Received July 29, 2021, accepted August 5, 2021, date of publication August 12, 2021, date of current version August 24, 2021.
Digital Object Identifier 10.1109/ACCESS.2021.3104294

An Intuitionistic Fuzzy Based Approach to Resolve Detected Ambiguities in the User Requirements Document

YASIR AHMAD [1], WAN MOHD NASIR WAN-KADIR [1], SADIA HUSAIN [2], AND NORAINI IBRAHIM [1], (Member, IEEE)
[1]Faculty of Engineering, School of Computing, Universiti Teknologi Malaysia, Johor Bahru 81310, Malaysia
[2]Faculty of CS and IT, Jazan University, Jazan 45142, Saudi Arabia

Corresponding author: Yasir Ahmad (ahmad.yas@gmail.com)

This work was supported in part by the Research Management Center (RMC), Universiti Teknologi Malaysia (UTM), and in part by the Ministry of Higher Education Malaysia (MOHE) through the UTM High Impact Research (UTMHR) Grant Scheme under Vot Number Q.J130000.2451.08G55.

This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

ABSTRACT Ambiguous user requirements are usually considered problematic in software engineering. Therefore, many studies have been conducted on its avoidance and detection. However, the detected ambiguities were resolved manually using interviews, brainstorming, and group discussion sessions among the elicitors and stakeholders for whom the software was developed. If not addressed efficiently, it gives rise to the explicit issues of additional time and cost involved and the stakeholders' availability to clarify them during multiple sessions. However, if appropriately addressed, it can reveal some implicit issues, such as tacit knowledge, hesitation, and terminological discrepancies. Identifying these implicit issues is not easy, as it requires expert elicitation skills that usually come with experience. In addition to the increasing demand for an automated approach to address these implicit issues, the recent COVID 19 pandemics has also amplified the demand to address the explicit issue of stakeholder availability. This paper proposes an implementable semi-automated approach to help elicitors address these demands. The proposed approach uses intuitionistic fuzzy logic to address hesitation and statistical functions to identify discordance and tacit knowledge. It also uses the heuristic knowledge gained in each iteration to improve itself. We implemented it in an online tool and conducted controlled experiments to evaluate our approach, and the results were compared. We achieved precision, recall, and F1 score of 0.769, 1, and 0.869, respectively, during our experiments. The results show that the proposed approach may minimize the explicit issues and help novice elicitors address the implicit issues discussed earlier.

INDEX TERMS Fuzzy logic, requirements engineering, requirement ambiguity, software engineering.

I. INTRODUCTION

Requirement elicitation (RE) is one of the most critical tasks in requirement engineering. It involves many activities; one of the essential activities of RE is the refinement of user requirements to prepare SRS, which acts as an artifact to build software as desired. If user requirements are ambiguous, it may lead to project failure [1]. Therefore, resolving ambiguous data in requirement documents is considered one of the most critical tasks for the elicitor during the refining phase of requirement elicitation activities. Many researchers have proposed tools and approaches to avoid ambiguities. However, these approaches cannot prevent all types of ambiguity. Hence, ambiguity-detection techniques are used to detect and resolve ambiguities. Many semi-automated or automated approaches have been proposed for detecting ambiguities. However, they still need to be resolved manually using techniques such as interviews, brainstorming, and group discussions [2]. It is still performed manually because it involves expert elicitation skills to identify the reasons for

The associate editor coordinating the review of this manuscript and approving it for publication was Porfirio Tramontana.

the ambiguities. If these problems are not appropriately addressed, it may lead to undetected and unresolved ambiguities in the SRS that may be discovered in the later stages, which may prove costly or result in project failure. Traditional approaches to requirement elicitation are not feasible in COVID-19 circumstances due to restrictions; the companies promote work from home culture. The proposed approach rescues this situation, as it does not require physical interaction between people involved in the elicitation process.

Bano *et al.*, in 2021, emphasize the importance of the non-functional requirement category due to the unexpected demand for technical aid in contact tracing during the COVID-19 pandemic [3]. Furthermore, other researchers like Geogey, in 2021, highlighted that due to the COVID-19 pandemic, to make a strong requirement engineering foundation, there is an immense need to build new methods and practices that are both standards for engineering curricula and readily transferable to industry [4].

The reason for poor requirement elicitation is addressed by [5], [6], who reported nine factors that influence requirement elicitation activities. These factors are grouped under the following three categories of elicitation issues:

The problem of scope occurs when the requirements convey too little information to comprehend or too much information to handle appropriately.

The problem of volatility is the level of alterations that the requirements must undergo during the project development life cycle.

The problem of understanding caters to the level of requirements understanding that is correctly absorbed during the elicitation process.

While the problems of volatility and scope are vital, most of the challenges encountered by the elicitor are related to the problem of understanding [2], [5]. This describes the extent of the following reasons for ambiguity:

1) The stakeholders are uncertain about their needs.
2) Some tacit knowledge might be essential to describe but omitted by stakeholders, as they consider them apparent.
3) Terminological discrepancies or discordances showed by the stakeholders among themselves.

Several researchers argue that ambiguities help elicitors better understand the requirements by identifying the reasons for their occurrence [7]–[9]. There is still no implementable approach to automatically or semi-automatically identify these reasons because it needs to mimic the following soft skills that usually come with experience:

1) Observational skills to identify the presence of tacit knowledge and discordance among stakeholders.
2) Cognitive skills to address uncertainty in stakeholders.
3) Deduction skills to accurately predict the sense of ambiguous data.

This research intends to uncover the significant sources of ambiguity, namely discordance and tacit knowledge, while catering to hesitation. Fuzzy logic itself is not sufficient to cater to hesitation. Advanced fuzzy logic, such as neutrosophic fuzzy logic (NFL) and intuitionistic fuzzy logic (IFL), are used to rescue this situation. This research proposes a semi-automated approach that uses advanced fuzzy logic to identify discordances and tacit knowledge while catering for hesitations and resolving detected ambiguities in the user requirements document. The approach is evaluated using experiments conducted online among the subjects from three universities, namely, Universiti Teknologi Malaysia (UTM) Malaysia, Aligarh Muslim University (AMU) India, and Jazan University (JU), Saudi Arabia.

The remainder of this paper proceeds as follows. Section 2 provides the problem background and discusses the factors that lead to ambiguity. The latter part of the same section discusses the related research carried out by other researchers in resolving ambiguities, identifying these factors, and decision-making under uncertainty. In Section 3, the research questions and objectives are presented. Section 4 deals with the preliminaries that are important to know before understanding the proposed approach discussed in Section 5, followed by an illustrative example. The experimental details, along with the results and findings, are presented in Section 6. A discussion of the results, advantages, limitations of the approach, and future scope of studies are presented in Section 7. Finally, section 8 concludes the study.

II. BACKGROUND AND RELATED WORK

A. PROBLEM BACKGROUND

1) AMBIGUITY

This means the quality of being open to more than one interpretation. In some scenarios, it is desirable as it can open new possibilities that can be optimized to enhance acceptability, such as fuzzy clustering in complex networks [10], [11] and fuzzy region segmentation in image processing [12]. Moreover, an experienced elicitor can address it effectively to identify tacit knowledge and discordance in human interpretations [7]–[9]. However, in the requirement elicitation process, in contrast to its benefits, the problems it can cause are paramount. In the context of software engineering, the Ambiguity Handbook [13] classifies ambiguity into several types: lexical, syntactic, semantic, pragmatic, vagueness, and language errors. There are numerous reasons for the occurrence of ambiguity. Many researchers have described these in different ways. For example, Patel and Priya (2014) provide a more detailed classification, describing it as missing information, communication errors, different interpretations, incorrect suppositions, and changing requirements [14].

In 2016, Kumari and Anitha identified uncertainty, stakeholders' scope, and understanding of the common source for all three types of problems, namely, scope, volatility, and understanding [5]. Furthermore, studies such as [1], [2], [5], [6], [9], [15]–[23] pinpoint the importance of handling tacit knowledge, discordance, and hesitations among stakeholders as the reason for the occurrence of ambiguities that require special attention from expert elicitors to identify and resolve them. The reasons for the occurrence of ambiguities are discussed below.

2) TACIT KNOWLEDGE

The word tacit means implicit or unspoken; tacit knowledge refers to the requirements that the stakeholder implies as being visible and does not communicate explicitly. Typically, requirement elicitation starts with an interview between the analyst and the customer or stakeholders. Since the interviews are conducted in natural language, ambiguities may occur due to tacit knowledge that is not communicated. The dialog discourse may reveal the presence of tacit knowledge that needs to be made explicit. Hence, it is crucial to provide analysts with cognitive tools to identify and alleviate ambiguities [15]. The requirement elicitor has to put extra effort into pushing the customer to the limit of their tacit knowledge [21]. This statement may seem entirely unambiguous. However, as soon as tacit knowledge comes into consideration, the statement becomes unacceptable. For example, consider the following statement; "The train moving at the speed of 100 km/h must stop within 5 meters if the full brake is applied." This statement seems unambiguous, but it cannot be accepted as tacit knowledge about the train's movement at 100 km/h indicates that it is impossible to stop the train safely within 5 m. In this situation, the statement is interpreted correctly by the Elicitor, and the meaning of the statement matches the meaning of the stakeholder, but it cannot be accepted. This is known as acceptance unclarity [15]. In the confusion matrix terminology, we can say that the precision is acceptable, yet the accuracy is unacceptable.

3) TERMINOLOGICAL DISCREPANCIES AND DISCORDANCE AMONG STAKEHOLDERS

The stakeholders involved in a project may be from different backgrounds, knowledge, regions, or departments; they may have a different understanding of the language. This leads to a prevalent problem of terminological discrepancies [15], [19], [21]. This happens when different users interpret the same word differently based on their understanding and interest. In some other cases, stakeholders may have a conflict of opinion regarding the correct interpretation of the word, leading to discordance among them. Conflict of opinion may be for personal or professional reasons. It becomes essential for the elicitor to identify the presence of discordance [24]. If it is not appropriately identified, it may create unnecessary confusion and may finally lead to the project's failure. Hence, the experienced elicitor identifies discordances and requires all stakeholders to agree to a particular point. To do so, he may conduct several rounds of interviews and brainstorming sessions.

4) HESITATIONS OR UNCERTAINTY

Uncertainty is another crucial reason for the presence of ambiguous requirements. It is reported as one of the prominent contributing factors in two out of three problems categorized in the previous section, that is, the problem of scope and problem of understanding [5]. In 2014, Sethia and Pillai identified the following characteristics of uncertainty [6]:

1) Stakeholders are not entirely sure of what they need.
2) Stakeholders have little understanding of the capabilities and limitations of their computing environment.
3) Stakeholders have little understanding of the problem domain.
4) Requirements fluctuate during the entire project.

All these will lead to project failure if not handled carefully. If the severity of the project is very high, then uncertainty or hesitation must be very low. Identifying the severity of the project and the allowance of uncertainty among stakeholders are critical for the elicitor. Hence, an expert elicitor is required to handle these uncertainties among stakeholders.

Another critical reason for ambiguities, as mentioned by several researchers, is the lack of context knowledge that leads to hesitation or terminological discrepancies among the stakeholders and Elicitor [2], [15], [19], [21], [25]. However, context knowledge tools such as WordNet help elicitors make mature decisions to some extent.

In addition to these reasons for ambiguities, some explicit factors need to be addressed while resolving the detected ambiguities. One significant factor that needs to be addressed is the lack of availability of stakeholders. To resolve detected ambiguities, the elicitor conducts interviews and group discussions with stakeholders. It requires them to be available to give their remarks and clarifications during these sessions. Although there are tools available to conduct meetings online, which eliminates the necessity of physical presence, it still requires them to be available at a given time for group discussions or interviews.

B. RELATED WORK

Various studies have been proposed to handle ambiguities in requirement elicitations; some identify ambiguities once they occur, while others tend to avoid ambiguities from occurring. However, some studies related to our work to automate the elicitation process, identify the reasons for the occurrences of ambiguities, or propose rule-based or corpus-based solutions to help elicitors in better decision-making are discussed below. Some of these approaches involve manual others involving different levels of automation using NLP or fuzzy logic.

Bano *et al.* [21] have presented a list of common mistakes that novice elicitors make in requirement elicitation interviews to enhance their soft skills to identify tacit knowledge. Their study identified 34 unique mistakes and classified them into 7 high-level themes on which the elicitors could be trained.

Spoletini *et al.* [19] proposed identifying tacit knowledge by audio recording the interviews that shall be inspected by the analyst who conducted the interview and the reviewer. The motive was to create questions for follow-up interviews to handle probable tacit knowledge.

Elrakaiby *et al.* [15] proposed an approach based on argumentation theory to detect tacit knowledge missed during verbal communications, such as interviews. They use argumentation and consider attacks on argumentation as ambiguous.

Dalpiaz *et al.* [20] use a blend of NLP (conceptual model extraction and semantic similarity) along with information visualization techniques to identify terminological discrepancies. During their quasi-experiment, they found a significant increase in recall but a non-significant increase in precision compared to manual inspection. In another study, Dalpiaz *et al.* [26] discussed a tool based on two NLP techniques to identify terminological ambiguities.

Ferrari *et al.* [24] present an NLP-based approach to identify and cater to terminological discrepancies by building domain-specific language models, one for each stakeholder's domain. Words from each language model are compared to measure the differences in the use of a word, thereby estimating its potential ambiguity across other domains of interest. It can be helpful to prepare lists of dangerous terms to consider during requirements elicitation meetings, such as workshops or focus groups, that involve stakeholders from different domains.

Ezzini *et al.* [27] have proposed an NLP-based automated approach that generates a domain-specific corpus from Wikipedia, which can help improve the accuracy of ambiguity detection and interpretation. This approach addresses coordination ambiguity (CA) and prepositional-phrase attachment ambiguity (PPA). Further, they have also developed an automated tool called MAANA to handle these ambiguities using domain-specific corpora and heuristics-based inspections [28].

In 2011, Alfawareh used context knowledge and fuzzy logic to resolve ambiguities by randomly assigning fuzzy membership values to a word based on the context in which the sentence is written [29]. The context was considered by classifying the subject associated with the sentence. Although during the experiment, they achieved a precession of 0.857 and a recall of 0.803, it was limited to resolving only lexical ambiguities; furthermore, it does not cater to the reasons for the occurrence of ambiguity.

Gulzar *et al.* [30] presented a framework using fuzzy logic to map usability requirements attributes with linguistic assessment from users. This framework automates the identification and resolution of usability requirements conflicts and helps requirement analysts to make better decisions.

Ahmad *et al.* [31] proposed an implementable approach based on fuzzy logic and context knowledge to resolve detected ambiguities. This approach uses the consents of the stakeholders in the form of fuzzy values iteratively to resolve detected ambiguities. This approach addresses the explicit issue of the availability of stakeholders and the time and cost involved in resolving the detected ambiguities manually. It can also be tweaked to handle discordance. However, this approach cannot identify the source of discordance, such as tacit knowledge or hesitation, as it cannot be addressed by fuzzy logic alone. It requires advanced fuzzy logic such as intuitionistic or neutrosophic fuzzy logic to handle human hesitation, as shown in a study by Ahmad *et al.* [32] in which they proposed an approach that is based on intuitionistic fuzzy sets (IFSs) to considerably reduce the domain of ambiguous data while catering to the hesitation ordinarily present in human behavior.

Shen *et al.*[33] proposed an outranking sorting method using the IFS for group decisions. It is further extended to develop a method for group consensus using an adaptive search and adjustment approach [28].

Ji *et al.* [34] focus on group decision-making under uncertainty in a situation such as a talent search competition. They used a new approach by combining hesitancy and fuzziness to construct intuitionistic fuzzy entropy. Their approach avoids invalid data and results from deviations. Moreover, compared to the traditional method, their approach improves accuracy and time consumption.

In 2019, Metzger Spengler [35] proposed a model based on intuitionistic fuzzy logic for the formulation and solving of decision problems where the decision-maker has insufficient information due to ambiguous utility values.

To date, no automated or semi-automated research has been found that caters to hesitation and tacit knowledge together in requirement elicitation while addressing the explicit issues mentioned earlier. In addition, many manual and automated approaches have been used to populate a corpus that can be compared for better decision making. Since IFL can handle human hesitation, it would be interesting to study its use in identifying the reasons for the occurrence of ambiguity while using IFV to populate the corpus and compare its effectiveness.

III. RESEARCH QUESTIONS

This research proposes an implementable, semi-automated approach to help the Elicitor address the explicit and implicit issues while resolving detected ambiguities and using the heuristic gained during this activity to improve itself. It can be leveraged to improve the Elicitor's accuracy of decision making in the future and reduce the time and requirement for the availability of the stakeholders for interview and group discussion sessions to provide clarification. Therefore, keeping this in consideration, we mention the following four research questions (*RQs*) along with their corresponding objectives:

RQ1: *How can the explicit requirements of time, cost, and stakeholder's availability to provide clarifications upon detected ambiguities be reduced?*

If we can reduce the domain of ambiguous requirements that need to be resolved manually, we can reduce the total time involved in the process, which reduces the total cost involved in this activity. Second, if the approach can be implemented in a network-based environment that can be accessed remotely, it reduces the requirement for the availability of the stakeholders for meetings or interviews with elicitors to clarify the detected ambiguities. Therefore, the objective of addressing *RQ1* is summarized as follows:

Objective 1: To propose an automated/semi-automated approach that can be implemented online and reduce the total domain of ambiguous requirements that must be resolved explicitly through interviews or discussions among stakeholders and elicitors.

RQ2: *How can the implicit issue of identifying the reasons for discordance that leads to imprecision among stakeholders and elicitors be addressed?*

As discussed in the previous section, discordances among the stakeholders and elicitor can be identified using fuzzy logic. However, fuzzy logic alone cannot address hesitation, which is part of human understanding. Therefore, if we can cater to discordance along with hesitation by using advanced fuzzy logic, we can classify the cause of discordance as either due to hesitation or tacit knowledge. Therefore, the objective of addressing *RQ2* is summarized as follows:

Objective 2: To formulate a technique based on advanced fuzzy logic to address implicit issues such as tacit knowledge, discordance, and hesitation, leading to ambiguity.

RQ3: *How can the factors identified during RQ2 be used to improve the facticity among stakeholders and elicitors in addition to resolving ambiguities?*

If the identified sources for the occurrence of discordance among the stakeholders and between the stakeholders and the elicitor are adequately addressed, it can further improve the precision of their understanding. It may resolve ambiguities further, either through the previously mentioned automated approach, manual process, or both. Therefore, the objective of addressing *RQ3* is summarized as follows:

Objective 3: To improve the facticity among stakeholders and elicitors to resolve ambiguities further.

RQ4: *How can the knowledge gained during RQ1 and RQ2 be used to improve the correctness of the elicitors to suggest more accurate suggestions for* detected *ambiguities in the future?*

While resolving the ambiguities, the elicitors gain much experience that helps them make mature decisions. If we can devise a mechanism to store and retrieve the heuristic knowledge gained during this activity, we would ease even a novice elicitor to make better decisions while suggesting solutions to resolve detected ambiguities. If this suggestion is accurate, it may have a better chance of acceptance among the stakeholders, reducing the number of iterative interactions required among the stakeholders and Elicitor. It may reduce the total time involved and improve the accuracy of understanding among stakeholders and elicitors. Therefore, the objective of addressing *RQ4* is summarized as follows:

Objective 4: To formulate a heuristic technique for inducing self-improvement to ease the elicitor from the cognitive load of making decisions.

IV. PRELIMINARIES

A. FUZZY SETS

Zadeh proposed fuzzy sets in 1965 as an extension of the classical set with a difference in its membership range [36]. The classical set only considers crisp values like 0 or 1, or agree or disagree. In contrast, the fuzzy set uses a range of values for agreement and disagreement, where the value of the agreement is called the degree of membership value (μ) and the value of disagreement is called the degree of non-membership value (ν), where μ and ν are complementary to each other.

$$\mu\left(\mathrm{x}\right)+\nu\left(\mathrm{x}\right)=1 \tag{1}$$

However, in real-life situations where humans are involved, they may possess some degree of hesitation; in such cases, advanced fuzzy sets such as intuitionistic fuzzy (IF) sets or neutrosophic fuzzy (NF) sets are considered.

B. INTUITIONISTIC FUZZY SETS

Atanassov and Stoeva introduced intuitionistic fuzzy sets in 1983 [37]. Unlike fuzzy sets, where the sum of membership and non-membership values is 1, the IF sets introduce one more variable, that is, hesitation (π) into the equation as the sum of μ, ν and π must be equal to 1.

$$\mu\left(\mathrm{x}\right)+\nu\left(\mathrm{x}\right)+\pi\left(\mathrm{x}\right)=1 \tag{2}$$

However, the IF sets components, that is, μ, ν, π, are tightly bonded and interdependent. This situation is not always easy to explain and implement, especially in cases with limited human interaction.

C. NEUTROSOPHIC FUZZY SETS

Smarandache [38] introduced Neutrosophy as a new branch of philosophy. In NF sets, the neutrosophic components can be independent of each other. Hence, their sum is not necessarily 1. NFS components are defined as T, F, and I, where T is Truth, F is False, and I is Indeterminacy. In single-valued neutrosophic sets, the sum of T, F, and I is different in the different scenarios shown below [39].

$$0 \leq \mathrm{T}+\mathrm{I}+\mathrm{F} \leq 3 \tag{3}$$

When all the three components are independent,

$$0 \leq \mathrm{T}+\mathrm{I}+\mathrm{F} \leq 2 \tag{4}$$

When one component is independent, and two components are dependents,

$$0 \leq \mathrm{T}+\mathrm{I}+\mathrm{F} \leq 1 \tag{5}$$

When all the three components are dependent,

Atanassov and Vassilev [40] showed that NFS and IFS are equivalent, and the NFS can be represented by IFS values. If the values of T, I, and F are as mentioned below,

$$\mathrm{T}\left(\mathrm{x}\right)+\mathrm{I}\left(\mathrm{x}\right)+\mathrm{F}\left(\mathrm{x}\right)\neq 0 \tag{6}$$

then,

$$\mu\left(x\right)=\frac{T\left(x\right)}{\mathrm{T}\left(\mathrm{x}\right)+\mathrm{I}\left(\mathrm{x}\right)+\mathrm{F}\left(\mathrm{x}\right)} \tag{7}$$

$$\nu\left(x\right)=\frac{F\left(x\right)}{\mathrm{T}\left(\mathrm{x}\right)+\mathrm{I}\left(\mathrm{x}\right)+\mathrm{F}\left(\mathrm{x}\right)} \tag{8}$$

$$\pi(x) = \frac{I(x)}{\mathrm{T}(\mathrm{x}) + \mathrm{I}(\mathrm{x}) + \mathrm{F}(\mathrm{x})} \tag{9}$$

Otherwise, if the values of T, I, F is,

$$\mathrm{T}(\mathrm{x}) + \mathrm{I}(\mathrm{x}) + \mathrm{F}(\mathrm{x}) = 0 \tag{10}$$

then we define,

$$\mu(\mathrm{x}) = \nu(\mathrm{x}) = 0 \text{ and } \pi(\mathrm{x}) = 1 \tag{11}$$

Huang and Li reviewed several methods proposed by Wang *et al.* to determine the hesitation in IFS [41]. These methods include the average method where π is equally divided, and each part is added to μ and ν, the proportion method that uses following the heard approach where the value of π is divided into μ and ν based on their proportion in the IFS and the difference adjustment methods the value of H attributed to μ is μ plus one half of the π. He also proposed a hybrid method, which is complex but more reliable when the value of π is high. For experimental purposes, an improved approach proposed by Huang and Li was adopted to determine the hesitation.

$$\alpha = \frac{1}{2} + \frac{\mu - \nu}{2} + \frac{\mu - \nu}{2} \times \pi \tag{12}$$

However, based on the project's complexity, the Elicitor can choose any of the approaches to determine hesitation. Hereafter, the membership value (μ) is denoted as ***mv***, the non-membership value (ν) is denoted as ***nmv,*** and hesitation (π) is denoted as ***h***.

V. PROPOSED APPROACH

The proposed approach is divided into three stages based on the objectives deduced from each of the research questions. This is motivated by earlier studies that use the fuzzy approach to resolve ambiguous requirements [31], intuitionistic fuzzy approaches to address human hesitation to reduce the domain of data [32], and various studies that populate the corpus to improve the accuracy of ambiguity detection [27], [29].

A. STAGE 1: AMBIGUITY SOURCE DETECTION AND RESOLUTION

1) The elicitor receives corpus A of detected ambiguities ($a_1, a_2, \ldots.$ belongs to set A) along with its type ($t_1, t_2, \ldots$ belongs to set type) and the context ($c_1, c_2, \ldots$ belongs to set C).
2) For each ***a*** in A, the Elicitor suggests a solution ***s***, such that $\boldsymbol{s_1}$ corresponds to $\boldsymbol{a_1}$ and so on. The suggestions are based on Elicitor's understanding while considering the context, ambiguity type, and available context knowledge tools. Suggestions are collected in set ***S***.
3) The values of ***a, c, t,*** and ***s*** for each ambiguity in Set A are sent to every stakeholder for review. They provide the following information in the form of a Likert scale of 0 to 10, where 0 indicates ''not at all'' and 10 indicates ''Completely''. The level of agreement (***mv***), disagreement (***nmv***), and hesitation (***h***) are collected such that mv_1, h_1, nmv_1 correspond to $a_{1,}$ and so on. In IFS, these values range from 0 to 1, so these values are converted accordingly.
4) If the stakeholders disagree more than agree, they provide an alternate suggestion (x) that they think is better than the value suggested by the Elicitor. The values of mv_1, $mv_2, \ldots$ belongs to set ***mv***, h_1, $h_2, \ldots$ belongs to set ***h***, nmv_1, $nmv_2, \ldots$ belongs to set ***nmv*** and x_1, $x_2, \ldots$ belongs to set ***x***.
5) The average of ***mv, nmv, h,*** is calculated as ***amv, anmv,*** and ***ah,*** and the ranges of ***mv*** and ***h*** are also calculated as ***rmv*** and ***rh***.
6) Next, for the average IFV obtained, hesitation was determined using any of the available methods depending on the severity of the project. The newly determined ***mv*** and ***nmv*** were calculated as ***dmv*** and ***dnmv,*** respectively.

Based on these calculations, *RQ2* is addressed by identifying the following factors for the problem of understanding:

1) PRESENCE OF TACIT KNOWLEDGE

For each ***s*** in ***S***, if the value of the ***dmv*** is in-significant, along with the nominal values of ***rmv, rh***, and ***ah***; indicates that the stakeholders have widely rejected the suggestion by the Elicitor. It shows discordance between the understanding of the Elicitor and the stakeholders due to the tacit knowledge that is not communicated to the elicitor. In this scenario, the stakeholders provide alternate suggestion ***x*** based on their understanding, and the approach is proceeded to stage 2.

2) DISCORDANCE OR TERMINOLOGICAL DISCREPANCIES AMONG THE STAKEHOLDERS

The higher value of ***rmv*** indicates that all the stakeholders were not at the same perception; this shows the presence of terminological discrepancies. For example, suppose that among five stakeholders, three assigns ***mv*** as 9, but two assign it as 2. It is clear that out of the five stakeholders, two almost disagree with the suggestion. This shows the presence of discordance among the stakeholders. This may be due to either hesitation or tacit knowledge, as discussed below.

3) DISCORDANCE DUE TO HESITATION

If the value of ***ah*** among the stakeholders is significant, it shows that the discordance is due to the poor understanding of the stakeholders regarding that particular ambiguity.

4) DISCORDANCE DUE TO TACIT KNOWLEDGE

If the value of ***ah*** and ***rh*** provided by the stakeholder is not significant, it means that they are pretty sure of their answer, and since they show discordance among themselves, it must be due to the presence of tacit knowledge, which is not shared among the stakeholders.

These results categorize the suggestions provided by the Elicitor. In the first case, it is considered ***rejected***, the rejected

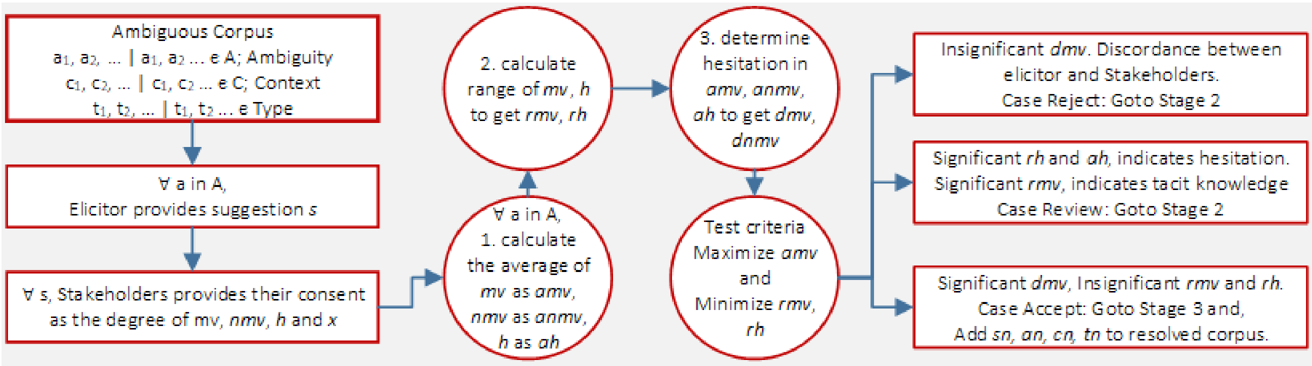

FIGURE 1. Illustration of stage 1 of the proposed approach.

cases are moved from ***ambiguous corpus*** to ***rejected corpus***, and the approach proceeds to stage 2. The second, third, or fourth case is considered a ***review***; all the review cases are moved to a ***review corpus*** that needs to be resolved manually. However, if the suggested solutions for which the average of the stakeholder's consent ***amv*** is significant and all of the other parameters, i.e., the average hesitation ***ah***, the range of hesitation ***rh*** and the range of stakeholder's consent ***rmv*** are insignificant indicates that the stakeholders have widely ***accepted*** the Elicitor's suggested solution ***s*** for that particular ambiguity without hesitation and discordance. All the accepted cases are moved from the ***ambiguous corpus*** to the ***resolved corpus*** along with its IFVs calculated from the stakeholder's response. After this stage, the ambiguous corpus containing the ambiguities that need further discussion among elicitors and stakeholders is reduced to the ***review corpus*** as the accepted solutions are removed from the original ***ambiguous corpus.*** Finally, the accepted cases proceed to stage 3, and the rejected cases proceed to stage 2. Hence, the objective of *RQ1* is achieved. Stage 1 of the proposed approach is shown in Fig. 1.

B. STAGE 2: IMPROVE PRECISION

The focus of stage 2 is to reduce the elements of the ***rejected corpus*** and move them to either ***resolved corpus*** or ***review corpus***. For the rejected corpus that contains cases where the stakeholders disagree with the Elicitor's suggested solution ***s,*** the most widely suggested alternative solution, ***x*** by the stakeholders for the corresponding ambiguity, replaces the Elicitor's suggestion ***s.*** Finally, the process is reiterated as in stage 1, and the review, rejected, and resolved corpus are populated again.

In an ideal situation, where there is no discordance among the stakeholders, they collectively accept the alternative suggestion ***x,*** so the corresponding element of the ***rejected corpus*** is moved to the ***resolved corpus*** and proceeds to stage 3 of the approach. Thus, it improves the precision of accepted cases, that is, mutual consent among the stakeholders and the elicitor. However, it is also possible that in the consecutive iteration, the stakeholders collectively do not agree with the alternative suggestion ***x,*** which shows discordance among stakeholders. As a result, it indicates that the precision cannot be further improved. In this case, the Elicitor can stop the iterative process and move these elements of ***rejected corpus*** to the ***review corpus***.

Finally, only the available cases of the ***review corpus*** are considered to be discussed manually from the total detected ambiguities. Hence, after stage 2 of the approach, the total number of cases that need to be discussed manually is reduced. Furthermore, the Elicitor can also identify some additional information regarding each case of the ***review corpus*** It includes the following: First, identify hesitation or tacit knowledge as the source of discordance collectively for all stakeholders. Second, the individual responses of the stakeholders can be observed to identify those stakeholders who are mainly responsible for discordance. Finally, the source of discordance for each stakeholder is also identified. The elicitor can use this information during the manual resolution of the ambiguities. Thus, the objective of RQ3 is addressed.

C. STAGE 3: ELICITOR CAPABILITY ENHANCEMENT

After the first and second stages of the approach, the ***resolved*** corpus gradually matures with the accepted solutions. It contains ambiguous statements, context, accepted solutions, and corresponding IFVs that indicate ***mv, nmv,*** and ***h*** for all the statements in a particular context.

For future reference, while suggesting solutions for ambiguous statements, the Elicitor refers to the ambiguity in the resolved corpus and the context and associated IFVs.

There could be four possibilities.

1) Ambiguity and context were present in the resolved corpus. In this case, the Elicitor suggests the accepted solution used in earlier studies and updates the IFV as an average of the earlier study and the current study.
2) The ambiguity is detected in the corpus, but the context does not match.
3) The ambiguity does not match, but the context is present in the corpus.
4) Neither the ambiguity nor the context matches in the corpus.

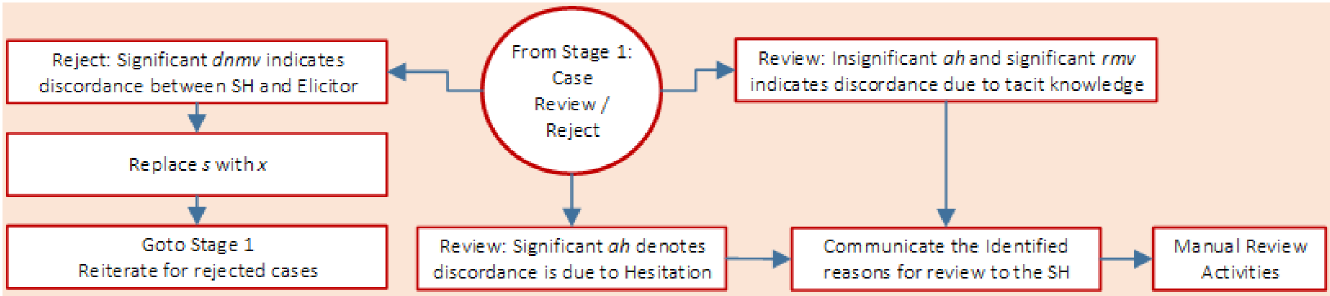

FIGURE 2. Illustration of stage 2 of the proposed approach.

Stage 3 of the approach is ineffective when there is no match. In the case of a perfect match, the heuristic knowledge gained from earlier resolved cases acts as a benchmark to refer to by the elicitor. This may help even novice elicitors make better decisions while suggesting more accurate solutions to stakeholders based on earlier studies. Hence, the overall accuracy of resolving ambiguity may improve. Although it is out of the scope of this paper, if there is a partial match, it may provide some idea about the stakeholders' perception of the ambiguity or its context. Stage 2 of the proposed approach is shown in Fig. 2.

D. ILLUSTRATIVE EXAMPLE

In this section, we illustrate our approach using an example containing four ambiguous statements. We present different criteria in which the statements are accepted, rejected, and reviewed. In Fig 3., ambiguous statements a_1, a_2, a_3, and a_4 are presented along with the multiple interpretations that make them ambiguous. For each ambiguous statement, an interpretation is considered as Elicitor's suggestion (s). Then, it is sent to stakeholders to express their views in terms of membership, non-membership, and hesitation. Based on the individual IFV given by the stakeholders, the average membership value (*amv*), average non-membership value (*anmv*), average hesitation (*ah*), range of membership value (*rmv*), and range of hesitation (*rh*) were calculated. Also, if the stakeholders collectively agree with s, it is considered as the *mode* value; otherwise, the most suggested alternative by stakeholders is considered as mode value. The significant level of discordance for this example is considered to be 0.4 or more, and the significant level of membership value (*mv*), non-membership value (*nmv*), and hesitation (h) is considered to be 0.5 or more. Based on these considerations, the following cases were determined:

Case 1: Considering the statement a_1, weekly is a vague word with multiple interpretations. The value of *rmv* is significant that indicates discordance; further, the value of *ah* is also significant, which indicates that the discordance is due to hesitation. Hence, the statement is added to the *review corpus*

Case 2: Consider statement a_2; it is ambiguous because the type of report' the software is expected to be generated is unclear. Here *rmv* is significant, indicating discordance but h and *rh* are not significant. This indicates that discordance is not due to hesitation but tacit knowledge. Hence, the statement is also added to the *review corpus.*

Case 3: Consider statement a_3; here, it is unclear whether the word new refers to the guideline or customer. Here, the value of *nmv* is significant, but the values of *rmv, h,* and *ah* are insignificant. This indicates that the stakeholders collectively disagree with the suggestions provided. Hence, the statement, along with its *mode* value, is stored in the *rejected corpus.*

Case 4: Consider statement a_4, here older is the vague value that can have multiple interpretations. The value of *mv* is significant, but the values of *rmv, h,* and *ah* are insignificant. This indicates that stakeholders collectively agree with Elicitor's suggestion. Hence, the statement is stored in the *resolved corpus* with ambiguous text, context, and IF values.

In the review case, the *review corpus* statements can be resolved using traditional approaches such as interviews or group discussions. Since it also contains the reason for the review, it helps the Elicitor address the problem better. In the rejected case, the Elicitor's suggestion is replaced by the mode value in the *rejected corpus* and the process reiterates. Finally, the accepted statements of the resolved corpus are stored for future reference.

VI. EXPERIMENTATION AND RESULTS

The method to evaluate the proposed research was adopted from the studies of Sabriye and Zainon [42] and Ferrari *et al.* [22]. However, we used different levels of effort and rigor throughout the experimental study. For the experiment, we implemented the proposed approach online using PHP and MySQL. The experiment was conducted in two phases. Initially, in phase 1, a pilot scenario was created, and an exploratory study was conducted to identify the limitations of the experimental setup and the tweets that need to be adjusted to proceed toward the controlled experiment effectively. Once the modification is implemented, a controlled experiment is carried out among the subjects, hereafter referred to as stakeholders, from three different universities, namely UTM, JU, and AMU. Two corpora, A and B, were created containing ambiguous statements from five types of ambiguities: lexical, vague, semantic, syntactic, and pragmatic. These corpora cover statements in 5 different contexts: academics, travel, banking/finance, medicine/health,

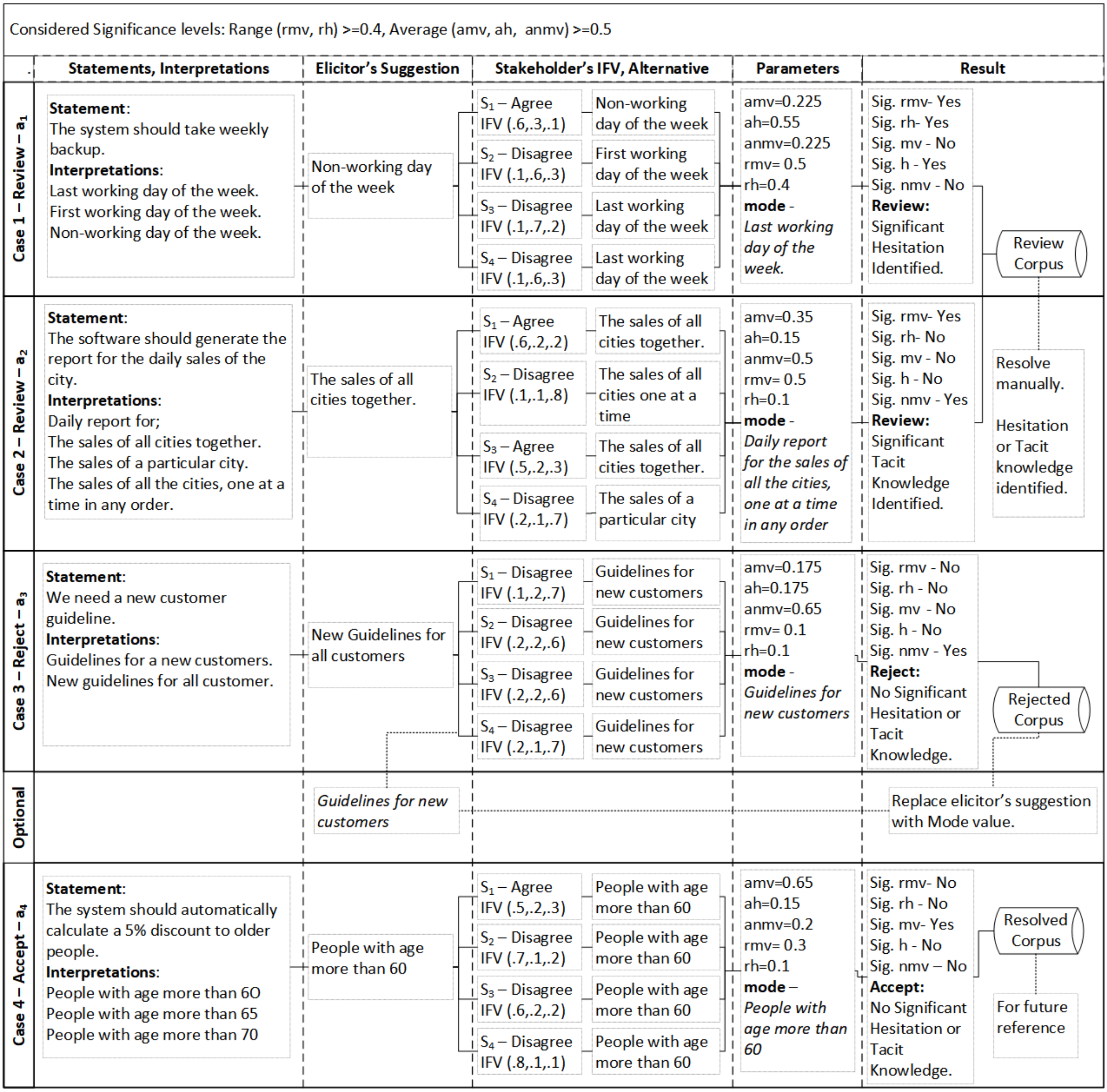

FIGURE 3. Illustration of the proposed approach using an example.

and generic. These statements were not created on our own but were collected from earlier published studies [22], [29], [43], [44], and online sources. A detailed description of the experimental setup is provided in the corresponding sections.

A. PILOT STUDY

An exploratory study was conducted to identify the problems in the experimental setup, instead of identifying the answers to our research questions. A group of 8 research scholars from UTM was considered as the stakeholders to provide suggestions for 15 ambiguous statements covering 5 types of ambiguities. The author acts as the Elicitor and provides suggestions for ambiguity based on his understanding. The respondents were asked to enter their level of agreement and hesitation as required in the intuitionistic fuzzy triplet. We requested them to share their experiences with the experiment. Their feedback was beneficial for improving the experimental setup.

1) LEARNING OUTCOMES FROM THE PILOT STUDY

We identified two issues that need to be addressed during the experiment. First, from the feedback, we found that

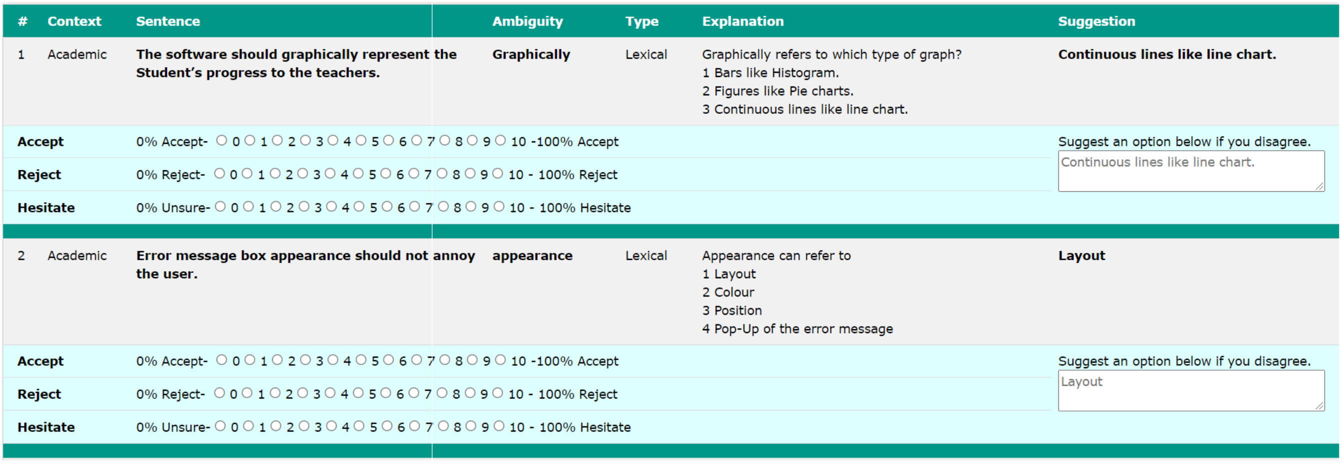

FIGURE 4. Excerpt of the interface for the stakeholders to give their agreement, disagreement, hesitation, and alternate suggestions.

TABLE 1. Results based on the individual cases of experiment A of stage 1 of the approach.

Statement		Average			Determined		Range		Acceptable Levels of Discordance									
ID	Type	*amv*	*anmv*	*ah*	*dmv*	*dnmv*	*rh*	*rmv*	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
1	Lexical	0.77	0.09	0.13	0.88	0.12	0.5	0.65	H	H	H	H	H	T	A	A	A	A
2	Lexical	0.71	0.16	0.13	0.81	0.19	0.41	0.75	H	H	H	H	T	T	T	A	A	A
3	Vague	0.22	0.57	0.21	0.29	0.71	0.47	0.73	H	H	H	H	T	T	T	R	R	R
4	Vague	0.8	0.11	0.09	0.88	0.12	0.41	0.82	H	H	H	H	T	T	T	T	A	A
5	Syntactic	0.77	0.12	0.11	0.86	0.14	0.41	0.82	H	H	H	H	T	T	T	T	A	A
6	Syntactic	0.75	0.1	0.15	0.87	0.13	0.38	0.6	H	H	H	T	T	T	A	A	A	A
7	Semantic	0.68	0.15	0.16	0.81	0.19	0.47	0.79	H	H	H	H	T	T	T	A	A	A
8	Semantic	0.85	0.06	0.09	0.93	0.07	0.33	0.46	H	H	H	T	A	A	A	A	A	A
9	Pragmatic	0.71	0.11	0.18	0.85	0.15	0.47	0.67	H	H	H	H	T	T	A	A	A	A
10	Pragmatic	0.7	0.16	0.14	0.81	0.19	0.38	0.73	H	H	H	T	T	T	T	A	A	A
11	Lexical	0.23	0.56	0.22	0.30	0.70	0.5	1	H	H	H	H	H	T	T	T	T	T
12	Lexical	0.74	0.13	0.13	0.84	0.16	0.33	0.58	H	H	H	T	T	A	A	A	A	A
13	Vague	0.82	0.07	0.11	0.92	0.08	0.44	0.67	H	H	H	H	T	T	A	A	A	A
14	Vague	0.78	0.1	0.12	0.88	0.12	0.47	0.67	H	H	H	H	T	T	A	A	A	A
15	Syntactic	0.7	0.16	0.14	0.81	0.19	0.47	0.79	H	H	H	H	T	T	T	A	A	A
16	Syntactic	0.72	0.15	0.13	0.82	0.18	0.44	0.83	H	H	H	H	T	T	T	T	A	A
17	Semantic	0.66	0.19	0.15	0.77	0.23	0.38	0.73	H	H	H	T	T	T	T	A	A	A
18	Semantic	0.74	0.15	0.1	0.82	0.18	0.44	0.82	H	H	H	H	T	T	T	T	A	A
19	Pragmatic	0.75	0.13	0.13	0.85	0.15	0.41	0.76	H	H	H	H	T	T	T	A	A	A
20	Pragmatic	0.78	0.13	0.09	0.85	0.15	0.33	0.73	H	H	H	T	T	T	T	A	A	A
21	Syntactic	0.75	0.12	0.13	0.86	0.14	0.44	0.73	H	H	H	H	T	T	T	A	A	A
22	Pragmatic	0.6	0.19	0.21	0.75	0.25	0.47	0.73	H	H	H	H	T	T	T	A	A	A
23	Lexical	0.27	0.57	0.16	0.33	0.67	0.5	1	H	H	H	H	H	T	T	T	T	T
24	Vague	0.75	0.14	0.11	0.84	0.16	0.44	0.73	H	H	H	H	T	T	T	A	A	A
25	Semantic	0.78	0.11	0.11	0.87	0.13	0.44	0.73	H	H	H	H	T	T	T	A	A	A

the respondents were not at ease in understanding the IFS concept because, while filling the membership and hesitation value as in IFS, these values are very tightly bound. In IFS, the sum of agreement, disagreement, and hesitation should be equal to 1. Although in the feedback, eight respondents mentioned that they compromised their quality of responses due to this limitation, five respondents suggested that agreement and disagreement may complement each other, but hesitation should be independent. In the second issue, we found that three of the respondents may be responding inaccurately, as their responses are seen to be similar and biased to either side, but we have no measures to validate this.

2) CORRECTIVE MEASURES

To address the first concern, we adopted the neutrosophic fuzzy sets (NFS) approach to collect responses from the respondents. It makes sense as all three components–agreement, disagreement, and hesitation–are considered independent. Thus, the respondents can better focus on describing their level of agreement, disagreement, and hesitation without bothering to calculate their sum and adjust the values accordingly.

To address the second issue, we deliberately induced some incorrect suggestions. If we find a false positive value in the responses, we tag them and check all the responses from those respondents; if we find it biased, we delete all their responses.

TABLE 2. Results based on the individual cases of experiment B of stage 1 of the approach.

Statement		Average			Determined		Range		Significance Level									
ID	Type	*amv*	*anmv*	*ah*	*dmv*	*dnmv*	*rh*	*rmv*	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
26	Semantic	0.77	0.19	0.04	0.80	0.20	0.17	1	H	T	T	T	T	T	T	T	T	T
27	Pragmatic	0.68	0.21	0.11	0.76	0.24	0.44	0.9	H	H	H	H	T	T	T	T	T	A
28	Pragmatic	0.88	0.08	0.03	0.91	0.09	0.29	1	H	H	T	T	T	T	T	T	T	T
29	Vague	0.75	0.17	0.08	0.81	0.19	0.41	0.93	H	H	H	H	T	T	T	T	T	A
30	Vague	0.79	0.09	0.13	0.90	0.10	0.5	0.65	H	H	H	H	H	T	A	A	A	A
31	Lexical	0.7	0.16	0.15	0.81	0.19	0.41	1	H	H	H	H	T	T	T	T	T	T
32	Lexical	0.35	0.51	0.14	0.41	0.59	0.47	0.63	H	H	H	H	T	T	R	R	R	R
33	Vague	0.23	0.56	0.22	0.30	0.70	0.44	0.61	H	H	H	H	T	T	R	R	R	R
34	Vague	0.79	0.13	0.08	0.86	0.14	0.47	1	H	H	H	H	T	T	T	T	T	T
35	Syntactic	0.75	0.16	0.09	0.82	0.18	0.33	1	H	H	H	T	T	T	T	T	T	T
36	Syntactic	0.91	0.04	0.05	0.96	0.04	0.29	0.5	H	H	T	T	T	A	A	A	A	A
37	Semantic	0.83	0.08	0.09	0.91	0.09	0.33	0.6	H	H	H	T	T	T	A	A	A	A
38	Semantic	0.86	0.1	0.04	0.90	0.10	0.29	1	H	H	T	T	T	T	T	T	T	T
39	Pragmatic	0.72	0.1	0.18	0.87	0.13	0.5	0.8	H	H	H	H	H	T	T	T	A	A
40	Pragmatic	0.81	0.1	0.08	0.88	0.12	0.38	0.9	H	H	H	T	T	T	T	T	T	A
41	Lexical	0.69	0.21	0.1	0.76	0.24	0.44	1	H	H	H	H	T	T	T	T	T	T
42	Lexical	0.27	0.57	0.16	0.33	0.67	0.5	0.65	H	H	H	H	H	T	R	R	R	R
43	Vague	0.82	0.07	0.11	0.92	0.08	0.47	0.63	H	H	H	H	T	T	A	A	A	A
44	Vague	0.72	0.13	0.15	0.84	0.16	0.47	0.81	H	H	H	H	T	T	T	T	A	A
45	Pragmatic	0.91	0.05	0.05	0.95	0.05	0.41	0.71	H	H	H	H	T	T	T	A	A	A
46	Pragmatic	0.91	0.04	0.05	0.96	0.04	0.23	0.33	H	H	T	A	A	A	A	A	A	A
47	Semantic	0.81	0.13	0.05	0.86	0.14	0.23	1	H	H	T	T	T	T	T	T	T	T
48	Semantic	0.78	0.14	0.09	0.85	0.15	0.44	1	H	H	H	H	T	T	T	T	T	T
49	Syntactic	0.72	0.12	0.17	0.85	0.15	0.47	0.67	H	H	H	H	T	T	A	A	A	A
50	Syntactic	0.66	0.18	0.17	0.78	0.22	0.44	0.83	H	H	H	H	T	T	T	T	A	A

The final calculations were carried out using the cleaned data. These changes were implemented in the approach, and the experiment was repeated for stage 2 with 8 ambiguous statements from the pool of rejected or reviewed suggestions. The feedback from the respondents suggested that they found the neutrosophic approach to be much more comfortable in relation to their understanding. However, we did not find any cases of bias or false positives.

B. CONTROLLED EXPERIMENT

Each stage of our approach is associated with its respective research question. Consequently, the experimental setup was designed to correspond to each stage of our approach.

1) SETUP

A total of 43 subjects from two universities, namely AMU and JU, were considered for stakeholder roleplay for stages 1 and 2. They were divided into two groups, A and B, based on their university affiliations. In group A, 4 lecturers, 6 research scholars, and 13 postgraduate students were considered from the AMU, and for group B, 5 assistant professors, 13 lecturers, and 2 teacher assistants were considered from JU.

In stages 1 and 2, two parallel experiments were conducted among groups A and B. Experiment A was associated with ambiguous corpus A and group A, and experiment B was associated with ambiguous corpus B and group B. As discussed in the pilot study, the stakeholders were asked to give their level of agreement, disagreement, and hesitation with the suggestion provided by the Elicitor. If they tend to disagree, alternate suggestions should be provided. Fig. 4 shows the excerpt of the online form, where respondents gave their consent. Once the responses were collected from all respondents, they were cleaned to avoid any bias.

C. RESULTS OF THE EXPERIMENTS FOR STAGE 1

In the following results, *H, T, A, R, amv, anmv, ah, dmv, dnmv, rh,* and *rmv* represent significant hesitation, significant tacit knowledge, accepted, rejected, average membership value, average non-membership value, average hesitation, determined membership value, determined non-membership value, range of hesitation, and range of membership value, respectively. The average IF values for each statement based on the stakeholders' responses are shown. Tables 2 and 3 show the distribution of values for each ambiguous statement asked in Experiments A and B, respectively, in order of the statement ID. Table 4 shows the combined results achieved in Experiments A and B, and the same is graphically represented in Fig. 5 for a better understanding. For the sake of the experiment, the acceptance criteria that we set are that the membership value is more significant than 0.5. To make it into more straightforward linguistic terms, we can say that if the level of agreement is more than 50%, that is, if the agreement is more significant than disagreement, we consider it accepted otherwise as rejected.

Similarly, we maintained the same criteria for both the output variables, that is, hesitation and tacit knowledge. However, this can be set differently for each. We compare the output at two different levels to analyze the results, i.e., 0.5 and 1.0. linguistically, we can say that we compare the results at the significance levels of 50% and 100%.

By answering *RQ1* and *RQ3*, we can see that we can reduce the total ambiguous corpus of 25 statements that need to be resolved manually by 4% considering the acceptable

TABLE 3. Values of hesitation, tacit knowledge, rejection, and acceptance for experiments A and B based on the different significance level.

	Experiment A										Experiment B									
Sig. Level	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Hesitation	25	25	25	19	3	0	0	0	0	0	25	24	19	16	3	0	0	0	0	0
Tacit	0	0	0	6	21	23	18	6	2	2	0	1	6	8	21	23	16	15	12	9
Reject	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	3	3	3	3
Accept	0	0	0	0	1	2	7	18	22	22	0	0	0	1	1	2	6	7	10	13

TABLE 4. Results of individual cases rejected and re-iterated in stage 2.

Statement		Average			Determined		Range		Significance Level									
ID	Type	*amv*	*anmv*	*ah*	*dmv*	*dnmv*	*rh*	*rmv*	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
3	Vague	0.82	0.07	0.11	0.92	0.08	0.33	0.5	H	H	H	T	A	A	A	A	A	A
33	Vague	0.72	0.1	0.18	0.87	0.13	0.23	0.2	H	H	A	A	A	A	A	A	A	A
32	Lexical	0.75	0.16	0.09	0.82	0.18	0.38	0.4	H	H	H	T	A	A	A	A	A	A
42	Lexical	0.68	0.21	0.11	0.76	0.24	0.47	0.4	H	H	H	H	A	A	A	A	A	A

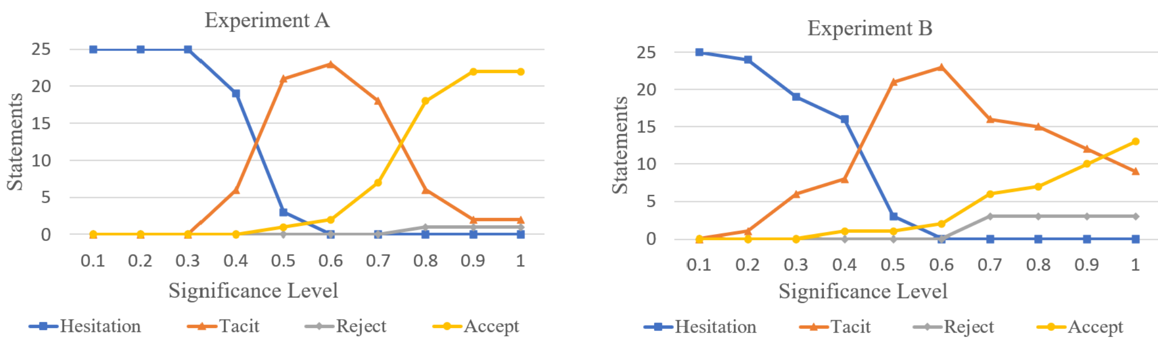

FIGURE 5. Illustration of total hesitation, tacit knowledge, rejection, and acceptance for experiment A and B based on the different significance level.

discordance level of 50%. The same is further increased up to 88% for an acceptable discordance level of 100% in experiment A. In experiment B, these figures are 4% and 52% for the same discordance level. The figures further improved after stage 2 of our experiments, where the rejected suggestions were accepted and hence considered resolved. In experiment A, the ambiguous corpus was further reduced by 4% to 8% and 88% to 92 % for discordance levels of 50% and 100%, respectively. The same for experiment B was reduced by 4% to 16% and 52% to 64%, respectively. Thus, our approach can reduce the total size of the ambiguous corpus that needs to be addressed manually. Furthermore, it reduces the overall work that needs to be carried out in this activity, reducing the total time and cost involved.

Furthermore, the stakeholders can give their consent any time they want, reducing the need to be explicitly present for group discussions or interviews. In this regard, our approach is comparable to the fuzzy approach proposed by Ahmad *et al.*, which was discussed earlier. However, the proposed approach also identifies discordances and the reasons for their occurrence. To answer *RQ2*, it is evident from the data that the approach can identify discordance among stakeholders. Through our approach, we address only two reasons: hesitation or tacit knowledge. The data show that after stage 2 of experiment A, the identified cases of hesitations and tacit knowledge at the discordance level of 50% are 3 and 20, respectively, and at a discordance level of 100%, it was 0 and 2. For experiment B, these values at the same discordance level of 50% were 1 and 20, and 0 and 9 for 100% discordance. The results verify that the precision of understanding between elicitors and stakeholders and among stakeholders is less for the strict significance level. Moreover, there is an inverse relationship between the two values.

D. RESULTS OF THE EXPERIMENTS FOR STAGE 2

Table 4 shows the individual cases rejected by the stakeholders and were reiterated with the alternate suggestion in stage 2 for acceptance. Table 5 shows the overall improvement in the acceptance level from stage 1 to stage 2. In addition, it shows that the cases that need to be reviewed manually are further reduced by 4% in experiment A and 12% in experiment B. Fig. 6 shows the improvement in the acceptance level after Stage 2 compared to Stage 1 of Experiments A and B.

E. RESULTS OF THE EXPERIMENT FOR STAGE 3

1) SETUP

In stage 3 of our experiment, we studied the effectiveness of data gathered from the experiments of stage 1 and stage 2.

TABLE 5. Improvement in the acceptance level after stage 2.

Sig. Level	Exp. A after Stage 1	Exp. B after Stage 1	Exp. A after Stage 2	Exp. B after Stage 2
0.1	0%	0%	0%	0%
0.2	0%	0%	0%	0%
0.3	0%	0%	0%	4%
0.4	0%	4%	0%	8%
0.5	4%	4%	8%	16%
0.6	8%	8%	12%	20%
0.7	28%	24%	32%	36%
0.8	72%	28%	76%	40%
0.9	88%	40%	92%	52%
1	88%	52%	92%	64%

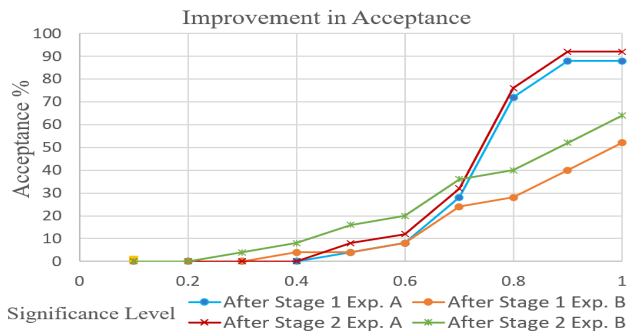

FIGURE 6. Improvement in acceptance level after stage 2.

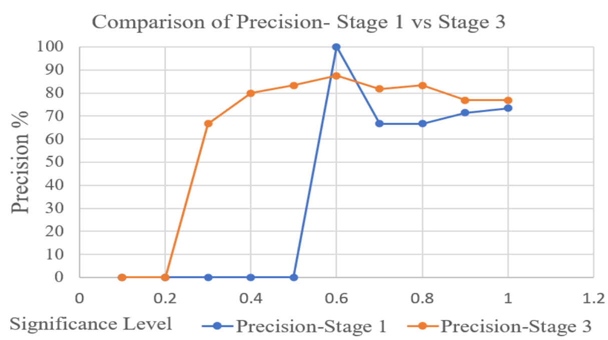

FIGURE 7. Improvement in the precision level of stage 1 vs. stage 3.

For the experimental setup of stage 3, we considered the word-based ambiguities of corpora A and B. Therefore, we created a new corpus C with only lexical and vague ambiguities. Further, the Elicitor's suggestions were replaced by the accepted values from the resolved corpus. The subjects for this study were the same subjects that were considered in the pilot study because they were already familiar with the task they had to perform in the experiment, which saves our efforts in explaining the same things to the new respondents, although statements of corpus C were not discussed with them earlier.

Table 6 shows the total accepted and rejected cases for each significance level in stages 1 and 3. Fig. 7 compares the precision between stages 1 and 3 based on the total accepted or rejected cases for each significance level. This does not include cases that need to be reviewed. In stage 1, the elicitor uses their intellect to suggest a solution for the detected ambiguities. In stage 3, the elicitor uses the resolved corpus instead. It is interesting to see in Fig. 7 that at a significance level of 0.6, the graph shows better precision in stage 1 than in stage 3. It can be observed from Table 6 that at this point, the total accepted case in stage 1 was only 1 with no rejected case, whereas in stage 3, the accepted cases at this stage are 7 and 1 rejected case. As we can see, the heuristics gained from earlier studies from stage 1 and stage 2 improve the accuracy to suggest a value that can be more widely accepted in a particular context.

Table 7 shows the data derived from the resolved corpus from both experiments. Table 8 shows the results of the experiment of stage 3 based on individual cases; the same is illustrated in Fig. 8 for better understanding. The data show a significant improvement in accepting the suggestion given from the resolved corpus instead of Elicitor's intellect. It addresses our *RQ4*, whereas this stage helps the Elicitor make better decisions to suggest the same sense of the sentence.

TABLE 6. Precision comparison between stage 1 and stage 3.

Sig. Level	Accepted Cases Stage1	Rejected Cases Stage1	Accepted Cases Stage3	Rejected Cases Stage3
0.1	0	0	0	0
0.2	0	0	0	0
0.3	0	0	2	1
0.4	0	0	4	1
0.5	0	0	5	1
0.6	1	0	7	1
0.7	6	3	9	2
0.8	8	4	10	2
0.9	10	4	10	3
1	11	4	10	3

We used a confusion matrix to evaluate the performance of the approach. The calculations were based on the experiment conducted in stage 3.

The data in the resolved corpus are based on the heuristics obtained from earlier experiments. Thus, the corpus can only be used to suggest values for ambiguous instances that are available in the corpus. Considering this, we evaluate our approach by defining the elements of the confusion matrix as follows:

True Positive (TP) are those cases that are accepted earlier and are also accepted using corpus C.

False Positive (FP) are those cases that are accepted earlier but are rejected using corpus C.

False Negative (FN) are those cases that are rejected earlier but are accepted using corpus C.

True Negative (TN) are those cases that are rejected earlier and are rejected using corpus C.

Because the resolved corpus that we use in stage 3 of our experiment contains only those values that are accepted in earlier stages, any instance rejected or revised cases are not included in it. Therefore, the instances of FN and TN were 0.

TABLE 7. Table derived from the resolved corpus for stage 3 experiment.

S-ID	Type	Context	Remark	Ambiguity	Accepted values / explanation	*mv*	*nmv*	*h*
1	Lexical	Academic	progress	graphically	continuous lines like a line chart.	0.77	0.09	0.1
2	Lexical	Academic		appearance	pop-up of error message repeatedly	0.71	0.16	0.1
3	Vague	Academic	accuracy	poor	less than 50%	0.82	0.07	0.11
4	Vague	Academic		weekly	non-working day of the weekend	0.8	0.11	0.1
12	Lexical	Travel		log	the written record of events on a voyage	0.74	0.13	0.1
13	Vague	Travel		elderly	people with age more than 60	0.82	0.07	0.1
14	Vague	Travel		young	up to 10 years	0.78	0.1	0.1
24	Vague	Generic		light	light fabric suit	0.75	0.14	0.1
29	Vague	Generic		significant	more than 3 hours	0.8	0.17	0.1
30	Vague	Generic		sufficient	60 seconds	0.8	0.09	0.1
32	Lexical	Banking / Finance		invalid	file type	0.75	0.16	0.09
33	Vague	Banking / Finance	logout	long	Waiting more than 1 minutes	0.72	0.1	0.18
42	Lexical	Medicine / Health	compare	graphically	bars like a histogram.	0.68	0.21	0.11
43	Vague	Medicine / Health	age	old	age of more than 60 years.	0.8	0.07	0.1
44	Vague	Medicine / Health	visits	frequently	more than 8 times in a month.	0.7	0.13	0.2

TABLE 8. Results for the experiment of stage 3 of the approach based on individual cases.

ID.	Text	*amv*	*anmv*	*ah*	*dmv*	*dnmv*	*rh*	*rmv*	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
1	graphically	0.51	0.35	0.14	0.59	0.41	0.16	0.55	H	T	T	T	T	A	A	A	A	A
2	appearance	0.74	0.1	0.16	0.87	0.13	0.21	0.27	H	H	A	A	A	A	A	A	A	A
3	poor	0.77	0.14	0.09	0.84	0.16	1	0.82	H	H	H	H	H	H	H	H	H	H
4	weekly	0.5	0.47	0.3	0.52	0.48	0.67	0.62	H	H	H	H	H	H	A	A	A	A
12	log	0.79	0.11	0.1	0.87	0.13	0.27	1	H	H	T	T	T	T	T	T	T	T
13	elderly	0.41	0.42	0.17	0.49	0.51	0.3	0.84	H	H	T	T	T	T	T	T	R	R
14	young	0.74	0.19	0.07	0.79	0.21	0.17	0.35	H	T	T	A	A	A	A	A	A	A
24	light	0.51	0.35	0.14	0.59	0.41	0.43	0.55	H	H	H	H	T	A	A	A	A	A
29	significant	0.68	0.21	0.11	0.76	0.24	0.51	0.68	H	H	H	H	H	T	A	A	A	A
30	sufficient	0.79	0.09	0.13	0.9	0.1	0.23	0.35	H	H	T	A	A	A	A	A	A	A
32	invalid	0.35	0.51	0.14	0.41	0.59	0.23	0.2	H	H	R	R	R	R	R	R	R	R
33	long	0.51	0.35	0.14	0.59	0.41	0.44	0.2	H	H	H	H	A	A	A	A	A	A
42	graphically	0.75	0.19	0.06	0.8	0.2	0.29	0.71	H	H	T	T	T	T	T	A	A	A
43	old	0.07	0.82	0.11	0.08	0.92	0.47	0.63	H	H	H	H	T	T	R	R	R	R
44	frequently	0.51	0.35	0.14	0.59	0.41	0.29	0.2	H	H	A	A	A	A	A	A	A	A

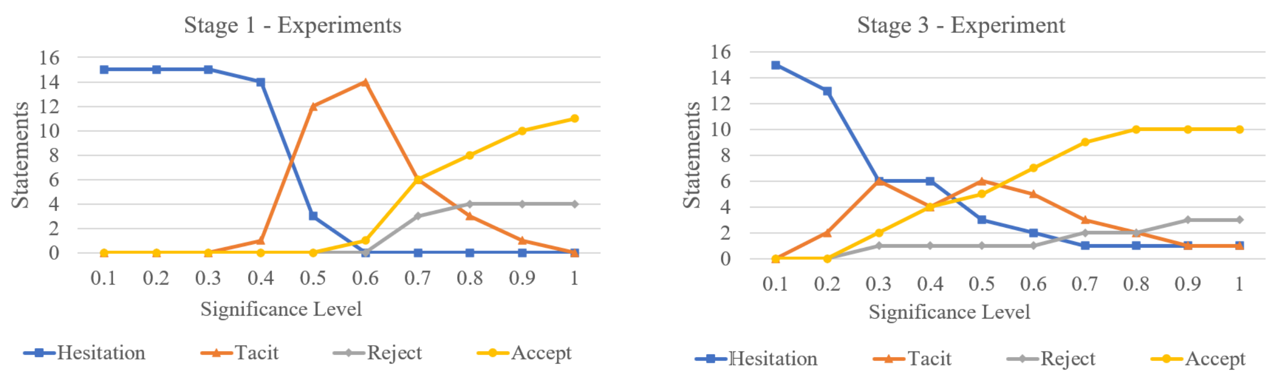

FIGURE 8. Comparison between the results of stage 1 experiments and stage 3 experiment of the approach based on individual case.

Based on these criteria, we evaluated the ability of the resolved corpus in terms of precision, recall, and accuracy at an allowable discordance level of 1. However, a similar approach can be used to evaluate different discordance levels, as shown in Fig. 7.

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \tag{13}$$

Precision = 0.769,

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \tag{14}$$

Recall = 1,

Interestingly, because the value of FN in our experiment is 0, the value of recall is 1, which is perfect. However, this comes with a price for the limited applicability of the resolved corpus. Conversely, if we allow multiple instances of the same ambiguous word and its context but different suggested values, it may result in higher applicability of the approach, but lower recall value as instances of false-negatives will occur. Thus, it may lead to lower accuracy. Perhaps, as the resolved corpus matures over time, the precision tends to improve, which may compensate for the lower recall values; hence, high accuracy can be maintained along with high applicability or flexibility.

The accuracy can be calculated using the F1 score as;

$$F1score = \frac{2 * Preciision * Recall}{Precision + Recall} \tag{15}$$

F1 score = 0.869.

VII. DISCUSSION

We conducted controlled experiments to evaluate the proposed approach. The results of the experiment show that our approach is capable of resolving detected ambiguity. In the experiments, we achieved a precision of 0.769 (76.9%), recall of 1 (100%), and F1 score of 0.869 (86.9%). In comparison when we applied the fuzzy-based approach given earlier by Ahmad *et al.* [31] to our data using only membership values, after stage 1, the total number of unaccepted cases were 15 for both experiments. However, in contrast to our approach, in which we identified the reasons for rejected cases as hesitation, tacit knowledge, and discordance at multiple acceptance levels, the earlier fuzzy approach was limited to only accepted and rejected cases at the 100% acceptance level only. Multiple discordance levels have the additional advantages. The elicitor can communicate with the stakeholders, and an allowable discordance level can be approved for the project before its initial release, which can be subsequently improved. Furthermore, it could be based on multiple factors, such as the project's severity, budget, time, priority, and model. Thus, it adds agility to the project.

In another approach, Ezzini *et al.* [27] address the accuracy of interpretation which can be attributed to catering discordances. They achieved an average accuracy of 85.2% and 84.4% in their experiments using NLP and domain-specific corpora. However, it did not address other sources of ambiguity like hesitation or tacit knowledge. Identifying these sources is crucial as it equips the Elicitor with additional information, as discussed earlier in Section V. The results that we achieved are comparable to those of other studies that target similar problems in the requirement elicitation process of the software development industry. A comparison of the issues addressed by these approaches in contrast to the proposed approach is shown in Table 9. However, the proposed approach is unique compared to other approaches because it involves multiple problems, as discussed earlier, in a single approach. To the best of our knowledge, no other approach exists that addresses all of these problems collectively.

However, the accuracy of our approach depends on various implicit factors. One such factor is the sincerity of the stakeholder in providing consent to the ambiguous statement.

TABLE 9. Issues addressed by other approaches in contrast to the proposed approach.

Study	Level of Automation	Issues addressed
Elrakaiby et al., [15]	Manual	Tacit Knowledge
Spoletini et al., [19]	Manual	Tacit Knowledge
Dalpiaz et al., [20]	Automated	Tacit Knowledge
Bano et al., [21]	Manual	Tacit Knowledge
Ferrari et al., [24]	Automated	Discordance
Dalpiaz et al., [26]	Automated	Tacit Knowledge
Ezzini et al., [27]	Automated	Interpretation accuracy / Discordance
Ahmad et al., [31]	Semi - Automated	Discordance
Proposed Approach	*Semi - Automated*	*Discordance, Tacit Knowledge, Hesitation*

We also have to acknowledge that the respondents of our experiment are not real stakeholders, so the results may vary if taken in a live environment.

Few exciting areas remain to be investigated to improve the performance of our approach and validate its success in a real environment. First, in the future, we plan to study the results of our approach in a live industrial environment and compare it with manual approaches such as interviews and group discussions that are widely used in the industry. Second, so far in our approach, we used mean and range as the statistical functions; it would be interesting if we also use median; perhaps it may provide a better view of the distribution of stakeholders' responses. Third, we study the applicability of our approach to various types of ambiguities individually. Finally, since the resolved corpus that we use in stage 3 of our approach is designed to address only word-based ambiguities such as lexical and vagueness, which limits its effectiveness, perhaps integrating NLP as used by Ezzini *et al.* [27] for coordination and attachment ambiguities with IFS may broaden the scope of this approach.

VIII. CONCLUSION

In this study, we proposed a semi-automatic approach to resolve the detected ambiguity in requirement statements. This approach reduces the time, cost, and explicit requirements for the availability of stakeholders at a particular time during the ambiguity-resolving process. Furthermore, the proposed approach identifies discordances among the stakeholders and the elicitor and determines the reason for its occurrence as either tacit knowledge or hesitation. In addition, the IF logic combined with the heuristic knowledge gained helps the Elicitor improve the facticity of resolved ambiguities between stakeholders and the elicitor. Thus, this approach can be helpful to a novice elicitor in identifying tacit knowledge, discordance, and hesitation among stakeholders collectively and individually, an ability that usually comes with experience. Furthermore, this additional information may also help the Elicitor address cases that need to be resolved manually using traditional methods. Social distancing and other such movement-controlled restrictions during the COVID19 pandemics especially stand as proof for the necessity of such approaches to reduce physical involvement yet works well with appreciable accuracy.

REFERENCES

[1] M. Hagal and F. Kandemili, "Reducing missed requirements issues: Complete, unambiguous and necessary requirements elicitation," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 7, no. 1, pp. 10–14, Jan. 2017, doi: 10.23956/ijarcsse/v7i1/01110.

[2] L. R. Wong, D. Mauricio, and G. D. Rodriguez, "A systematic literature review about software requirements elicitation," *J. Eng. Sci. Technol.*, vol. 12, no. 2, pp. 296–317, 2017.

[3] M. Bano, D. Zowghi, and C. Arora, "Requirements, politics, or individualism: What drives the success of COVID-19 contact-tracing apps?" *IEEE Softw.*, vol. 38, no. 1, pp. 7–12, Jan. 2021, doi: 10.1109/MS.2020.3029311.

[4] S. Gregory, "Requirements for the new normal: Requirements engineering in a pandemic," *IEEE Softw.*, vol. 38, no. 2, pp. 15–18, Mar. 2021, doi: 10.1109/MS.2020.3044403.

[5] S. N. Kumari and S. P. Anitha, "An extended study on the association between elicitation issues and software project performance: A theoretical model," in *Innovations in Bio-Inspired Computing and Applications*. Cham, Switzerland: Springer, 2016, doi: 10.1007/978-3-319-28031-8_46.

[6] N. K. Sethia and A. S. Pillai, *The Effects of Requirements Elicitation Issues on Software Project Performance: An Empirical Analysis* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 8396. 2014, pp. 285–300, doi: 10.1007/978-3-319-05843-6_21.

[7] K. C. Arnold and H. Lieberman, "Embracing ambiguity," in *Proc. FSE/SDP Workshop Future Softw. Eng. Res.*, 2010, pp. 1–6, doi: 10.1145/1882362.1882364.

[8] N. Maiden, "Cherishing ambiguity," *IEEE Softw.*, vol. 29, no. 6, pp. 16–17, Nov. 2012, doi: 10.1109/MS.2012.152.

[9] A. Ferrari, P. Spoletini, and S. Gnesi, "Ambiguity as a resource to disclose tacit knowledge," in *Proc. IEEE 23rd Int. Requirements Eng. Conf. (RE)*, Aug. 2015, pp. 26–35, doi: 10.1109/RE.2015.7320405.

[10] L. Hu and K. C. C. Chan, "Fuzzy clustering in a complex network based on content relevance and link structures," *IEEE Trans. Fuzzy Syst.*, vol. 24, no. 2, pp. 456–470, Apr. 2016, doi: 10.1109/TFUZZ.2015.2460732.

[11] L. Hu, K. C. C. Chan, X. Yuan, and S. Xiong, "A variational Bayesian framework for cluster analysis in a complex network," *IEEE Trans. Knowl. Data Eng.*, vol. 32, no. 11, pp. 2115–2128, Nov. 2020, doi: 10.1109/TKDE.2019.2914200.

[12] B. N. Li, J. Qin, R. Wang, M. Wang, and X. Li, "Selective level set segmentation using fuzzy region competition," *IEEE Access*, vol. 4, pp. 4777–4788, 2016, doi: 10.1109/ACCESS.2016.2590440.

[13] D. M. Berry, "From contract drafting to software specification: Linguistic sources of ambiguity, version 1.0," *Autom. Softw. Eng.*, pp. 1–80, Nov. 2003. [Online]. Available: https://cs.uwaterloo.ca/~dberry/handbook/ambiguityHandbook.pdf and http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.9.7928&rep=rep1&type=pdf

[14] G. A. Patel and A. S. Priya, "Resolve the uncertainty in requirement specification to generate the UML diagram," in *Proc. Int. Conf. Adv. Eng. Technol. (ICAET)*, May 2014, pp. 1–7, doi: 10.1109/ICAET.2014.7105213.

[15] Y. Elrakaiby, A. Ferrari, P. Spoletini, S. Gnesi, and B. Nuseibeh, "Using argumentation to explain ambiguity in requirements elicitation interviews," in *Proc. IEEE 25th Int. Requirements Eng. Conf. (RE)*, Sep. 2017, pp. 51–60, doi: 10.1109/RE.2017.27.

[16] R. Chugh, "Do Australian universities encourage tacit knowledge transfer?" in *Proc. 7th Int. Joint Conf. Knowl. Discovery, Knowl. Eng. Knowl. Manage.*, 2015, pp. 128–135, doi: 10.5220/0005585901280135.

[17] R. Chugh, "Tacit knowledge transfer in Australian universities: Exploring the barriers and enablers," in *Proc. Int. Conf. Circuits, Syst., Commun. Comput.*, 2018, Art. no. 04054, doi: 10.1051/matecconf/201821004054.

[18] B. Davey and K. R. Parker, "Requirements elicitation problems: A literature analysis," *Issues Informing Sci. Inf. Technol.*, vol. 12, pp. 71–82, Jun. 2015, doi: 10.28945/2211.

[19] P. Spoletini, A. Ferrari, M. Bano, D. Zowghi, and S. Gnesi, "Interview review: An empirical study on detecting ambiguities in requirements elicitation interviews," in *Proc. Int. Working Conf. Requirements Eng., Found. Softw. Qual.*, 2018, pp. 101–118, doi: 10.1007/978-3-319-77243-1_7.

[20] F. Dalpiaz, I. van der Schalk, and G. Lucassen, "Pinpointing ambiguity and incompleteness in requirements engineering via information visualization and NLP," in *Proc. Int. Working Conf. Requirements Eng., Found. Softw. Qual.*, 2018, pp. 119–135, doi: 10.1007/978-3-319-77243-1_8.

[21] M. Bano, M. Bano, D. Zowghi, A. Ferrari, P. Spoletini, and B. Donati, "Learning from mistakes: An empirical study of elicitation interviews performed by novices," in *Proc. IEEE 26th Int. Requirements Eng. Conf. (RE)*, Aug. 2018, pp. 182–193, doi: 10.1109/RE.2018.00027.

[22] A. Ferrari, P. Spoletini, B. Donati, D. Zowghi, and S. Gnesi, "Interview review: Detecting latent ambiguities to improve the requirements elicitation process," in *Proc. IEEE 25th Int. Requirements Eng. Conf. (RE)*, Sep. 2017, pp. 400–405, doi: 10.1109/RE.2017.15.

[23] A. Ferrari, P. Spoletini, and S. Gnesi, "Ambiguity and tacit knowledge in requirements elicitation interviews," *Requirements Eng.*, vol. 21, no. 3, pp. 333–355, Sep. 2016, doi: 10.1007/s00766-016-0249-3.

[24] A. Ferrari, A. Esuli, and S. Gnesi, "Identification of cross-domain ambiguity with language models," in *Proc. 5th Int. Workshop Artif. Intell. Requirements Eng. (AIRE)*, Aug. 2018, pp. 31–38, doi: 10.1109/AIRE.2018.00011.

[25] M. S. Husain and M. A. Khanum, "Word sense disambiguation in software requirement specifications using WordNet and association mining rule," in *Proc. 2nd Int. Conf. Inf. Commun. Technol. Competitive Strategies*, 2016, pp. 1–4, doi: 10.1145/2905055.2905179.

[26] F. Dalpiaz, I. van der Schalk, S. Brinkkemper, F. B. Aydemir, and G. Lucassen, "Detecting terminological ambiguity in user stories: Tool and experimentation," *Inf. Softw. Technol.*, vol. 110, pp. 3–16, Jun. 2019, doi: 10.1016/j.infsof.2018.12.007.

[27] S. Ezzini, S. Abualhaija, C. Arora, M. Sabetzadeh, and L. C. Briand, "Using domain-specific corpora for improved handling of ambiguity in requirements," in *Proc. IEEE/ACM 43rd Int. Conf. Softw. Eng. (ICSE)*, May 2021, pp. 1485–1497, doi: 10.1109/icse43902.2021.00133.

[28] S. Ezzini, S. Abualhaija, C. Arora, M. Sabetzadeh, and L. C. Briand, "MAANA: An automated tool for DoMAin-specific HANdling of ambiguity," in *Proc. IEEE/ACM 43rd Int. Conf. Softw. Eng., Companion*, May 2021, pp. 188–189, doi: 10.1109/icse-companion52605.2021.00082.

[29] H. Alfawareh, "Resolving ambiguous entity through context knowledge and fuzzy approach," *Int. J.*, vol. 3, no. 1, pp. 410–422, 2011. [Online]. Available: http://www.enggjournals.com/ijcse/doc/IJCSE11-03-01-163.pdf

[30] K. Gulzar, J. Sang, M. Ramzan, and M. Kashif, "Fuzzy approach to prioritize usability requirements conflicts: An experimental evaluation," *IEEE Access*, vol. 5, pp. 13570–13577, 2017, doi: 10.1109/ACCESS.2017.2725321.

[31] Y. Ahmad, W. Nasir, and S. Husain, "A fuzzy base approach to reduce the domain of ambiguities in software requirement," in *Proc. Int. Seminar Res. Inf. Technol. Intell. Syst.*, 2018, pp. 674–678, doi: 10.1109/ISRITI.2018.8864235.

[32] Y. Ahmad, S. Husain, and A. Alam, "Applying intuitionistic fuzzy approach to reduce search domain in an accidental case," *Int. J. Adv. Comput. Sci. Appl.*, vol. 1, no. 4, pp. 1–4, 2010, doi: 10.14569/ijacsa.2010.010412.

[33] F. Shen, J. Xu, and Z. Xu, "An outranking sorting method for multi-criteria group decision making using intuitionistic fuzzy sets," *Inf. Sci.*, vols. 334–335, pp. 338–353, Mar. 2016, doi: 10.1016/j.ins.2015.12.003.

[34] X. Ji, L. Wang, and H. Xue, "Interval intuitionistic fuzzy decision model with abnormal information and its application in talent selection," *Math. Problems Eng.*, vol. 2021, pp. 1–10, Mar. 2021, doi: 10.1155/2021/6620438.

[35] O. Metzger and T. Spengler, "Modeling rational decisions in ambiguous situations: A multi-valued logic approach," *Bus. Res.*, vol. 12, no. 1, pp. 271–290, Apr. 2019, doi: 10.1007/s40685-019-0087-5.

[36] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965, doi: 10.1016/S0019-9958(65)90241-X.

[37] K. Atanassov and S. Stoeva, "Intuitionistic fuzzy sets on interval and fuzzy mathematics," in *Proc. Polish Symp. Poznan*, 1983, pp. 23–26.

[38] F. Smarandache, "A unifying field in logics: Neutrosophic logic," in *Philosophy*, 2nd ed. Rehoboth, NM, USA: American Research Press, 1999, pp. 1–141. [Online]. Available: http://cogprints.org/1919/3/eBook-Neutrosophics2.pdf

[39] F. Smarandache, "Degree of dependence and independence of the (sub) components of fuzzy set and neutrosophic set," *Neutrosophic Sets Syst.*, vol. 11, no. 6, pp. 95–97, 2016.

[40] K. Atanassov and P. Vassilev, "Intuitionistic fuzzy sets and other fuzzy sets extensions representable by them," *J. Intell. Fuzzy Syst.*, vol. 38, no. 1, pp. 525–530, Jan. 2020, doi: 10.3233/JIFS-179426.

[41] M. Huang and K. W. Li, "A novel approach to characterizing hesitations in intuitionistic fuzzy numbers," *J. Syst. Sci. Syst. Eng.*, vol. 22, no. 3, pp. 283–294, Sep. 2013, doi: 10.1007/s11518-013-5213-x.

[42] A. Sabriye and W. M. N. W. Zainon, "An approach for detecting syntax and syntactic ambiguity in software requirement specification," *J. Theor. Appl. Inf. Technol.*, vol. 96, no. 8, pp. 2275–2284, 2018.
[43] O. Al-Harbi, S. Jusoh, and N. Norwawi, "Handling ambiguity problems of natural language interface for question answering," *Int. J. Comput. Sci. Issues*, vol. 9, no. 3, pp. 17–25, 2012.
[44] S. F. Tjong and D. M. Berry, *The Design of SREE—A Prototype Potential Ambiguity Finder for Requirements Specifications and Lessons Learned* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 7830. Berlin, Germany: Springer-Verlag, 2013, pp. 80–95, doi: 10.1007/978-3-642-37422-7_6.

YASIR AHMAD received the M.Sc. degree in information technology from HNB Garhwal University, India, and the M.Phil. degree in computer science from Madurai Kamaraj University. He is currently pursuing the Ph.D. degree with Universiti Teknologi Malaysia (UTM). In addition, he has more than 14 years of teaching experience in various universities, including Delhi University, India, and Jazan University, Saudi Arabia. His research interests include software engineering, fuzzy and intuitionistic fuzzy logic, neural networks, and digital security.

WAN MOHD NASIR WAN-KADIR received the Ph.D. degree in software engineering from The University of Manchester. Since 1997, he has been with Universiti Teknologi Malaysia (UTM), where he is currently a Professor of software engineering with the School of Computing. He was the Head of the Software Engineering Department, from 2005 to 2009, and the Deputy Dean of the Faculty of Computing, from 2010 to 2014. He is the Chair of the School of Computing. In addition, he served the program committee for various local and international conferences related to software engineering. His research interests include SE knowledge areas based on the motivation to reduce the cost of development and maintenance and improve the quality of large and complex software systems, including software testing, software quality assurance, requirements engineering, adaptable software architecture, software evolution, service-oriented computing, and model-driven development. His research and consultancy works were supported by numerous grants from the government and industries.

SADIA HUSAIN received the Ph.D. degree in artificial intelligence from Jamia Hamdard University, India. Since 2009, she has been with Jazan University (JU), where she is currently an Assistant Professor with the Faculty of Computer Science and Information Technology. She was the Head of the Department of Information Systems, Female Section, from 2015 to 2017. She is the Head of the Research Unit. She had more than 15 years of academic experience. Her research interests include fuzzy and intuitionistic fuzzy sets and their applications, cloud computing, and software engineering.

NORAINI IBRAHIM (Member, IEEE) is currently a Senior Lecturer with the School of Computing (SC), Faculty of Engineering, Universiti Teknologi Malaysia (UTM). She is a passionate educator and actively involved in innovative research for software engineering education, which she invented generic project-oriented problem-based learning (PoPbL) ©2016 and 2018. She is also interested in other SE areas, namely requirements engineering, software maintenance, and evolution. She was a Research Fellow at UTM Centre for Engineering Education (CEE). She is a special taskforce for UTM Online Learning during the COVID-19 pandemic, UTM Future-Ready Educator (FREE) Curriculum Task Force, and UTM e-Learning Task Force.