6 respectively.

Table 3: Classification of advantages of Information Fusion technique in the evaluation stage

Category	Subcategory	Reference
Value modeling	Classification	(151-171)
	Extract and display of best information	(161, 172-177)
	Segmentation	--
	Disclose detail and summarized information	(174)
	Tracking	(178, 179)
	Estimate	(180-186)
	Better understanding of complexity	(187, 188)

	Detection	(154, 155, 165, 168, 178, 185, 188-212)
Preferable management of uncertainty and variability	----	(169, 180, 192, 213-227)
Excellent decision making	----	(225, 228)
Comprehensive interpretation and representation	Representation	(154, 193, 229)
	Interpretation	(168, 189, 224, 230-232)
Data management	Quality	(177, 184, 214, 228)
	Retrieval	(170, 176, 233)
	Conflict management	(188)
Simplicity of infrastructure	System	--
	Security	----

Table 4: Classification of challenges of Information Fusion technique in the evaluation stage

Category	Subcategory	Reference
Hardware and software requirements for processing and maintaining the process	Hardware and software	---
	Security	----
	Visualization	(193, 208)
Data	Lack of data quality	(151, 178, 194, 216)
	Data with unclear and varied structures	(151, 167, 189, 194, 216, 217, 222, 229)
	Streaming data	(178)
	Unstructured correlated data	(208, 232)
Data analysis method	-----	(189, 193, 194, 208, 216, 222, 229)

Table 5: Evaluation of proposed framework for advantages

Category	Subcategory	Design		Evaluation
Value modeling		n(%)	95% CI	n(%)
	Classification	58(43.94)	35.32-52.84	31(34.44)
	Extract and display of best information	21(15.91)	10.13-23.29	8(8.89)
	Segmentation	7(5.30)	2.16-10.62	0(0)
	Disclose detail and summarized information	3(2.27)	0.47-6.50	54(60.00)
	Tracking	3(2.27)	0.47-6.50	2(2.22)
	Estimate	5(3.79)	1.24-8.62	7(7.78)
	Better understanding of complexity	5(3.79)	1.24-8.62	2(2.22)
	Detection	33(25.00)	17.88-33.28	33(36.67)
Preferable management of uncertainty and variability	----	15(11.36)	6.50-18.05	20(22.22)
Excellent decision making	----	5(3.79)	1.24-8.62	2(2.22)
Comprehensive interpretation and representation	Representation	3(2.27)	0.47-6.50	3(3.33)
	Interpretation	2(1.52)	0.18-5.37	6(6.67)
Data management	Quality	5(3.79)	1.24-8.62	4(4.44)
	Retrieval	4(3.03)	0.83-7.58	3(3.33)
	Conflict management	4(3.03)	0.83-7.58	1(1.11)
Simplicity of infrastructure	System	4(3.03)	0.83-7.58	0(0)
	Security	1(0.76)	0.02-4.15	0(0)

Table 6: Evaluation of proposed framework for challenges

Category	**Subcategory**	**Design**		**Evaluation**
Hardware and software requirements for processing and maintaining the process		n(%)	95%CI	n(%)
	Hardware and software	5(3.79)	1.24-8.62	0(0)
	Security	2(1.52)	0.18-5.37	0(0)
	Visualization	3(2.27)	0.47-6.50	2(2.22)
Data	Lack of data quality	7(5.30)	2.16-10.62	5(5.55)
	Data with unclear and varied structures	37(28.03)	20.57-36.51	9(10.00)
	Streaming data	4(3.03)	0.83-7.58	1(1.11)
	Unstructured correlated data	5(3.79)	1.24-8.62	2(2.22)
Data analysis method	-----	8(6.06)	2.65-11.59	7(7.77)

As shown in tables 5 and 6, the categories of the proposed framework were verified in the evaluation stage with a high confidence interval.

Comparing the proposed framework with existing framework

In this field, a framework for challenges has been previously introduced that has identified a number of disadvantages associated with the use of the Information Fusion technique in the UDF / JDL framework(11).These challenges include:

Semantic: what symbols should be used and how are they meaningful?

Epistemic: what information should be presented and how it should be displayed and processed in the machine?

Paradigm: How does paradigm manage the interdependency between the sensor fusion and Information Fusion paradigm?

Interface: How to interface ourselves with people with sophisticated information stored in a machine?

System: How should the system manage the data-fusion system that is formed from the human-machine combination?

After comparing our proposed framework of challenges to the prior framework (11), we added the 'data analysis method' as an additional category. This is an important challenge of the information fusion technique, which needs to be addressed. Figure 5 maps each category from the proposed framework in comparison to the existing framework.

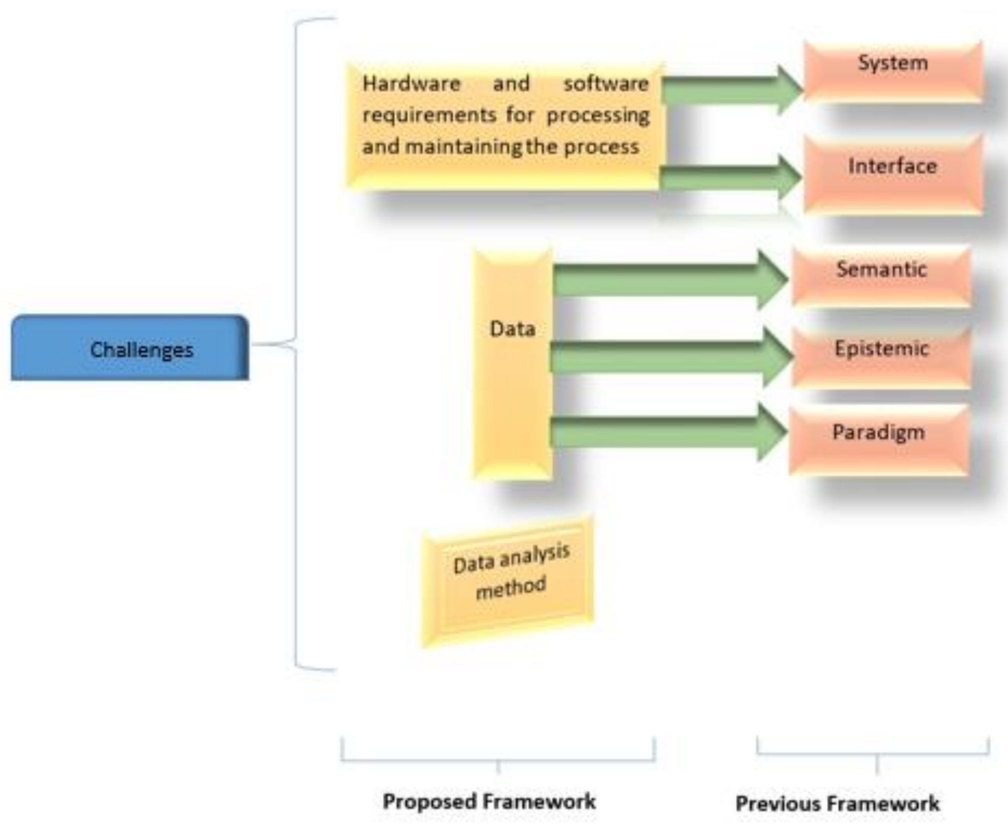

Figure 5: Mapping the proposed framework against existing framework

Table7: Resultant percentages of each category of the framework for challenges

Challenges	Design	Evaluation
Hardware and software requirements for processing and maintaining the process	0.14	0.08
Data	0.75	0.65
Data analysis method	0.11	0.27

As shown in table 7, the category 'data analysis method' was identified as 11% in the design stage and 27% in the evaluation stage. Thus, we conclude that this category should be studied further in future studies.

Discussion and Conclusion

Given the importance of the use of the information fusion technique in big data analysis, we introduced a proposed framework that classifies the advantages and challenges of this technique within this study. The categories identified for the challenges of this technique include "hardware and software requirements to process", "data", and "data analysis method". The categories for the advantages of this technique include "value modeling", "preferable management of uncertainty and variability", "excellent decision making", "comprehensive interpretation and representation", "data management" and "simplicity of infrastructure". We verified the proposed framework during the evaluation stage for its effectiveness. After comparing the proposed framework with the existing framework for challenges, we introduced "data analysis method" as an additional category. This category is deemed important, given that it has been identified as a potential challenge by a number of studies as identified above. Considering these challenges while selecting this technique for data analysis is crucial, as it will affect the nature of the results.

Overall, presenting information within a framework acts as a guide for researchers, thereby, making it possible to understand research goals. A proper understanding of the technique will help utilize the true potential of this technique, while, addressing the challenges will help offer meaningful solutions. Like any other methodology, this novel technique has a number of advantages and challenges for its use, and while we present the most representative categories within our framework, future studies may focus on developing a new framework or modifying this framework to include new categories that we may not have captured here.

To our knowledge, this a first study that introduces a framework for both the advantages and challenges of this technique, compares the proposed framework with the existing framework for challenges, and evaluates the proposed framework for effectiveness. These results serve as a general overview of the technique for researchers to make informed decisions pertaining to its use.

There are few possible limitations that need to be discussed here. First, our review of literature was restricted to articles published in English, which limited our ability to identify relevant literature published in other languages. Second, our review was restricted to primarily peer-reviewed articles indexed in five electronic databases (Science Direct, IEEE, Web of Science, Scopus and Google Scholar), which limited our ability to identify articles published in other databases, or newer journals which are not indexed in these five databases. Third, we only included peer-reviewed journal article during the evaluation stage, which limited our ability to review other types of scientific literature. Fourth, we were not able to evaluate the framework for advantages with an existing framework, since it is presently unavailable.

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