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Enabling Deeper Linguistic-Based Text Analytics–Construct Development for the Criticality of Negative Service Experience

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ABSTRACT Significant progress has been made in linguistic-based text analytics particularly with the increasing availability of data and deep learning computational models for more accurate opinion analysis and domain-specific entity recognition. In understanding customer service experience from texts, analysis of sentiments associated with different stages of the service lifecycle is a useful starting point. However, when richer insights into issues associated with negative sentiments and experiences are desired to inform intervention, deeper linguistic analyses such as identifying specific touchpoints and the context of the service users become important. While research in this direction is beginning to emerge in some domains, we are yet to see similar efforts in the domain of healthcare. We present in this paper the results from our construct development effort for quantifying how critical a negative patient experience is using different elements of the available textual feedback as a key basis for prioritizing interventions by service providers. This involves the identification of the different dimensions of the construct, associated linguistic markers and metrics to compute the criticality index. We also present the results of the application of our developed conceptualization to linguistic-based text analysis of a small dataset of patient experience feedback.

INDEX TERMS Customer experience, construct development, linguistic analysis, intensity markers, negative event, magnitude of consequences.

I. INTRODUCTION

One of the most important sources of knowledge about customer service experience and associated critical issues is the customer's feedback survey data. The collection of feedback using predetermined attributes of the perception and personal experience of clients has been shown to be useful for quantifying and ranking a-priori known problems [1], [2].

However, customer feedback in a free-text form is very valuable for a true understanding of the essence of issues and for assessing the intensity of the reported customer experience. When customers have the opportunity to express personal experience and perception with minimal restrictions on the content, the degree of detail, length of the stated thoughts, the information content is usually high. Such free-text information usually contains several dimensions characterizing the reported experience, namely: the resources or actors involved in the service; the context, personal situation or emotional condition of the customer; and other details describing the nature of the experience.

A powerful method for extracting knowledge from free text of customer service experience is Text Mining and Natural Language Processing (NLP) techniques [1]–[3]. These technologies allow extracting hidden knowledge contained in the comments and to establish relationships among issues, resources~~,~~ and actors~~,~~ as well as the patient's emotions expressed in the comments.

In our domain of interest – healthcare – an extensive literature review of the field shows the identification and analysis of the most important negative healthcare events perceived by

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the customers (or patients). However, there is still a gap in the development of a method for measuring the degree of criticality of the identified problems. A starting point in tackling this problem when using structured or semi-structured interviews as a data source could be formalizing quantitative (points) or qualitative (fuzzy) indicators as suggested answers. In the case of free-text descriptions and comments, some sense of the problem's importance can be estimated using sentiment s analysis or by calculating the frequency of the topic (category) being described (e.g. those with a negative valence). Unfortunately, these techniques do not offer domain-specific analyses that are important to accurately establish the criticality of problems in healthcare or other specific domains.

Recent progress in Machine Learning and specifically Deep Neural Nets models for domain-specific entity extraction offers a pathway to identify and quantify markers in the free text that denote the criticality of events. However, the use of the computational approaches must be guided by a sound process of construct development and conceptualization.

The challenge we undertake in the research is: (1) *the development of a construct that can measure the criticality of negative customer service or patient care experience in the healthcare domain and* (2) *a procedure to operationalize the construct by integrating different categories of markers in free texts that denote elements of patient's perceptions of the criticality of negative events.*

The rest of the paper is organized as follows: Section 2 provides an extensive review of text analytics methods in the customer experience domain in general. Section 3 describes the methodology in detail. The construct development process is described in Section 4 while the operationalization based on our case study of patient experience feedback data is presented in Section 5. Our findings are discussed in Section 6 with some concluding remarks in Section 7.

II. TEXT ANALYTICS FOR CUSTOMER EXPERIENCE

Understanding the nature of the problems described by customers in a form of free-text survey's feedback is an important goal and one of the key aspects of improving the quality of services provided by organizations. Unstructured data contains a huge variety of explicit and implicit knowledge about customer experience expressed in a form of opinions, suggestions, comments, and reviews. While there are several definitions of customer experience in literature, we define customer experience as follows ([4], [5]): ''*The Customer Experience originates from a set of interactions between a customer and a product, a company, or part of its organization, which provoke a reaction. This experience is strictly personal and implies the customer's involvement at different levels (rational, emotional, and sensorial physical). Its evaluation depends on the comparison between customer expectations and the stimuli coming from the interaction with the company and its offering in correspondence of the different moments of contact or touch-points''*.

This scientific direction is one of the most actively studied over the last decade. However, the development of methods and techniques for extracting specific knowledge from text to solve specific practical problems is still a research challenge [6]–[8]. In [7], [9], the author divides the free-text feedback analysis problem domain into the following typologies – *subjectivity* and *polarity* classification; opinion *summarisation*; opinion *source* and opinion *target* identification. In our work, the *entities* extracted from free-text feedback help in understanding the nature and degree of problems perceived by customers. These entities may be related to (1) sentiment – negativity or positivity of experience; (2) subjectivity – the presence of facts or expression of one's own feelings; and (3) atomic features of products or services.

A. SENTIMENT AND SUBJECTIVITY ENTITIES

The most developed method for entities extraction is *sentiment polarity and subjectivity analysis* of free-text feedback. There are two levels of sentiment/subjectivity analysis – document and sub-document units (paragraphs or sentences) levels. These analyses can be conducted either separately or in conjunction with the feature-based classification [10]. Mostly, this category of analyses is based on a manual creation of a sentiment lexicon via unsupervised labeling of words or phrases or using online resources like WordNet [11], NRC Emotion lexicon [12], SentiWord Net [13] with their sentiment polarity and subjectivity status [14], [15]–[21]. The sentiment labels typically represent binary classification or a multi-point scale measuring the degree of polarity of expression and emotions. Unsupervised machine learning methods have been extensively applied to sentiment polarity-based classification of consumer reviews [7], [9], [22]–[29].

However, all the presented methods in this category are focused on extracting and assessing the degree of negativity of the customer experience based on the evaluation of the general tonality of feedback. None of the methods are associated with any specific lexicon of criticality cues (LCC). Such lexical cues will be used as ''word-markers'' that signify a critical negative client experience. This kind of LCC, in comparison to the general one, should consider the specific *problem domain* vocabulary. For example, the word ''*uncomfortable*'' in a *room* or *bed* context may have a different degree of criticality depending on the associated context, e.g. in *hotel services* or *healthcare context*.

B. ATOMIC FEATURES ENTITIES

The studies that focused on the extraction of **atomic features** aimed at identifying the main properties of products and services that are associated with the experience and most powerful emotions of the customer [11]. It could be specific features of goods, product components/attributes or service aspects, individuals, organizations, events, topics, activities, resources, context, suggestions, etc. In [11], [23], [30]–[46], the authors presented the results of the studies of the problem of feature-based opinion mining of customer reviews of products sold online. Typically, these approaches are part of the sentiment polarity and subjectivity analysis.

One of the separate scientific directions for extracting *atomic features* or aspects from free-text feedback is the **suggestions** retrieval. Suggestions refer to the variant of active experience exchange based on the possibility for the client to express their proposals for decision-making by the management of the company [47]–[49]. A majority of the suggestion extraction methods aims at detecting suggestion/wishes in documents using NLP techniques combined with Machine Learning techniques. They are usually based on the assumption that the suggestions have the pivotal phrases-patterns like ''should have, could be, can be, could give, better if, I wish,'' etc. The studies [48]–[52] use the rule-based (on modal verbs, ''needs to'' and other rules) approach for identifying user wishes from product reviews and political discussions. In [6], [53], the classification-based approaches were used for extracting explicit suggestions from the students' course feedback.

The limitation of these approaches is the fact that extracted single- or multi-level feature s structures only allow the classification of opinions being analysed in *one dimension* which is based on the results of *direct* context analysis of textual feedback. The process of sentiment analysis is not used to extract additional features of the event under study. We also observe here that none of the reviewed work under this category addresses the criticality of events or experience in their different dimensions of features.

C. FEATURES/ENTITIES PATTERNS

Extracting atomic features of products/services from free-text feedback quite often gives a one-sided or distorted view of the real situation. In this regard, parallel with the traditional direction of feature extraction, approaches and methods for substantiating, forming and extracting various patterns that are contextually interrelated in customer-expressed opinions of properties, aspects, entities are being actively developed. In [54], the authors extract the *products-attributes* patterns based on implicit (semantic) and explicit entities from product descriptions. Authors of [55] use the semi-supervised approach to recognize contextually dependent *word-category*. In [56], the following three levels of features for each product are extracted: *brand*-level, *semantic*-level (subjectivity and orientation) and *product*-level. The research described in [57] *event typology pattern structure* contains the distinctions characterizing experiences. This *typology* assumes the presence of the following event features: Sentiment (Emotion, Evaluation, Reputation); Happening (General, Availability, Usability) and Action (Buying/Selecting, Using, Stopping). The authors of [1] propose a conceptual framework for analysing customer feedback by accounting for the three key *components of the value (co)creation process*: Activities, Resources and Context (ARC). In [58], the authors proposed opinion-related entities: expressions of opinions and sources of opinions with the relationship that exists between them.

D. ENTITIES EVALUATION AND RANKING

In the majority of studies, the qualitative ***evaluation*** and relative ***ranking*** of opinions, products, features, components, etc. were examined. In the evaluations, the following measures were used: polarity strength [59]; subjective and comparative features importance [60]; composite score for a specific product by including star rating, number of positive reviews, number of negative reviews, helpfulness score of reviews, review age [61]; weight that customers place on individual product features and the polarity and strength of the underlying evaluations [62]; latent weights of aspect (topic) for individual reviews [12]. In studies [63]–[67], the *level of satisfaction/dissatisfaction* by specific factors of hotel products and services based on the evaluation of positive and negative reviews is introduced. In [65], satisfaction/dissatisfaction measurement was carried out using a singular value based on the LSA algorithm. For customer satisfaction assessment in [68], a multivariate linear regression of the following qualitative entities was employed – subjectivity, diversity, readability, length – and two factual variables (involvement and hotel ranking) are used. The *ranking score* of a product reported in [56] was determined using a linear regression model taking into account the review contents, the relevance of a review to the product quality, helpful votes and total votes from posterior customers, posting date and durability of reviews. While in [68] an approach to *predicting* the overall *rating* of cold-start items based on latent aspect distribution of review and reviewer factors. The study [21] proposes an adaptation of the sentiment analysis approach in [69] in determining the *product rating* based on the integrated indicator characterizing the level of positive customer feedback in relation to seven selected product features: Frequency of Occurrence in Search Engine Results Page (SERP), Useful Content, Extraneous Content, Sufficient Material, Physical Attributes, Market Availability and Price. The work presented in [70] proposes an opinion mining and *ranking algorithm* that first classifies a review as positive, negative or neutral but also identifies the product's more representative features and assigns overall ''impression'' weights to each of them. In [71], the feedback rating algorithm concentrates on finding the strength of the emoticons associated with the sentence and it covers both text emoticons and graphical emoticons. In [5], researchers *rank the five trip modes* based on the association between the customers *attributes* and their expectations of hotel *factors*, in order to compare them with the trip modes.

In [72], the authors introduce the *intensity* as the measure of the strength of a private state – speculations, evaluations, sentiments, beliefs, and other mental and emotional states [73]. They use the lexicon of subjectivity clues for recognizing the *intensity*, such as intensifying adverbs modifying adjectives (e.g., *quite good* and *very bad*). The *intensity attributes* (terms) proposed to code by low, medium, high, and extreme values and *expression intensity* - by neutral, low, medium, high, and extreme values. Such an approach allows classifying the intensity of nested clauses in all sentences in the corpus.

From the literature review, we can conclude that only a limited number of theoretical and empirical studies allow the ranking of the extracted features, topics, aspects, tonality, etc. (Appendix I). Most of the existing studies are dedicated largely to improving the quality of entities recognition algorithms and different types of feedbacks classification. Additionally, the majority of existing approaches to quantitative evaluation and ranking are based either on the calculation of the frequency of occurrence of entities in the analyzed data sample or additionally on the degree of negativity (tonality) of opinions. Moreover, among the above-described specific approaches to quantify the rating of opinions (entities, events or topics), the concept or notion of the criticality of negative events or experience is yet to be studied. The studies closest to addressing this gap are those that deal with the analysis of the intensity of opinion, in which each of the words-marker from the lexicon of subjectivity clues, depending on the degree of intensity of the subjectivity of the experience expression, is assigned a certain qualitative indicator.

III. METHODOLOGY

To tackle our research challenges described in Section I, we propose a comprehensive three-stage approach to compute the Criticality of Negative Customer experience: (1) developing the domain of the construct; (2) generating a set linguistic markers based on the domain description, designing a domain study instrument which is evaluated and refined through multiple iterations; and finally (3) collecting experimental data, examining its measurement properties, synthesized and interpreted.

A. STAGE I: DOMAIN

The first stage in developing a construct is to establish the problem domain. The stage aims to establish the following four items of information: conceptual definitions of (1) customer experience in the domain of study; (2) negative event related to the client experience for the specific problem domain; (3) list of dimensions, which represent the elements of the construct; (4) criticality of negative customer experience index. These definitions are usually derived from different sources, such as a review of the literature, case studies, open-ended questionnaires, interviews, or some combination of these sources.

In this paper, we consider the domain of patient healthcare (Figure 1). In this regard, we introduce the above concepts in the context of our specific problem domain.

Patient Experience of healthcare is shaped by what *individuals feel, observe, perceive, recognize, understand and remember about their medical care and treatment, the people they interact with, and the facilities they visit* [35], [74], [75].

Negative Event(NE) exists if any issue, incident, decision, and circumstances, which are part *of patient experience, are reported as resulting in or/and having the potential for*

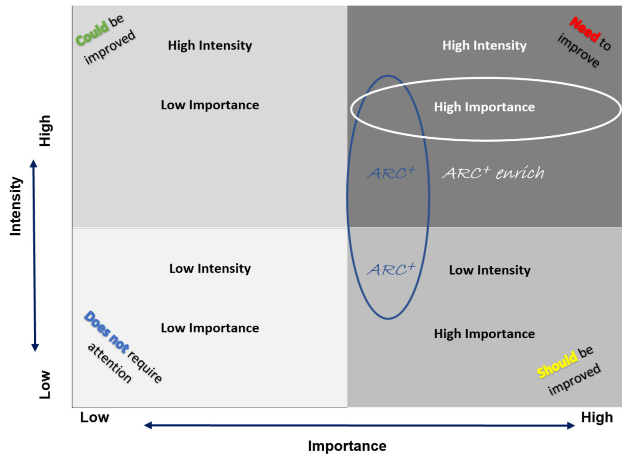

FIGURE 1. Importance/Intensity map for identifying the high-criticality-level negative healthcare event.

physical, emotional, psychological, or financial harm to the patient (adapted from [76], [77]).

In order to provide (1) more in-depth analysis of the negative healthcare event *causes* related to the patient and (2) identification of *factors* (or contextual *patterns*) that determine the specificity of Negative Events in healthcare, we adopt the *ARC* (activities, resources and context) concepts as the key components of the value (co) creation process in any service delivery context including patient or healthcare [1] and extended it by *Actors* and *Reasons* components.

An actor can be defined as a *human that accepts, provides, supports, or controls healthcare services (adapted from* [78]) *and that is perceived in the patient experience as an active participant and one of the reasons for the reported negative healthcare event*. Clinical and non-clinical (healthcare support, technical and administrative) groups of actors are usually identified in healthcare services ([79]). Each of the Actors is associated with a specific *role* in the healthcare system (for example, in clinical group – Doctor, Nurse, etc. roles; in the non-clinical group – Administration, Receptionist, etc. roles).

Reasons are the group of factors characterizing different aspects of the causes of Negative Event in healthcare services.

The ***Criticality index*** of negative patient experience (CI), is proposed as a measure comprising two components:

- the ***Magnitude of Consequences*** as a level of the perceived *seriousness of the negative consequences, which are associated with a negative event and its impact on physical, emotional, financial, social, or psychological patient's conditions/outcomes*(adapted from [2], [80]);

- the ***Power of Consensus*** as the degree to which *patients collectively agree that a reported negative eventhas a particular level of intensity in terms of the actual and potential consequences* [2].

B. STAGE II: INSTRUMENT CONSTRUCTION

At the second stage of our methodology, we developed and improved our *"measurement instrument"* over multiple iterations. The goal here is to determine what constitutes the criticality of negative customer experience. The steps involve specifying: (1) the principles of the data collecting and selection; (2) measurement components and their quantitative assessment; (3) application of the measurement instrument and interpretation.

1) DATA COLLECTING AND SELECTION PRINCIPLES

The step is designed to extract knowledge about the ***criticality*** of the negative patient experience from data presented in **textual** format (such as interview or open surveys responses, essays, etc.). Our dataset comprises 100 comments obtained from http://www.ratemyhospital.ie/. All the comments were first anonymized by removing names of people, specific places and other details that could be used to identify the author of the comment.

Next, a group of three researchers assigned labels to the dataset as either positive, negative or neutral based on the overall sentiments of the comments. Following these, one of the authors looked through negative comments with rich linguistic features and selected 20 for the purpose of operationalizing the criticality construct.

Source: free-text responses dataset. *Output*: anonymized sample of free-text comments coded by negative labels.

2) MEASUREMENT COMPONENTS

To identify the degree of negative patient experience, the following basic measurement components are suggested:

- the list of Intensity**Markers** as special trigger words, which reflect the seriousness of patient experience and contribute to an extraction of the knowledge about the degree of intensity of the patient perception of the impact of reported actions, decision, and circumstances of the negative consequences (adapted from [81]).

All semantic meanings of the Intensity markers are proposed to be measured using a fuzzy-logic scale: {Low, Medium, High} to formalize the processes of qualitative assessment of the Intensity indicator; quantitative scale {0, 1} to formalize the processes of calculation of the Intensity indicator value.

- **Frequency** as a number of identical negative healthcare events, mentioned in all analysed patient responses (in Activity-Resources-Context patterns or Activity/Resources/Context elements formats), which reflect the consistency of the patient experience and contribute to an extraction of the knowledge about the degree of agreement of patient perception that a reported negative event has such level of the magnitude of the negative consequences.

3) ALGORITHM OF LINGUISTIC-BASED DATA PROCESSING

The presented algorithm is based on a multi-stage coding framework [31], [82], [83] and contains the two steps of coding: semantic patterns-level and intensity-level.

a: STEP ONE – SEMANTIC PATTERNS-LEVEL CODING

The semantic patterns-level coding approach used at this step allows extracting the domain-oriented knowledge about Negative Events in the form of semantic patterns: Activities, Resources and Context (ARC+) [1]. For example, for comment: "*Once you DEMAND a few doctors or nurses speak with you, but the majority did not*" instead of coding it by theme and subtheme: Communication / Information Exchange with Patient, in proposed methodology, it will be coded by the following semantic pattern: ACTIVITY: Communication / Information Exchange with Patient; RESOURCES: Doctors, Nurses; CONTEXT: on-demand communication by Doctor, Nurse.

Such semantic patterns allow identifying that: (1) healthcare resources (actor, equipment, room) took a part in the negative event; (2) healthcare activity (action) caused this event and (3) context (concrete situation) was the action and resources involved the described Negative Event.

As a coding approach, a combined method is recommended~~,~~ which involves: gathering of information from various mentioned above coding elements sources after performing the test coding step (with a randomly selected sample of comments); further refining and revising coding results after the procedure of systematization, comparison and evaluation of test coding step results.

Source: (1) anonymized sample of free-text comments coded by negative labels; (2) previous literature research results; (3) workshop/consultation with patients and healthcare actors' results. *Output*: free-text comments coded by ARC+ semantic pattern.

b: STEP TWO - INTENSITY-LEVEL CODING

In this step, the Intensity Markers are proposed for simultaneously using them: (1) as an approach to implement the intensity-coding procedure and (2) as a measure of the degree of negative patient experience criticality.

Intensity-Level Coding: The intensity-coding procedure is proposed to perform (1) according to the classification proposed above: four types of negative healthcare event Reasons types (professional, inter-personal, service quality and technical) and Expanded Amplifiers (frequency, related information, consequences, and sentiment); and (2) also using the combined method: (i) carry out preliminary test coding step on a randomly selected sample of comments with the aim, in addition to the process of text coding, to form a list of possible Intensity Markers (only with negative context), grouped by mentioned above classes; (ii) in parallel, to conduct a literature review considering the problems of semantic, linguistic and sentiment aspects of the use of intensifiers in the free-text comments; (iii) to organize the workshop with patients and clinicians to assess the relevance of identified markers classes.

Source: (1) free-text comments coded by ARC+ semantic pattern; (2) previous literature research results; (3) results of the workshop/consultation with patients and healthcare actors. *Output*: (1) free-text comments coded by intensity markers; (2) list of classified intensity markers

Intensity-Level Scaling: To prepare for the process of intensity degree of the negative healthcare event measuring, it is proposed to perform the Intensity Markers scaling via: classification of the obtained lists of Intensity Markers in accordance with the qualitative intensity levels {Low, Medium, High} of the expression of patient experience in particular context; the subsequent assignment to each of the Intensity marker of the corresponding quantitative weighting coefficient (from 0 to 1); matching and refining of the obtained qualitative and quantitative scales of the healthcare negative healthcare event intensity degree of each Intensity marker with a group of experts (patients and healthcare actors).

Source: (1) list of classified intensity markers; (2) previous literature research results; (3) results of workshop/consultation with patients and healthcare actors. *Output*: (1) intensity markers qualitative levels; (2) intensity markers weighting coefficients

C. STAGE III: INTERPRETATION OF MEASUREMENT PROPERTIES

In the third stage of the methodology, experimental data are collected, its measurement properties are examined, synthesized and interpreted. The main efforts should be aimed to determine the concept of the negative customer experience criticality *quantifying* while implementing: (1) algorithm of measurement elements syntheses; (2) principals of negative customer experience criticality evaluation and interpretation.

1) STEP ONE – MEASUREMENT ELEMENTS SYNTHESES

The process of *Criticality index* quantification involves three phases of the experimental data (result of semantic patterns-level and intensity-level coding steps) synthesis, namely:

(1) phase one: calculation of the *Intensity* $INT_{ij}$of each (*i-th*) negative healthcare event (in Activity-Resources-Context patterns or Activity / Resources / Context elements formats) in each (*jth*) unit of information by *summing* the Weighting Coefficients (w_{ijk}) of all the Intensity Markers (n_{ij}) coded for this Negative Event:

$$\boldsymbol{INT_{ij}} = \sum\nolimits_{k=1}^{n_{ij}} \boldsymbol{w_{ijk}} \tag{1}$$

(2) phase two: calculation of the *Importance* of each (*i*-th) Negative Event. It should be noted that the *Importance of* Events **ARC^{+}**and for **ARC^{+} enriched** could be distinguished because of the following features: in **ARC^{+}** the *Importance* indicator IMT_i of the negative healthcare event is measured as the number of identical semantic *ARC* patterns found in the semantic patterns-level coding results of each comment; in**ARC^{+} enriched**, the *Importance* indicator IMT_i^{Int}can be interpreted as the *Importance of the Intensity* of the healthcare NE, since it is measured as the number of identical *ARC* patterns found in the *semantic patterns-level + intensity-level* coding results for each *information item* (*j=1, m*).

(3) phase three: calculation of the value of the negative healthcare event*Criticality* index HIC_i as a product of the *Intensity* of each (*i-th*) negative healthcare event and its *Importance:*

$$\boldsymbol{HIC_i} = \sum\nolimits_{j=1}^{m} \boldsymbol{INT_{ij}} * \boldsymbol{IMT_i^{Int}} \tag{2}$$

The obtained *Criticality index* values allow ranking the negative healthcare event according to the *degree of urgency* of this issue solving for healthcare service management.

Source: (1) free-text comments coded by ARC^{+} semantic pattern; (2) free-text comments coded by intensity markers; (3) intensity markers weighting coefficients. *Output*: NE Criticality index.

2) STEP TWO – DATA INTERPRETATION

This step may include the following phases: analysis and interpretation of the causes for the discrepancy of the ranking results of the degree of *Importance* of negative healthcare event, as well as their *Criticality;* analysis and interpretation of the degree of *Criticality* of negative healthcare event ranked using various negative healthcare event *aspects dimensions* (activities, resources, context, roles); carrying out the ranking of the negative healthcare event *Criticality* by various *Intensity markers* classes (Reasons types and Expanded Amplifiers) with the subsequent comparison, analysis and interpretation of the results.

The *principal use* of this methodology and the focus of this paper is the development of a linguistic-based measurement instrument for quantifying the criticality of the negative customer experience based on different elements of the free-text feedback. There are two clear contributions regarding the exploratory use of the methodology. First, this method guides researchers to allows a deeper understanding of the contextual nature and of the customer experience in the specific domain. Second, the methodology challenges the researchers to deliver justified support for prioritizing interventions by service providers.

IV. CONSTRUCT DEVELOPMENT

Based on the presented methodology, in this section, we present the construct for identifying and measurement of the Criticality of Negative customer experience for the healthcare domain.

A. HEALTHCARE DOMAIN ANALYSIS

Understanding the nature and criticality of the problems described by clients in the form of free-text survey feedback is an important goal and one of the key aspects of improving the quality of services provided by companies. To ensure the process of identifying and interpreting this kind of information, appropriate methods and techniques are needed. Among the key areas of development of methods for extracting knowledge about the nature and degree of criticality of negative healthcare events, the following can be highlighted: (1) studies of the structure, nature, and importance of negative healthcare event using Statistical techniques for the processing of **pre-structured** questionnaires responses. The knowledge received in this research can serve as a theoretical basis and also as a tool for evaluating the results of extracting and assigning topics/entities for identifying negative healthcare event from free-text customer reviews; (2) revealing and measuring the importance of negative healthcare event via applying the Thematic-oriented and Conceptual Framework techniques for **free-text** questionnaires responses. These studies make it possible to lay the methodological foundation for identifying healthcare problems from the unstructured patients' responses which contain different vocabulary, ways of expressing opinions, etc.; (3) measuring patient perception of negative healthcare event degree via development and/or using linguistic and NLP approaches. Such studies are based on modern methods of Artificial Intelligence and allow to automate the process of extracting knowledge from the free-text feedback, considering the tonality of the expressed opinion and its nature.

Processing of responses from pre-structured questionnaires

The main *themes* and *entities* extracted in this first group of studies could be applied for coding the negative healthcare event components. The authors [84] highlighted the following as the main **component** required for **patient experience** measurement: *Characteristics of interactions*; *Organizational aspects*; *Overarching assessments*. In ([85]), the authors propose to review qualitative studies that report directly from patients on how they define quality and develop the Conceptual model of patient perception of**quality**, which contains: patient *expectations*, patient *perception* of the *experience*, patient *experience* of *seeking* and *using services*, patient *definition/criteria* of quality. In [86], for qualitative analysis of relevant patient perceptions and experiences for evaluating the **quality of interaction** with physiotherapists during outpatient rehabilitation, the following themes (**factors**) were used: (1) *interpersonal* manners; (2) *providing information* and education; (3) *technical expertise*. In [87], the patients' satisfaction with nursing care is well recognized as an indicator of the **quality of care**. Using individual items that were identified in earlier studies such as [88], [89], the authors built the instrument consisting of 36 items distributed among eight dimensions: *interpersonal relationships* between nurses and patients, *efficiency* in *serving* patients, *comforts* provided in the ward, *sanitation*, *personalized* information, *physical environment* in the ward, *provision* of general instructions by nurses, and *competency* of *nurses* in caring for patients. The studies [90], [91] introduce patient **satisfaction** definition as a *health care recipient's reaction to salient aspects of his or her service experience*. The following categories were proposed as the main categories of patient satisfaction measurement: *Patient Characteristics*; *Structure* and *Processes*.

As for the **methods** of patient experience studying, in [86] data analysis was undertaken using a modified grounded theory approach [34], which presupposes that two authors (moderator and assistant) review the transcripts independently and code sentences that contain meaningful incidents. These were labeled in categories using a combination of predetermined and emergent codes. The next level of analysis involved the identification of relationships between categories and the grouping of categories with hierarchical conceptual uniformity into themes and subthemes. A somewhat different approach to the study of **patient experience** is applied in the work [92]. Using the multiple logistic regression, the independent effects of patient characteristics and of specific aspects of provided health care on patient's satisfaction were examined. The results showed that the likelihood of overall satisfaction was significantly and independently increased first of all due to the physician's ability to *give explanations* and their *empathy* [92].

It should be highlighted that, as the main problems characterizing the survey approach to measure patient experience noted by the authors [84], two were identified, perceived by us both as an advantage and as a challenge for improving and resolving the existing constraints, namely: (1) it is more likely to gain negative than positive comments from some groups; (2) clinicians sometimes report that those survey findings are difficult to interpret. The first fact emphasizes the advantages of this method for determining exactly the Negative Events in healthcare. The second fact confirms the relevance of developing methods and tools for solving challenges that exist in the field of interpretation of the results of conducted surveys (especially using free-text answers).

Thematic-oriented and Conceptual Framework techniques for analysing the responses from free-text questionnaires

The second group of patient experience study allows to highlight the following methods of free-text deep analysis of the *themes* and *entities*, which could be useful for coding the negative healthcare event components: in [31] using *Framework Analysis*, 15403 comments from London National Cancer Patient Experience Survey were studied [93], [94]. The initial framework was developed based on a review of the patient experience literature and a preliminary analysis of the data. In this process, two different researchers independently looked at comments. Following the identification of potential themes, the researchers discussed and compared the themes and devised the framework. After this, the framework was piloted by the research group with the data from the first trust. A few minor changes were made before using the framework as a basis for analyzing all the data. The *most significant 17 topics* requiring improvement were determined by counting the *number of references* to this topic in the patient comments. Among them the most frequently mentioned are the following (top five): *Poor care; Poor communication; Waiting times; Information; Understaffed*. Similar research was conducted based on the Scottish Cancer Patient Experience Survey [95]. Data were analyzed by tonality and then coded using thematic analysis [32] by the content of the comments. Analysis of the large data set was carried out using a structured approach [33]. The *frequencies* of similar themes and subthemes were measured. The results of the analysis indicated the importance of the following categories of themes for the patients: *Feeling confident or secure within the system*; *Feeling that individual needs were met*; *Structures* and *Processes*.

A similar approach was applied in [34], [96]. The data sources used comprised the notes written during ethnographic observations, transcribed interviews of nurse-patient communication during procedural care, interviews with patient participants, and a document review. Two main themes were identified: (1) Nurses' *workload* and the *environment,* (2) Nurse-patient *partnership* and *role expectations*. In the [75], instead of statistical processing of patient responses to closed questions (considering the demographic factors), a **coding framework** was developed to carry out a thematic analysis of the open-ended responses to the free-text questions at the end of the questionnaire. All open-ended questions were analyzed and multi-coded using the following 20 codes (**categories**): *Dignity, respect and privacy*; *Communication with the patient; Emergency department management and environment; Emergency department waiting times; Staffing levels; Staff availability and responsiveness; Other healthcare staff; Other staff; Food and drink; Cleanliness and hygiene; Nursing staff; Doctors or consultants; Waiting times for planned procedures; Discharge and aftercare management; Staff in general; Communication with family and friends; Physical comfort; Hospital facilities; Parking facilities; Clinical information and history; Private health insurance*. In [83], the three stages of **multi-stage coding** [82] of the free text data were implemented: semantic-level coding for areas of cancer patient experience; semantic-level coding for specific categories within different areas of cancer patient experience; identification of latent themes within the different areas. And the fourth stage included comparisons between closed questions and free-text responses.

Linguistic -based and NLP approaches for analysing the responses from free-text questionnaires

In this direction of study, mostly the *sentiment* analysis in combination with *theme* identification is used. Above all, these methods aimed: to automate the processes of (1) recognition of the text polarity (highlighting negative opinions associated with NE); (2) analysis of the context of feedback (extraction of themes, entities, etc.) and (3) their use for further statistical processing. So, in [97] authors applied *Machine Learning* and *Natural Language Processing* techniques to online comments about hospitals for **predicting** the patient's opinion **context** and **sentiment** within the concrete themes. The result of [98] is the development of the Design Science-based **Framework** Research [99] for the National Health Service patient experience in England, Scotland, and Wales. Such a Framework contains three iterations: *Sentiment* Analysis (Strength of Association, Support Vector Machine and Naïve Bayes); *Topic* Identification (the Latent Dirichlet Allocation approach) and *Rationale* Identification of Patient *Sentiment*. Each of these steps provides a procedure of Identification, Designing, Evaluating and Testing. *Sentiment analysis* approaches were also realized for: English National Health Service website comments [100], on-line forums, blogs and news comments [101] with an additional multi-steps algorithm [102], Chinese reviews on 'euthanasia' from various Web pages, Blog postings, and online forums [103], English-language Internet conversations (ICs) regarding prostate cancer treatment with active surveillance (AS) [104]; for medical domain sentiment lexicon creation and evaluations [105], the drug review dataset using Artificial Neural Networks algorithms [106]. In [107], the TagCrowd tool for *unigrams* and Many Eyes tool for *bigrams* retrieving were used to analyse the patient experience of primary care. Voyant Tools with *Keyword in Context* (KWIC) function [108] were applied for searching for a keyword in the text and analysing its local meaning in relation to a fixed number of words immediately preceding and following it. The association of patient experience scores with the occurrence of certain words was tested with logistic regression analysis. In [109], three phases of the analysis were implemented. The first phase is primarily deductive development of *a thematic framework* (adapted from [110] to categorise comprehensively the survey comment. The framework allows comments to be coded as positive or negative experiences of specific areas of *care* and whether specific forms of *information* to prepare patients were *lacking*. The second phase is the application of *Machine Learning algorithms* to identify patients' comments concerning their experience of care quality. Next, comparative analysis using t-tests was conducted between categories of individuals' comments and their single index EQ5D score (summarizing five domains: mobility; self-care; usual activities; pain/discomfort; anxiety/depression), to identify associations between them. The final third phase was about *qualitative* analysis of retrieved comments. In [111], the method of combination of user-defined tags for blog messages with the *Automatically generated* subject terms from such standard vocabularies as Opinion Templates, Basic Resource, or Medical Subject Headings Resource Templates is proposed for providing more powerful subject access to cancer blog posts. In [112], the *Qualitative Text Processing Framework* is introduced. It contains the following: data *collection*; *qualitative* analysis (comprises a systematic expert annotation and rigorous analysis of the development of a dataset); *classification* phase (is intended to provide to the researcher the labels of the documents, paragraphs or sentences related to the general themes of interest); information *extraction* (aims to extract words and phrases mentioning the general classes of entity and the relationships between these entities); *term* recognition (FlexiTerm); *integration* and *scalability.* In the study [113], the goal was to categorize temporal expressions in clinical opinions text. Six main *categories* of temporal expressions were identified. The constructed temporal constraint structure models the time over which an event occurs by constraining its *starting* and *ending time*. Such constraint includes a set of fields for the endpoint(s) of an event, anchor information, qualitative and metric temporal relations, and vagueness.

As we can summarize from the scientific studies of patient experience (Table 1, Appendix II) in the light of the goal setting in the paper: (1) an indicator of the **frequency** of mentioning a theme extracted from the patient responses is still used as the main measure of patient perception of the negative event; (2) the main **techniques** (algorithms, methods, technologies) used to partially or fully automate the process of extracting knowledge about the main healthcare issues perceived by patients are: (i) Text Mining and Machine Learning methods, such as **topic modelling** and **sentiment analysis**, providing automatic extraction of the main topics contained in the comments, as well as finding associations between the extracted topics and their tonality; (ii) **conceptual frameworks** allowing to identify specific concepts (themes), and groups of related concepts (triplets) based on preliminary manual coding, training and testing the model, evaluated using the triangular approach (literature review, experimental results, intellectual workshops with experts). As a source for literature review, one can use the results of medical errors research and the evaluated results of the analysis of patient experience.

Thus, from the conducted literature review of the main trends in the field of research on the identification and analysis of the most important healthcare issues perceived by the patient, it follows that this scientific direction is rather thoroughly studied. However, there is still a gap in the development of a method for measuring the *degree of criticality* of the identified Negative Events. And if using *structured* or *semi-structured* interviews as a data source, this problem is solved by considering formalized quantitative (points) or qualitative (fuzzy logic) indicators as suggested answers while using *free-text* descriptions and comments for analysing the importance degree of the problem which is carried out only on the basis of the *frequency* of the topic (category) being described (with a negative tone recognition).

The results of the literature review have allowed the authors to come up with the following research questions:

Research Question 1: *What are the main measurement elements that will enable determining the criticality of the negative events related to reported healthcare experience?*

Research Question 2: *What type of information about the Criticality of negative healthcare events can be extracted from free-text patients' comments?*

B. IDENTIFICATION

The proposed concept for identifying and measuring the *Negative healthcare Event Criticality Index* is an enriched variant of the ARC framework in [1].

As a first step, we extend the ARC framework to capture salient information in the healthcare domain – we call this the ARC+ framework). The following knowledge can be extracted from a set of comments using ARC$^+$ framework: (1) a list of the negative healthcare events mentioned in patients' comments in the format of *Activity-Resources-Context* patterns; (2) a list of the individual Activity, Resource or Context elements in the *negative* healthcare events mentioned in patients' comments; (3) the possibility of categorizing the above lists by demographic dimensions; and finally (4) also categorizing the above lists by demographic dimensions;contextual sentiment.

As a method for determining the value of **High-level Negative Healthcare Event** indicator, there is a quantitative approach to calculate the **Frequency** of the mentions of the extracted (ARC) elements within the Corpus.

The contextual sentiment is an indicator of the presence of the commentary words that characterize the presence of a *positive* or *negative* tonality (for example, "intolerable conditions", "terrible noise", "polite and affable staff ") in the analysed fragment of the text.

This approach is a significant step forward in understanding the real problems in hospitals through the eyes of patients. It serves as an effective tool for improving the quality of health care services. However, it still has one significant **gap** in the methodology for determining patients-perceived negative healthcare event described below.

The *High-level Negative Healthcare Event* indicator is the only one of the components of the *Power of Consensus* indicator, which takes *into account* only the degree of patients agreement that a reported negative event is harmful in moral, physical and/or psychological form, but *without taking into account* the level of the seriousness or anticipated impact of the reported negative event on physical, emotional, financial, social, or psychological patient's conditions/outcomes.

The knowledge about the *Magnitude of Consequences* as a degree of patient perception of the problem intensity refers to the actual anticipated level of associated negative repercussions. This is introduced in the proposed Conceptual Framework (**ARC+ enrich**) as the decisive indicator for final scaling of the degree of *criticality* and, as a result, the *degree of urgency* to address an issue by the healthcare service management.

In order to identify the negative healthcare Event with a **high Criticality level**, the following *Importance-Intensity* concept is proposed:

Power of Consensus - will be used in the proposed Framework as an identifier of the **Importance** of the negative healthcare event in the context of the degree of the necessity to solve this problem in order to improve the quality of health services;

Magnitude of Consequences - we assume that this will be used in the proposed Framework as an identifier of the **Intensity** of the negative healthcare event in terms of the urgency for solving this problem.

Figure 1 presents the **ARC$^+$enrich** Importance/Intensity map for identifying the *High-Criticality*-level negative healthcare event reported by patients based on their own perception and experience and to be suggested as a guide to be used by hospital management to prioritize the improvement measures, i.e. only with **High Intensity** and

TABLE 1. Review of healthcare patient experience study results.

Dimension	Paper	Object of study	Components
Measurement Components	[84]	Patient and carers experience	Characteristics of interactions (patient-professional relationship, professional care, information and advice, communication skills, trust); organizational aspects (accessibility/availability, medical and technical facilities, office characteristics, office organization/waiting time, office staff); overarching assessments (success of outcome, general satisfaction, willingness to recommend service).
	[85]	Patient perception of quality	Patient expectations (reputation of the provider, needs of the patient, patent of choice, previous experience, personal characteristic of patient, social/cultural norms, knowledge of what patient should expect), patient perception of the experience, patient experience of seeking and using services, patient's definition/criteria of quality
	[86]	Patient perceptions and experiences for evaluating the quality of interaction with physiotherapists	interpersonal manners; providing information and education; and technical expertise and were processed using general statistical approaches, justifying their results by frequency characteristics broken down by the contexts (themes) introduced earlier
	[92]	Patient's satisfaction	patient characteristics (sociodemographic characteristics, disease severity, quality of life) and of specific aspects of provided health care (the time the physician spent with patients, physician's interpersonal skills, etc.)
	[90], [91], [114]		Patient Characteristics (sociodemographic characteristics; physical and psychological health; attitudes and expectations); Structure (the organization and financing of care; accessibility and continuity of care) and Processes (technical aspects of care; interpersonal aspects of care).
	[87], [88], [89]		36 items distributed among eight dimensions: interpersonal relationships between nurses and patients (12 items), efficiency in serving patients (7 items), comforts provided in the ward (4 items), sanitations (3 items), personalized information (3 items), physical environment in the ward (3 items), provision of general instructions by nurses (2 items), and competency of nurses in caring for patients (2 items)
	[31]	Patient experience	Topics requiring improvement (top 5): poor care; poor communication; waiting times; information; understaffed.
	[95]		Feeling confident or secure within the system (poor care; inadequate aftercare; difficulty getting into the system; inconsistent or inappropriate information; lack of faith in the system; inadequate contact); Feeling that individual needs were met (lack of information; poor communication; poor emotional support and responsiveness; involvement and choice; specific and unusual circumstances; family); Structures (unsuitable or uncomfortable environment; staffing levels; privacy; transport) and Processes (waits and delays; ineffective and unreliable processes (organizational systems); fragmented care).
	[96], [34]		Nurses' workload and the environment (sympathy for the busy nurses; prioritizing calls to the nurses) and Nurse-patient partnership and role expectations (partnership through relationship; nurses' role in psychosocial care; reduction of psychosocial concerns through physical care).
	[75]		Dignity, respect and privacy; communication with the patient; emergency department management and environment; emergency department waiting times; staffing levels; staff availability and responsiveness; other healthcare staff; other staff; food and drink; cleanliness and hygiene; nursing staff; doctors or consultants; waiting times for planned procedures; discharge and aftercare management; staff in general; communication with family and friends; physical comfort; hospital facilities; parking facilities; clinical information and history; private health insurance
Techniques	[90], [85]	Literature	Literature review of theoretical and empirical work on patient perception of health care systems quality
	[115], [115], [116]		Literature review of recent advances in clinical Natural Language Processing
	[84]	Pre-structured questionnaires	Quantitative, qualitative and comparative analysis
	[86], [34]		Statistical analysis after Grounded theory of coding and analysis
	[92]		multiple logistic regression
	[117]		Statistical analysis, Distribution of Responses
	[91], [114]	Open-ended and closed questions	Statistical analysis. Open questions manually categorized as positive, neutral, negative or ambivalent
	[88]		Item analysis and principal component factor analysis
	[89]		SERVQUAL and SERVPERF tools, Statistical analysis
	[87]		Descriptive design
	[96], [34]	Triangulation of data	Thematic analysis Ethnographic approach [118] Statistical (frequencies of similar themes and subthemes measuring) Triangulation of data: field notes written during ethnographic observations, transcribed interviews of nurse-patient communication during procedural care, interviews with patient participants, and a document review
	[31], [93], [94]	Free-text feedback	Framework analysis
	[95], [32], [33]		Thematic analysis Structured approach Statistical (frequencies of similar themes and subthemes measuring)
	[83], [82]		Multi-stage coding, Thematic content analysis
	[75]		Coding framework and comparative analysis

TABLE 1. ***(Continued)*** **Review of healthcare patient experience study results.**

[1]	Coding framework, Machine learning and natural language processing
[97], [98]	Design Science-based Framework Research, which contains three iterations: Sentiment Analysis (Strength of Association, Support Vector Machine and Naïve Bayes); Topic Identification (the Latent Dirichlet Allocation approach) and Rationale Identification of Patient Sentiment.
[106]	Support vector machine, Probabilistic neural network, Radial basis function neural networks
[105]	Medical opinion lexicon creating
[104]	NLP for sentiment analysis
[103]	Chinese Sentiment Word and Machine Learning Approaches
[100]	Machine learning and dictionary scoring algorithms for sentiment prediction. Topic modeling
[101], [102]	Sentiment Analysis, Topic Modelling
[107]	Text mining, TagCrowd tool for unigrams, Many Eyes tool for bigrams retrieving
[108]	Text mining, Voyant Tools with Keyword in Context (KWIC) function [108] Logistic regression analysis
[109]	Adapted and tested coding framework [83], learning-based text mining
[110]	Sentiment analysis, machine-learning algorithms, qualitative analysis
[111]	User-defined tags for blog messages Automatically generated subject terms (Opinion Templates, Basic Resource, or Medical Subject Headings Resource Templates)
[112]	Qualitative Text Processing Framework

High Importance levels (in compare with the ARC+ concept, in which a problem requiring improvements, is based on simultaneously identified issues with *High Importance*, but with both – *High* and *Low Intensity*).

As the main forms of knowledge representation extracted from a set of comments using ARC^{+} *enrich* framework, the following forms are guaranteed: (1) a list of the *High-Criticality-level* Negative Event mentioned (in patients' comments in the format of A ctivity-Resources-Context patterns); (2) a list of individual Activity, Resource and Context associated with the *High-Criticality-level* Negative Events; (3) categorization of the above lists by Actors and Reasons for the negative events.

C. METHOD

Taking into account the Negative Event Criticality Index Identification Methodology as well as the studied literature, we propose the Reasons (Factors) to be categorized into four following types: *Inter-Personal (IP)*, *Professional (P)*, *Service quality (SQ)*, and *Technical (T)*(Table 2).

Based on this classification and the results of manual coding of the test sample (20 comments of from http://www.ratemyhospital.ie/), it is proposed to divide the Intensity Markers into two classes (1) types of negative healthcare event Reasons (Factors) causing anticipated or received consequence and (2) Expanded Amplifiers of the patient perception intensity.

1) REASONS MARKERS

a: PROFESSIONAL REASONS MARKERS

The professional reasons markers allow to interpret patient perception degree of reported actions, decision and circumstances in terms of the presence of a certain level of skills, knowledge and abilities of negative healthcare event Actors related to the performance of professional duties directly.

For example, in the text of comment " *No explanations and limited English"*, the following Professional Reasons Markers could be identified: (1) *No* – contextually characterizing the problem of the absence of any explanations of the patient's health condition. This trigger can be classified as the *High* degree of the perceived consequences of a given issue contextually, i.e. the lack of any information could only aggravate the patient's psychological and physical condition; (2) *Limited*– contextually characterizing unsatisfactory professional communication skills of the doctor. This trigger can be classified as the *Medium* degree of perceived consequences of a given issue, i.e. there is a possible misunderstanding and unclear explanation by the doctor of the patient's problems.

b: INTER-PERSONAL REASONS MARKERS

The inter-personal reasons markers allow an interpretation of the degree of patient's perception of reported negative healthcare event in terms of the presence of a certain level of qualities of healthcare Actors, not directly related to their professional activity.

For example, in the text of the comment *"No information and nobody to talk to not even administration staff. The consultants on the other hand apart from a select fewI have found brutal"*, the following Individual Reasons Markers could be identified: (1) *Nobody* – contextually characterizing the problem of the absence of any communication, which may concern both professional and Inter-Personal Negative Events. In the context of this comment, the marker *Nobody* is more likely to relate to personal characteristics of hospital staff, since it stands out separately from the comment about the lack of information (*No information)* the provision of

TABLE 2. Negative healthcare event reasons.

Reasons types	Description	Components	Examples
IP	Characterized by the presence of a certain level of qualities of healthcare Actors, not directly related to their professional activity	Personal features Interpersonal skills	general communication; individualized attention; friendliness; patience and tolerance to the patient and his relatives
P	Characterized by the presence of a certain level of professional competences of negative healthcare event Actors	Knowledge Skills Competences Abilities Experience	the correctness of prescriptions for treatment; level of providing post-operative care; explanation of the diagnosis to the patient and his relatives
SQ	Characterized by the presence of a certain level of quality of medical service, which provides the ability to perform the promised service dependably and timely	Capacity Organizational structure Finances Care processes Care infrastructure	number of doctors at night; the optimal organization of registration of patients at the reception; time allocated for one patient service workload
T	Characterized by the presence of a certain level of hospital environment quality	Design Availability Maintenance	old, not clean, poorly or not at all working medical equipment; dirty warms

which relates to the direct professional duties of hospital staff. Trigger *Nobody* can be classified as the *High* degree of the perceived consequences of a given issue, i.e. absence of attention expressed primarily in communication and support adversely affects the patient's psychological state. (2) *Apart from a select few*– contextually characterizing personal qualities of the consultant, namely his brutality. This trigger can be classified as the *Medium* degree of perceived consequences of a given issue, i.e. reported attitude towards patients, according to the comment, is typical for the majority of hospital consultants and may cause a drastic decline in the quality of medical services.

c: SERVICE QUALITY REASONS MARKERS

The service quality reasons markers allow to interpret the degree of patient perception of reported actions, decision and circumstances in terms of presence of a certain level of medical service quality which provides the ability to perform the promised service reliably and timely.

The markers related to this Service quality reason are proposed to be divided into two groups: reasons of organizational *reliability* that ensure the general promised volume and expected quality of medical services (for example, enough doctors in the night shifts; the optimal organization of patient's registration at the reception, etc.); factors of organizational *timeliness* that ensure the specifically promised time accuracy of the provision of medical services (usually a reasonable time of one patient service; waiting of Emergency; waiting for any assistance in lines, etc.).

d: SERVICE RELIABILITY MARKERS

For example, in the text of comment "*The patient developed an allergy after a few days, and we found it quite difficult to get readmitted for observation. There was only one doctor on duty.*", the following Service Reliability Reasons Markers could be identified: (1) *Quite difficult* – contextually characterizing the problem of finding appropriate medical services. This trigger can be classified as the Medium degree of the perceived consequences of a given issue, i.e. there is still a real opportunity to find such services; (2) *Only one* – contextually characterizing a few doctors on duty. This trigger can be classified as the High degree of perceived consequences of a given issue, i.e. there is an extremely small opportunity to wait for the doctor without too long lines.

e: SERVICE TIMELINESS MARKERS

For example, in the text of comments "*Son waiting since 11 am to be put on a drip. Didn't get it for nearly 24 hour.*" And *"We waited 11 hours in the Emergency Department and could not manage to get any doctor examination*", the following Service Timeliness Reasons Markers could be identified: (1) *Since 11 am, Nearly 24 hours*– contextually characterizing the problem of the deviations from the promised waiting time for medical care; (2) *11 hours*– as information about a long waiting time for emergency care which especially enhances the degree of seriousness of the patient perception of the situation since the consequences of this fact can be inevitable.

All these triggers can be classified as the *High* degree of the perceived consequences of a given issue. Trigger *any* is found in the context that it is impossible to find any doctor for examination. In this case, it will be related also to *High* degree Service Reliability Marker.

f: TECHNICAL REASONS MARKERS

It characterizes the degree of the described issue perceived by the patient and is featured by the presence of a certain level of hospital environment quality.

For example, in the text of comment *"Equipment mostly old and notclean."*, the following Technical Reasons Markers could be identified: (1) *Mostly*– contextually characterizing the problem of the inadequate quality of equipment. This marker can be classified as the *High* degree of the perceived consequences of a given issue, i.e. the possibility of inoperability and errors in the work of most of the medical equipment; (2) *Not*– contextually characterizing of the inadequate cleanliness of equipment. This trigger can be classified as the *Medium* degree of perceived consequences of a given issue both from the point of view of a lower probability of high criticality of the consequences of this issue, and from the point of view that this situation is not characterized by additional reinforcements of the type "*very*", "*terrible*", etc.

2) EXPANDED AMPLIFIERS

Additional Expanded Amplifiers markers are proposed to include the trigger words and *expand* the expression of patient's perception of the issue seriousness level. They include general emphasizers of the negativity of the issue and a description of its unpleasant/irreversible consequences comprising the following: the *frequency* (countable and not countable) of the healthñare Negative Event described by the patient; the *related information* objectively and subjectively associated with the described negative healthcare event and its consequences (such as *prior facts*, *age of the patient*, *time of day*) in the patient experience; the *consequences* of healthñare Negative Event specified in the patient's experience comments; the patient's *opinion* representing the expression of patient's emotions about his perception of the described healthñare Negative Event.

a: FREQUENCY

In the text of comments " *Numerous attempts to talk to doctors hindered by nurses."* and *"The hospital had never phoned us to say he was moved.*", the following not countable Frequency Amplifiers Markers could be identified: (1) *Numerous* – contextually amplify the context of not being able to talk to the doctor. This marker can be classified as the Medium degree of the perceived consequences of a given issue. Based on the context, containing information on the Average level of the frequency of unsuccessful attempts to contact a doctor, the described situation is not characterized by the words "all attempts", i.e. the consequence of this issue is rather a long waiting time than a complete lack of consultation with a doctor; (2) *Never* – contextually characterizing the lack of respect to the patient. This trigger can be classified as the High degree of perceived consequences of a given issue as the situation described based on the patient experience occurred with a high frequency.

b: RELATED INFORMATION

In the text of comments "*Patient 76 years old. We traveled almost 60 miles every day to see my father in this hospital. We did this for three weeks.*", the following Related Information Markers could be identified:

c: PRIOR FACTS

three weeks, 60 miles every day– this amplifier increases the degree of patient perception of the described situation to a highly critical. These amplifiers characterize a high degree of patient's dissatisfaction with the subsequent issue, namely, the fact that after such long and frequent visits by patient's relatives, no one informed them that the patient had been taken to another hospital.

d: AGE OF PATIENT

76 years old – this amplifier increases the degree of patient perception of the described situation because of the advanced (and therefore dangerous in terms of consequences) age of patients.

e: TIME OF THE DAY

In the text of comment "*We were not the only ones to leave on the night*", the amplifier *Night* emphasizes the criticality of the negative healthcare event occurring at night.

f: CONSEQUENCES

In the text of comment "*The lack of professionalism caused great stress for us during our initial visit*", the Consequences Marker *Caused great stress* could be identified. This information is a rare fact of specific consequences that were caused by the issue noted in the comment and allow assessing the degree of its seriousness (1) not only by the patient's *emotional perception* but also (2) by the specified *facts* of negative impact on his/she present and future moral, physical and/or psychological condition.

g: OPINION (SENTIMENT)

In the text of comment "*The doctor I saw in AE was rude and arrogant while treating my wife.*", the following Opinion (Sentiment) Markers could be identified: *Rude and arrogant* – adds information to the patient's emotional assessment of the doctor's qualities, increasing the intensity of perception of negative professional reasons for the quality of the healthcare service.

3) CONTEXTUAL DIMENSION

In order to provide an opportunity for (1) a more in-depth analysis of the negative healthcare event *causes* related to the patient and (2) the identification of *factors* (or contextual *patterns*) that determine the specificity of negative healthcare event that has arisen, an introduction to the Conceptual Framework with the following *contextual dimensions* is proposed: *Roles*; *Hospital Department/Place*; *Patient Health Problem*; *healthcare Facilities/Medication*.

As a source for such dimensions identification, it is proposed to use the data from the ARC$^+$ components –– *Resource* (for Role) and *Context* (for all other dimensions); and the trigger words from the patients' text comments containing references to these dimensions:

1) Text comments, for example: (1) Role – *Consultant*. Text comment: " *Consultant not interested*". (2) Patient Health Problem –- *allergy*. Text comment: "*The patient developed an allergy after a few days*". (3) Hospital Department/Place –*Emergency.* Text comment: "*We waited 11 hours in the*

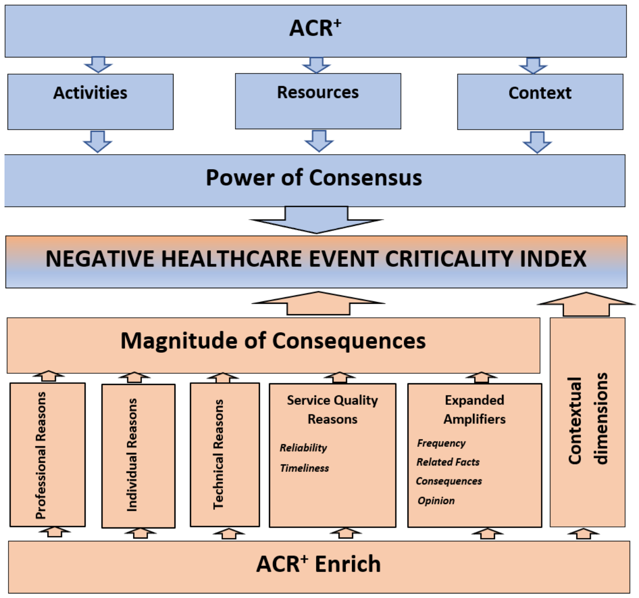

FIGURE 2. ARC+ enrich framework.

Emergency''. (4) healthcare Facilities/Medication – *Sedation, MRI*: Text comment: '' *Sedationdidn't work. MRI delay*''

2) Official reference books of roles and responsibilities of employees of Ireland Hospitals [79] corresponding to the *Context* ARC component of the described negative healthcare event.

Thus, the process of enriching the ARC^{+} framework by merging it with the concept of the *Intensity* of the negative healthcare event *identification* is presented in Figure 2.

V. OPERATIONALISATION ON CASE STUDY

A. DATA COLLECTION AND SELECTION

As described in Section III, in order to demonstrate the main results of the Conceptual Framework application, 20 free-text negative comments were selected out of the 100 anonymized and coded comments (as either positive, negative or neutral sentiments) taken from http://www.ratemyhospital.ie/.

B. DATA ANALYSIS RESULTS

1) SEMANTIC PATTERNS-LEVEL STAGE

During the *semantic patterns*-level coding stage two researchers (1) carefully read the comments sentence by sentence, (2) assigned paraphrases or labels ('*codes*') that describe what they have interpreted in the units as important elements of semantic ARC pattern. Additionally, one researcher reading the comments (3) performed the extended (*Enriched*) coding of the *Context* aspect enabling the clarification of the antecedents and circumstances of the reported negative healthcare event. All coding results conducted in parallel by two researchers passed this comparison and agreement through a joint discussion.

The general description of the data sample after performing this stage is provided in Table 3. The full report on *semantic patterns*-level coding results is presented in Appendix III.

TABLE 3. General results of the semantic patterns-level coding stage.

Coding elements	Number	List
Negative healthcare event Aspects		
Activities	8	Communication with Patient; Communication/Information Exchange between Health Professionals; Communication/Information Exchange with Patient; Relatives-related Care (Communication/Information Exchange); Patient Care; Patient Treatment; Staff Management; Cleanliness of the Premises
Resources	7	Other resources (instead Roles): Equipment; Insurance; Mattress; Pillow; Reception; Ward Area
Context	52	See Appendix III
Enriched Context		
Roles	5	Doctors; Nurses; Staff; Administrative Staff; Consultants
Hospital Department /Place	6	Emergency; Reception; Maternity Paediatrics; Admission; Surgery; Ward
Patient Problem	8	Toe Fracture; Head Injury; Pneumonia; Equipment; Fractures; Bloods; Allergy; Insurance
Healthcare Facilities/ Medication	10	X-ray Scan; Physiotherapy; Trolley; Equipment; MRI; Sedation; Drip; Mattress; Pillow; Doctor Examination

2) INTENSITY-LEVEL CODING STAGE

During intensity-level coding stage, two researchers simultaneously and independently (1) read each comment sentence by sentence taking into account the codes assigned at the previous stage and (2) attributes to the words (phrases) found in the comment text and containing knowledge about the degree of criticality of the described negative healthcare event, the corresponding code (Intensity Marker), (3) categorizing these codes in accordance with previously defined Intensity Markers classes. The general description of the data sample after performing the intensity-coding stage is shown in Table 4. The full report on intensity-coding results is presented in Appendix IV.

3) INTENSITY-LEVEL SCALING STAGE

In order to implement this stage of analysis, **first**, two researchers simultaneously and independently (1) explored and grouped the Intensity Markers of each negative healthcare events reasons class in accordance with the *qualitative* intensity levels {Low, Medium, High} of the expression of patient experience in *particular context*, (2) sorted the list of Intensity Markers within this Intensity Levels groups by increasing degree of intensity of the patient perception in the context of described negative healthcare events, (3) assigned the *quantitative* weighting coefficient (from 0 to 1) to each of Intensity Marker.

In the **second** step, all results of *quantitative* weighting coefficients assigning were discussed (via Delphi method application): (1) between researchers who perform the scaling to find consensus in assigned weighting coefficient; (2) with two independent experts (doctors), who were asked

TABLE 4. General results of the semantic intensity-level coding stage.

Coding elements	Number	List
Professional Reasons	12	Few doctors and nurses who care; No review; No information; No explanations; Limited English; completely clueless; Nobody bothered coming near me; Not interested; Not examined; One of the rudest; Nobody gave advice
Inter-Personal Reasons	4	The majority did not speak; Nobody to talk; Not even administration staff talk; Apart from a select few I have found
Technical Reasons	1	Equipment mostly old and not clean
	Service quality Reasons	
Timeliness	10	5 hours waiting; An hour Reception was empty; Twenty hours waiting; Seven hours in the hospital; only to be called back in the next day; Nearly 24 hours; Since 11 am; Waited 11 hours; 10-minute consultation
Reasons	14	Across in any hospital; No x-ray scan; No physiotherapy; No aftercare; No follow up; Consultant on leave; No given appointment; Quite difficult to get readmitted; Only one doctor on duty; Only fault was with the care assistants; Overall disappointed; Serious shortage; To get any examination; didn't even look
	Expanded Amplifiers	
Frequency	9	Care once; Not the only ones to leave; Numerous attempts to talk; Numerous mistakes; Never phoned; Never given an apology; appointments never happen; Never sent test results; Many times
Consequences	1	Caused great stress
Sentiment	35	See Appendix IV
	Related Information	
Prior facts	4	60 miles; three weeks; every day; developed an allergy after a few days
Age	1	Patient 76 years old
Time of day	2	Night; weekend

to assess the degree of intensity markers used in free-text comments, both (a) in terms of the *patient perception* of the criticality of the negative healthcare event described in the comments, and (b) in terms of *actual* or *potential* consequences for the patient of an negative healthcare event with a given intensity.

In the **third** step, the results of the first and second steps were revised taking into account the opinions of *researchers* and *experts* using the weight coefficients of *confidence* in ratings – 0.4 (for researchers) and 0.6 (for experts) correspondently.

The results of the Intensity-level scaling stage are presented in Appendix V.

C. INTENSITY-IMPORTANCE MEASUREMENT

This stage of the proposed methodology was implemented by performing the following steps:

- based on the *semantic patterns-level coding* stage results (Appendix III), the formation of *Activity-Context patterns* $ACP_i(i = 1, k)$, describing a specific (*i-th*) negative healthcare event;

- based on the *semantic patterns-level* & *Intensity-level coding* stages results, calculation of an indicator of *Importance of the Intensity* IMT_i^{Int}(frequency) for each Activity-Context pattern ACP_i;

- based on the *Intensity-level coding* & *Intensity-level scaling* stages results the (Appendixes IV, V), calculation of *Intensity* INT_{ij} indicators for each (*i-th*) Activity-Context pattern ACP_i and each (*j-th*) unit of information (sentence of particular comment);

- the *Intensity* index values normalization:

$$INT_{ij}^{norm} = \frac{INT_i}{max_{i=}^{k}(INT_{ij})} \tag{3}$$

- calculation of the *negative healthcare event Criticality* index HIC_i for each Activity-Context pattern ACP_i;

- ranking the normalized *Criticality index* values according to the *degree of Urgency* of negative healthcare event.

The results of *the Intensity-Importance measurement* stage are presented in Appendixes VI-VII.

VI. RESULTS

The results of conducted study allowed to highlight three major findings of the proposed Conceptual Framework for identifying the negative healthcare event Criticality Index: (1) extending the concept of negative healthcare event Importance indicator by the approach for its Criticality measure; (2) increasing the level of structure of the ARC^+ framework; (3) providing an opportunity to reveal the presence of causal relationships between Context-mechanism-outcome negative healthcare event aspects. The listed findings have the following features.

1. *Extending the concept of the importance indicator of the negative healthcare event by its Criticality for the patient.* This measure is complex and considers both (1) the power of patient *consensus* with the fact that this negative healthcare event is significant in terms of the presence of his/her negative experience and (2) the strength of the actual or expected negative *consequences* associated with this negative experience. This strength (magnitude) of consequences is a weighting factor increasing or reducing the significance of the degree of consensus statistical indicator (importance) of a negative healthcare event depending on how serious (intensive) this Issue is in the patient's eyes. This approach allows changing the structure of the rating of the most *Important* negative healthcare event highlighting the most *Urgent* among all the important ones that need to be improved in the first place.

For example, simulated sets of three comments that contain information about *Communication with patient* activity demonstrate the fact that they may have different degrees of intensity of negative patient experience assuming the same value of the degree of patient's *Power of Consensus* (Importance) which is equal to three. In the results given in Table 5, we can observe how the degree of *Criticality* for patient negative experience increases from first to the fourth example

TABLE 5. Example of the difference between degrees of negative healthcare event criticality.

#	Comments	rude 0.4	impolite 0.4	arrogant 0.3	rudest 0.6	a few 0.6	very 0.3	majority 0.9	most 0.6	across in any 0.2
1	*Rude staff.*	x								
	Nurse unhelpful.		x							
	The doctor I saw in AE was rude and arrogant.	x		x						
	IMPORTANCE = 3 CRITICALITY = 1.5									
2	*Rudest staff.*				x					
	A few nurses are very impolite.		x			x	x			
	Majority of the doctors I saw in AE were arrogant.			x				x		
	IMPORTANCE = 3 CRITICALITY = 3.1									
3	*Rudest staff in this hospital.*				x					
	The most impolite nurses have come across in any hospital.		x						x	x
	Majority of doctors I saw in AE were rude.	x						x		
	IMPORTANCE = 3 CRITICALITY = 3.4									
4	*The rudest staff I have come across in any hospital.*				x					x
	Majority of nurses are impolite.		x					x		
	Majority of doctors I saw in AE were rude and arrogant.	x		x				x		
	IMPORTANCE = 3 CRITICALITY = 4.0									

due to (1) the degree of medical staff impoliteness (rude, rudest, very, most), (2) different manifestations of this level of impoliteness (rude, arrogant, impolite), (3) the degree of prevalence of this impoliteness (a few, majority, across in any). This degree of *Criticality* expressed by the patient is directly related to how intense the negative healthcare event was in the eyes of the patient and how it is explained by the memories about the negative consequences that this experience left to the patient (level of stress, dissatisfaction, discomfort, deterioration of health that followed this event).

That is, for example, a comment describing the fact of "*rude staff*" has a lower degree of problem Criticality in comparison to the problem associated with the presence of the "*Rudest staff of across in any hospital*" that the patient visited. In the second comment, the word "*rudest*" underlines the high degree of impoliteness and the words "*across in any hospital*" express the degree of superiority of the rudeness of the hospital staff compared to all the others. These intensifiers emphasize the high degree of criticality of this problem according to the patient experience. At the same time, the *Importance* indicator is not able to reveal these differences in the levels of *Criticality* of the described problems.

The results of the comparison of the rating of *Important* and *Critical* negative healthcare event obtained by applying the ARC$^+$ and ARC$^+$ enriched frameworks are presented in Table 6. These results allow us to demonstrate the effect of considering the *Intensity* of perception and the expression of negative patient experience on the formation of the rating of the Most Important and Most Critical healthcare tasks for improvement. Especially these differences are important in cases where the number of identical Activity-Context templates in the comments is the same.

2. *Increasing the level of structure of the ARC$^+$ framework by the Reasons and Contextual Dimensions*. The proposed approach makes it possible not only to identify the most urgent health problems but also to reveal the main structural components of this negative healthcare event – persons causing negative patients' opinions and a group of factors that most significantly affect the intensity of patient perception of the described problem.

From the example given in Table 7, the following types of knowledge can be extracted: (1) generalized *rating* of the main negative healthcare event; (2) the most critical *factors* indicated in the comments (Reasons Criticality); (3) the structure of the most critical *factors* within *each negative healthcare event* (Activity Criticality); (4) rating of factors without taking into account Additional Amplifiers (in order to identify only specific facts not reinforced by amplifiers); (5) identifying the factors causing the most significant negative emotions, etc. Similar types of analysis can be performed using other combinations of contextual dimensions – for example, Roles & Factors, Roles & Activities, Activities & Patient Problem, Activities& Hospital Department, etc. Providing an opportunity for multi-level structural analysis of patient opinion contributes to better justification and making the decisions to improve healthcare services.

3. *Providing an opportunity to reveal the presence of causal relationships between the conditions in which the patient was in, the context of the described negative healthcare event and the degree of criticality of this issue*. This approach is based on the realistic evaluation theory of a *Context-Mechanism-Outcome* (CMO) configuration approach [119], [120], which allows answering the following questions: Under what *Context* the decision was

TABLE 6. The results of ARC+ and ARC+ enriched frameworks comparison.

ARC+ framework				ARC+ enrich framework			
Activity-Context Patterns		Rank	Importance Degree	Activity-Context Patterns		Rank	Criticality Index
Activity	Context			Activity	Context		
Patient Care	Lack of Care	1	11	*Patient Care*	Lack of Care	1	5.58
Communication/Information Exchange with Patient	Communication exchange gap	2	8	*Patient Care*	Staff rudeness	2	4.63
Communication with Patient	Impoliteness of communication	3	7	*Communication/Information Exchange with Patient*	Communication exchange gap	3	3.89
Patient Treatment	Low quality of treatment	4	6	*Communication with Patient*	Impoliteness of communication	4	3.37
Relatives-related Care (Communication/Information Exchange)	Lack of information	5	5	*Patient Treatment*	Low quality of treatment	5	3.21
Patient Care	Staff rudeness	6	4	*Patient Care*	Long waiting time	6	1.53
Service management	Delays in service	7	3	*Patient Care*	Lack of professionalism	7	1.47
Service management	Low quality of service	7	3	*Service management*	Delays in service	8	1.37
Service management	Dirty in the rooms	7	3	*Relatives-related Care (Communication/Information Exchange)*	Lack of information	9	1.26
Service management	Dirty in the rooms	7	3	*Service management*	Low quality of service	10	1.21
Communication/Information Exchange with Patient	Lack of medication information	11	2	*Patient Treatment*	Discharge Note	11	1.05
Communication with Patient	Doctors insufficient procedures and practices	11	2	*Service management*	Dirty in the rooms	12	1.00
Patient Care	Lack of professionalism	11	2	*Service management*	Dirty in the rooms	12	1.00
Patient Treatment	Discharge Note	11	2	*Communication/Information Exchange with Patient*	Lack of medication information	14	0.95
Patient Treatment	Lack of professionalism	11	2	*Communication/Information Exchange with Patient*	Lack of professionalism	15	0.79
Service management	Admission/Appointment Cancelled	11	2	*Service management*	Lack of personal	15	0.79
Service management	Old equipment	11	2	*Service management*	Admission/Appointment Cancelled	17	0.74
Communication/Information Exchange with Patient	Limited English	18	1	*Patient Treatment*	Lack of professionalism	18	0.68
Communication/Information Exchange with Patient	Lack of professionalism	18	1	*Service management*	NIGHT time	19	0.63
Communication with Patient	Staff unhelpful	18	1	*Service management*	Old equipment	20	0.58
Communication/Information Exchange between Health Professionals	Lack of medication information	18	1	*Communication/Information Exchange between Health Professionals*	Lack of medication information	21	0.53
Communication/Information Exchange between Health Professionals	Lack of professionalism	18	1	*Service management*	Low quality of care in public hospitals	21	0.53
Patient Care	Long waiting time	18	1	*Patient Care*	Elderly patient	23	0.42
Patient Care	Elderly patient	18	1	*Communication with Patient*	Doctors insufficient procedures and practices	24	0.37
Patient Treatment	Delay in admission	18	1	*Patient Treatment*	Delay in admission	25	0.37
Patient Treatment	MRI Delay	18	1	*Patient Treatment*	MRI Delay	25	0.37
Service management	Lack of personal	18	1	*Communication/Information Exchange between Health Professionals*	Lack of professionalism	27	0.32
Service management	NIGHT time	18	1	*Communication with Patient*	Staff unhelpful	28	0.21
Service management	Low quality of care in public hospitals	18	1	*Communication/Information Exchange with Patient*	Limited English	29	0.11

implemented? Using what *Mechanism* this decision was implemented? and How specific circumstances influenced the *Outcomes* of the implementation of this decision?

In our concept, the *Context-Mechanism-Outcome* elements were adapted in the following edition:

Context (C) is the set of *Personal Situation* and *Circumstances*, which influence both (1) the decision making and the implementation of mechanisms to eliminate the Patient Health Problem and (2) the patient perception of the negative actual and potential consequences of this decision making recognized as a negative healthcare event. Within the framework of the proposed concept, *Personal Situation* will be presented by Prior facts, Age and Time of day (*Individual Patient Situation*) and Hospital Department/Place, Patient Health Problem, healthcare Facilities/ Medication and Actors (*Healthcare Situation*).

TABLE 7. The example of structural analysis of negative healthcare event criticality.

Activities	Additional Amplifiers	Professional Reasons	Inter-Personal Reasons	Service quality Reasons		Technical Reasons	Activity Criticality	Activity Criticality (without Additional Amplifiers)
				Reliability	Timeliness			
Patient Care	12.1	2.6	0.3	2.7	3.5	0	**21.2**	**9.1**
Service management	9.0	0	0	1.5	1.4	1.1	**13.0**	**4.0**
Communication/Information Exchange with Patient	4.7	4.4	1.6	0	0.2	0	**10.9**	**6.2**
Patient Treatment	4.7	1.6	0	4.5	0	0	**10.8**	**6.1**
Communication with Patient	5.2	0.9	0.9	0.5	0	0	**7.5**	**2.3**
Relatives-related Care (Communication/Information Exchange)	2.4	0	0	0	0	0	**2.4**	**0**
Communication/Information Exchange between Health Professionals	1.6	0	0	0	0	0	**1.6**	**0**
Reasons Criticality	**39.7**	**9.5**	**2.8**	**9.2**	**5.1**	**1.1**		

TABLE 8. Example of comments with activity coding results.

#	Comment	Activity
2	"Disgraceful place. I was sent home with a toe fracture given advice that I would be back to normal in two weeks. I had no x-ray scan, no physiotherapy. Also, nobody gave me any further advice in case something went wrong, and I had no review"	Discharge Note, Patient Care, Communication/Informatio n Exchange with Patient
5	"Dirty and chaotic. Twenty hours on a trolley with 3 fractures, a head injury and pneumonia. Patient 76 years old. Equipment was mostly old and not clean. Patronizing doctors. No explanations and limited English. Would never go near this place again"	Patient Care, Communication/Informatio n Exchange with Patient, Service management
17	"Son waiting since 11 am to be put on a drip. Didn't get it for nearly 24 hours. Felt we were forgotten about. Every other parent on the ward was given a mattress."	Patient Care

TABLE 9. Example of generalized context-mechanism-outcome configuration for ARC^{+} enrich conceptual framework.

#	Context		Mechanis ms Activity	Outcomes	
	Personal Situation	Circumstanc es		Critical ity Degree	Critical ity Index
5	Old patient in Emergency	Long waiting time	Patient Care	High	1.53
17	Patient in the ward on a drip	Very long waiting time	Patient Care	High	1.20
2	Patient with toe fracture sent at home	Low quality of care	Patient Care	Averag e	0.60
5	Old patient in Emergency	No explanation	Communica tion/Inform ation Exchange with Patient	High	1.30
2	Patient with toe fracture sent at home	Lack of medication information (review, advice)	Communica tion/Inform ation Exchange with Patient	High	1.29
5	Old patient in Emergency	Limited/poo r resources in the hospital	Service managemen t	High	1.99
2	Patient with toe fracture sent at home	No necessary treatment	Patient Treatment	High	1.80

Mechanisms (M) are the results of decision making to eliminate the Patient Health Problem perceived by the patient as a negative healthcare event and presented in the form of *Activity* templates.

Outcomes (O) are the Consequences resulting from the activation of different Mechanisms in different Contexts and presented in the form of the Degree of Criticality.

For example, we have 3 comments coded by *Patient Care, Communication/Information Exchange with Patient, Service management* and *Patient Treatment* Activities (Table 8).

After analysing these comments using realistic evaluation (Table 9), we could receive the following general knowledge about *Context-Mechanism-Outcome* dependencies: (1) the healthcare Negative Event of *Patient care* associated with the long waiting time for the implementation of the Patient Health Problem solving *Mechanisms* (a) cause a higher degree of *Outcome* Criticality perception than the general negative experience of a low quality of care and (b) the criticality of this perception is increasing in *Context* of Old patient; (2) the Criticality degree of perception of the current and potential consequences (*Outcomes*) of the lack of medical information (*Communication/Information Exchange with Patient* Mechanisms) is almost independent of the patient's age Context; (3) the highest value of *Outcomes* Criticality Index regardless of the Circumstances are the *Limited/poor resources in the hospital* and *Lack of treatment* negative healthcare event Mechanisms. Criticality Degree indicators, used in Table 9 could be assigned by experts based on Criticality Index Values evaluated in accordance with the qualitative

TABLE 10. Review Customer Experience Study Results.

Paper	Approaches	Entities extracted	Feedback / Entities evaluation and ranking	Area of application
		ATOMIC PRODUCT FEATURES		
[23]	SVM Naive Bayes with Laplace smoothing	Sentiment reviews orientations Product features	-	Online product reviews
[122]	Support-based Red Opal's probability-based	Product features	-	Online product reviews
[42]	Statistical analysis Content analysis Text mining (Leximancer) Sentiment analysis (SentiStrength) Social network analysis	Post categories (topics) Sentiment posts orientations	-	Social media comments
[11]	Part-of-speech tagging Association rule mining	Product features Number of positive or negative opinions	Rank the features according to their frequencies that they appear in the reviews	Product reviews
[39]	Rule miner Extraction of polarized descriptors	Product attributes Polarity of opinions Number of positive and negative opinion sentences for a particular feature	Feature-based comparison of two products	Product reviews
[59]	The unsupervised information-extraction system based on Relaxation labelling technique	Product features (properties, parts, features of product parts, related concepts, parts, and properties of related concepts) Polarity of opinions	Rank opinions based on their polarity strength	On-line reviews in order to make an informed product choice
[60]	NLP and dynamic programming techniques Sentence classification techniques Graph of the product's relative quality PageRank ranking algorithm	Subjective/comparative sentences Product features Sentiment sentences orientations	Ranking list of products based on customer's subjective and comparative importance of one or more product features	Online customer reviews
[61]	Naive Bayes classification (to determine the polarity of the reviews) Topic modeling (Latent Dirichlet Allocation, Pachinko Allocation and Hierarchical LDA) - Feature Extraction	Sentiment reviews orientations Product features	The score for a specific product by including Star Rating, Number of Positive Reviews, Number of Negative Reviews, Helpfulness score of reviews, Age of Review	Online customer reviews
[62]	Econometric techniques Hedonic regressions	Product features The weight that customers place on individual product features and the polarity and strength of the underlying evaluations	Implicit evaluation scores for each adjective, in an objective and context-aware manner	Online product reviews
[40]	SAS Text Miner SAS Sentiment Analysis studio	Sentiment reviews orientations Topics	Ranking opinions by positivity and negativity scores	Customers of a retail & energy company reviews
[12]	Descriptive analysis LDA Boot-strapping algorithms to NRC Emotion lexicon Latent Rating Regression	Aspect-based sentiment reviews orientations Aspect ratings and their relative weights	Ranking opinions by aspect- sentiment weights	Airbnb customers experience
[13]	LDA Sentiment Analysis SentiWord Net	Aspect-based sentiment reviews orientations	Ranking opinions by aspect- sentiment weights	User reviews on the TripAdvisor website
[63], [64]	Frequency analysis Content analysis	Topics Frequency of Topics	Satisfaction and Dissatisfaction topics ranking by frequency	Online product reviews
[73], [67]	Syntactic features developed for opinion recognition Learning algorithm Feature organization Cross-validation experiments using support vector regression	Opinion's subjectivity Expressions intensity	Ranking opinions by intensity level	Online product reviews
[43]	Text segmentation Topic identification Maximal Marginal Relevance method	Topics Clustered opinions summary	-	Online product reviews
[123]	Factorized LDA	The hierarchical structure of categories and subcategories	Predicting the overall rating of the product	Online review for cold start items
[44]	Extensions of LDA and pLDA	Multi-grain topics	-	Online product reviews

intensity levels {*Low, Medium, High*}. More detailed Context-mechanism-outcome dependency patterns can be obtained by analysing a full range of aspects of the COM concept (Appendix VIII).

VII. DISCUSSION

The study was aimed at finding answers to two research questions. The first was developing a construct and the associated measurement instrument which will allow identifying

TABLE 10. ***(Continued)*** **Review Customer Experience Study Results.**

Paper	Approaches	Entities extracted	Feedback / Entities evaluation and ranking	Area of application
[124]	LSA Text regression	Factors of customers' positive/negative evaluations The influence of travel purposes, hotel's star level, editor recommendation and hotel type on customer satisfaction and dissatisfaction	Ranking the most significant factors of customer satisfaction/dissatisfaction	Hotel products and services online reviews
[68]	Text mining Multivariate linear regression analysis	Subjectivity Diversity Readability Length Customer satisfaction and dissatisfaction	Ranking by customer satisfaction as a multivariate linear regression of entities	Hotel products and services online reviews
[66]	Combining statistical and rule-based classifiers	Customer satisfaction and dissatisfaction	-	Online product reviews
[45]	Scrapy Text preprocessing Statistical Analysis	Set of words, represented Expensive/Inexpensive, High/Low Quality, High/Low CP Hotels	-	Customer reviews are collected from Yelp.com and
[46]	Pre-processing Conversation Retrieval Product feature extraction	Product features	-	Public Conversations on Twitter
[30]	Stanford NLP Parser The associative rule mining technique	Product attributes Polarity of opinions Number of positive and negative opinion sentences for a feature	Feature-based comparison of two products	Product reviews
[36]	Co-occurrence association-based method	Product features Features that relate to online transactions, such as sellers, services and logistics Associations between feature words and opinion words Associations between feature words and the rest of the notional words in the clause	-	Online customer reviews
[37]	Multinomial Naive Bayes, Random Forest, and Support Vector Machine (SVM)			Movie reviews
[38]	Sentiment Analysis	Elements of customer service that provide positive experiences Service processed and features that require further improvements	-	Twitter posts of customer about service in the airline industry
[5]	Contrast Targeted Positive and Negative Rules Mining Sentiment Analysis	Change in customer expectations when different trip modes: couple, business, solo, friends, and family Hotel's factors	Rank trip modes based on strength of customers' expectations of hotel factors	Reviews from TripAdvisor
SUGGESTIONS EXTRACTION				
[48], [52]	Feature-based opinion mining system with rule-based suggestions detector	Sentiment Mapping product components Suggestions for products improving	-	Customer reviews
[51]	Rule-based methods to identify customers 'wishes' of products improving	Customers wishes of products improving	-	Product reviews, customer surveys, and comments from consumer forums in Domains such as electronics and retail banking.
[49], [125]	Rule-based statistical classifier to detect wishes and suggestions.	Subjunctive mood Wishes and suggestions of products improving	-	Products Reviews Political Discussions
[6], [53]	Rule-based: Pattern matching, POS tagged and POS-tagged extended (based on phrases commonly used in expressing suggestion) Classification algorithms: decision tree, SVM, GLM, Ctree (manual labeling, training and testing)	Sentiment Suggestion of course improving	-	Educational courses improvement
FEATURES PATTERNS EXTRACTION				
[54]	Naive Bayes classification Expectation-Maximization technique	Attribute-value pairs: soft semantic and explicit physical attributes of products	-	Online product reviews Application: Demand forecasting, assortment optimization, product recommendations, and assortment comparison across retailers and manufacturers
[55]	Named Entity Recognition Semi-supervised approach Sentiment Analysis	Word-category pairs Word-category pairs sentiment	Ranking opinions by category- sentiment scores	Online product reviews

how critical a Negative Event in healthcare services is, based on the patients' perception. Previous studies presented methods for analysing the importance of free-text patients comments about Negative Events in healthcare based on the frequency of the identified and coded topics [33], [34], [82], [93], [94], [96], the categories of negative healthcare event

TABLE 10. ***(Continued)*** **Review Customer Experience Study Results.**

Paper	Approaches	Entities extracted	Feedback / Entities evaluation and ranking	Area of application
[56]	Supporting Vector Machine The supervised machine learning algorithm Linear regression model	Brand-level feature (brand name) Semantic-level feature are the subjective and objective words (positive or negative) describing products The product-level feature is the number of product specification attributes	Ranking products by a ranking score based on weights to product review factors	Online product reviews
[57]	User-generated contents-oriented language technology for experience mining	Experience database: Topic object, Experiencer, Event expression, Event type, Factuality, Source pointer Event typology: Sentiment (Emotion, Evaluation, Reputation); Happening (General, Availability, Usability) and Action (Buying/Selecting, Using, Stopping) Markup scheme: Event-time, Modality, Modality-time	-	Online personal experiences
[126]	The linguistics-based text mining model	Three key components of the value (co)creation process: Activities, Resources, and Context (ARC)	-	Customers textual feedback
[58]	Linear- chain Conditional Random Fields (CRF) Markov order-0 CRFs	Pairs: Expressions of opinions and Sources of opinions	-	Free-text comments

([74], [35], [75]) or of the type of Activity and its Context [1], in the whole sample of analysed patients' or clients' comments.

However, these previous works fail to exploit the linguistic features in the text providing valuable information on how critical negative customer or patient experiences are. For example, the following comments "*We were left waiting for 5 hours" OR "We were left waiting for 5 hours with no information" OR "We were left waiting for 5 hours with no information and nobody to talk to us*" describe the same problems (Long waiting and Lack of Communication /Information Exchange) but express different degrees of criticality of this negative healthcare event for the patient caused by the perceived negative actual (expectation and lack of information, excitement, fatigue) and potential (worsening health, stress) consequences for him/her. In the first comment, the patient emphasizes only the length of waiting for care and the lack of any medical information. In the second, the expression of his/her negative perception of the situation is reinforced by the fact that in the absence of any information no one wanted to talk to him/her (and perhaps these attempts were made by the patient). In the third – the increase in the negativity of patient experience occurs due to the increase in the waiting duration, which aggravates the patient perception of the negative healthcare event including the increasing influence on the patient of the consequences of this situation. Therefore, only the summation of three comments describing the same negative healthcare event does not provide a complete picture of the current situation criticality and is not able to measure the degree of need for healthcare management to urgently solve this problem which has a negative effect on the patient's health and general opinion about the quality of hospital services.

Thus, an additional component to identify the importance of a problem is the degree of the patient perception of the seriousness of the actual and potential negative healthcare event consequences which increase the intensity of the negative experience. Together with the frequency of reporting on such negative healthcare event, this component, named in presented Conceptual Framework as Magnitude of Consequences, allows to more precisely scale and rank the values of the problem importance indicator.

Regarding the second research question, the presented study was focused on building the concept of extracting and structuring the knowledge about (1) Degree and (2) Nature of negative healthcare event Criticality from free-text patient's comments. As a tool for extracting knowledge of the (1) *Degree of Criticality*, the Intensity markers have been proposed that allow, depending on the context and their semantic meaning, to measure the intensity of the patient negative experience. To determine the numerical value describing the degree of intensity of each of the markers, consultations with expert doctors were used. Most of the previous studies [97], [99], [100], [105] partially used the concept of intensifiers but only in the context of the definition of sentiment polarity of the comments. Most of the previous studies partially used the concept of intensifiers but in the context of the definition of commentary sentiment. The main difference in the use of these approaches is that the sentiment analysis uses as markers only words that describe the general comments tonality, but does not consider triggers words that carry information about the level of criticality for the patient of the situation described (for example, age of patient, time of day, frequency of reported problem, actors of this situation, and other important negative details). For example, [100] also realized the analysis of the degree of staff respect for patients with additional information about the frequency of situation ("all of the time", "most of the time", "some of the time", "rarely", and "not at all"). However, the source of such information was not the trigger words in the free

TABLE 11. Review Of Healthcare Patient Experience Study Results.

Paper	Data collection technique	Aim of study	Method of study	Results
		Statistical analysis		
[85]	Relevant researches form databases comprised Medline, Embase, the Cochrane Library and Controlled Trials Register, Google Scholar and Web of Science published between January 2000 and April 2013	To study the explicitly focused on issues relating to measuring patient or carers experience researches	Quantitative, qualitative and comparative analysis	Key **pros** and **cons** of measuring patient experience using Descriptive feedback (interviews and focus groups, patient stories, complaints or compliments, photovoice) Generalizable feedback (Surveys, Comment cards, Kiosk questions, SMS questions, Online ratings and Public meetings)
[91]	Review of the theoretical and empirical work on patient satisfaction with care	To provide a brief overview of the satisfaction literature	Literature review	**Factors** thought to be related to patient satisfaction include patient sociodemographic characteristics, physical and psychological status, attitudes and expectations concerning medical care, as well as the structure, process, and outcome of care
[86]	Review of the theoretical and empirical work on patient perception of health care systems quality	To find out what patients want, need and experience in health care, not what professionals (however well-motivated) believe they need or get	Literature review	Conceptual **model** of development of patient perception of quality
[118]	A randomly selected 100 patients were interviewed by using pre-structured questionnaires	To measure the patients' satisfaction towards health care services	Statistical analysis	**Distribution** of Responses from the Respondents according to Availability of Service; Regarding Clinical Care; Regarding Cost
[87]	A qualitative study with nine focus groups	To identify elements of the physiotherapist-patient interaction considered by patients when they evaluate the quality of care in outpatient rehabilitation settings	Statistical analysis after using a modified grounded theory approach ([34])	Patients' **experiences** and perceptions were analyzed regarding to interpersonal manners; providing information and education; and technical expertise.
[115]	A self-administered questionnaire with closed and open-ended questions	To compare replies to open-ended and closed questions about patient satisfaction with family doctors	Statistical analysis. Open questions manually categorized as positive, neutral, negative or ambivalent	Results of **discrepancies** between the closed-question response and the open-ended question replies
[93]	Sample of dermatology out-patients	To examine factors associated with patient satisfaction with care among dermatological out-patients.	Multiple logistic regression studying	The independent **effects** on patient's satisfaction of patient characteristics and of specific aspects of provided health care.
[89]	Patients stayed in general surgical or medical units' opinions from the National Hospital of Sri Lanka	To develop and validate an instrument to measure patient perception of quality of nursing care and related hospital services in a tertiary care setting	Item analysis and principal component factor analysis	Comprehensive, reliable and valid, 36-item instrument that may be used to measure patient perception of quality of nursing care
[90]	Questionnaire was developed and distributed to 300 patients and 210 nurses at three general hospitals	To measure the nursing service perceived value by consumer and providers, and to investigate the relationship among nursing service, general satisfaction and hospital revisiting intent, and to examine the tools that measures nursing service's reliability, construct validity and usefulness.	SERVQUAL and SERVPERF tools, Statistical analysis	The nursing service perceived value by providers is higher than that by consumers.
[88]	Self-reported questionnaires from the four healthcare sectors in Jordan	Exploring patients' perception of the quality of nursing care and related hospital services among Jordanian inpatients along with their intent to revisit the same hospital	Descriptive design	The perceived quality of care and related hospital services by patients were ranking by 36 items distributed among eight dimensions: interpersonal relationships between nurses and patients, efficiency in serving patients, comforts provided in the ward, sanitations, personalized information, physical environment in the ward, provision of general instructions by nurses, and competency of nurses in caring for patients.
		Thematic-oriented analysis		
[76]	National Patient Experience Survey 2017 in Ireland (in total, 13,706 people took part).	To describe their experiences of public acute healthcare in Ireland, to identify areas of good	Framework and comparative analysis	Patients' experiences and perceptions were analyzed regarding to demographic aspects. Open ended questions were analyzed and multi-coded using the following 20 codes (categories)

text~~,~~ but specific answers to the question with pre-provided answers.

In order to synthesise knowledge about (2) the *Nature of the negative healthcare event Criticality*, this Conceptual Framework proposed the approach of categorization of intensity markers in accordance with types of negative healthcare event Reasons for the anticipated or received consequence (Professional, Inter-Personal, Service Quality

TABLE 11. ***(Continued)*** **Review Of Healthcare Patient Experience Study Results.**

Paper	Data collection technique	Aim of study	Method of study	Results
		experience, and areas needing improvement		
[31]	2012/2013 National Cancer Patient Experience Survey (NCPES) from the 2 London Integrated Cancer Systems	To shed light on experiences of patients with cancer in London National Health Service (NHS) trusts that may not be fully captured in national survey data, to inform improvement action plans by these trusts	Framework analysis ([94]) of free-text data	Most comments for improvement related to quality of care, with a focus on poor care, poor communication and waiting times in outpatient departments.
[84]	Free-text data from the Welsh Cancer Patient Experience Survey (WCPES)	To examine themes that emerged from patients' comments and thereby obtain insights into their experiences of cancer care in Wales	Thematic content analysis, informed by a multi-stage coding of the free text data ([83])	Individual **areas** with these general comments are: Waiting for appointments; Communication between patients and staff; Communication between staff and/or institutions; Waiting to be seen on the day; Concerns about staffing levels; Out of hours and weekend care; Total respondents giving general comments.
[96]	First Scottish Cancer Patient Experience Survey (SCPES)	To analyse free-text responses to understand patients' experiences of care, identify valued aspects and areas for improvement.	Inductive thematic analysis of seven free text comment boxes covering all stages of the cancer experience	Positive and negative **themes** of patients' experiences. Differences in the proportion of positive to negative comments by demographics
[97]	Observations of the ward environment results, the activities and instances of nurse-patient communication, semi-structured interviews with patients, and a review of nursing documents	To explore patients' perceptions of their experiences with nurse-patient communication in an oncological clinical environment	Ethnographic approach ([119]3)	Main **themes** were identified: Nurses' workload and the environment and Nursepatient partnership and role expectations.
		NPL oriented analysis		
[116], [116], [117]	Clinical NLP research, PubMed and ACL proceedings, relevant referenced publications	Conduct the literature review which has focused on clinical oriented semantic analysis	Literature review	Review of recent advances in clinical Natural Language Processing
[101]	Online comments about hospitals on the NHS Choices website in 2010	To use machine learning to understand patients' unstructured comments about their care	Machine learning and dictionary scoring algorithms for sentiment prediction. Topic modelling	Prediction accuracy using free-text comments
[98], [99]	Feedback from online forums of hospitals	To develop an automated analysis of patient feedback to identify their sentiment and opinions about the healthcare service	Sentiment Analysis, Topic Modelling, and Dependency Parsing	Design Science Research ([100]) based framework for automated analysis of patient experience data.
[108]	Open-ended responses on patients' experience of primary care in a cross-sectional postal survey	To investigate the feasibility of using freely available Web-based text processing tools (text clouds, distinctive word extraction, key words in context) for extracting information about patient experience	Logistic regression analysis, Keyword in Context function ([109])	The five most frequent words in the patients' comments; three most frequent two-word combinations. Assosoation of the words "excellent" and "rude" with patient experience themes.
[110]	Free-text comments	To develop and teste a learning-based text-mining approach to facilitate analysis of patients' experiences of care	Adapted and tested coding framework ([84]), learning-based text mining	Of retrieved comments on experiences of care, over half described positive care experiences. Most negative experiences concerned a lack of post-treatment care and insufficient information concerning self-management strategies or treatment side effects.
[103], [102]	On-line forums, blogs and news comments; medical social media	Developing a novel approach to polarity classification of short text snippets, which considers the way data are naturally distributed into several topics in order to obtain better classification models for polarity	Sentiment Analysis, Topic Modelling	Multi-step approach, where in the initial step a standard topic classifier is learned from the data and the topic labels, and in the ensuing step several polarity classifiers, one per topic, are learned from the data and the polarity labels. Empirically show that this approach improves classification accuracy over a real-world dataset by over 10%, when compared against a standard single-step approach using the same feature sets
[112]	Cancer blog content	Exploring the efficacy of user-defined and software-generated subject tagging	Software–generated subject terms tagging	More effective subject access to blog messages via Text Analysis Portal for Research automatically generated subject used in combination with user-defined tags
[104]	Chinese reviews from various Web pages, Blog postings, and online forums	Investigate two complementary	Chinese Sentiment Word and Machine Learning Approaches	Results of comparizon of two methods ofsentiment analysis

and Technical). Various forms and methods of categorizing information extracted from tree-text patient responses were also used in previous studies. However, the main object of categorization was the themes (negative healthcare event) described by patients [31], [35], [74], [75], [84], [86]) and the categorization process that was carried out after coding

TABLE 11. ***(Continued)*** **Review Of Healthcare Patient Experience Study Results.**

Paper	Data collection technique	Aim of study	Method of study	Results
		approaches to Chinese opinion mining		
[105]	English-language Internet conversations (ICs) regarding prostate cancer treatment with active surveillance (AS) from 2002–2012	To determine if analysis of a large sample of anonymous ICs could be utilized to identify unmet public needs regarding AS	NLP for sentiment analysis	Potential utility of online patient communications to provide insight into patient preferences and decision-making
[106]	Patients' opinions in social madia	To develop the medical domain oriented lexicon	Medical opinion lexicon creating	Medical opinion lexicon and evaluation results
[107]	Drug review dataset	To apply neural network based methods for opinion mining from social web in health care domain	Support vector machine, Probabilistic neural network, Radial basis function neural networks	Improving the indirect opinions classification.
[113]	Experiences of Chronic Obstructive Pulmonary Disease (COPD) patients	Developing the Qualitative text processing framework	Text-minng approaches	The QuTiP framework describes a general approach to qualitatively analysing large volumes of data by utilising automated methods and the outcomes of smaller-scale analyses

TABLE 12. **Full Results Of Semantic Patterns-Level Coding Stage.**

#	Text of Comment	Units of information	ARC+			ARC+ enriched Context			
			Activity	Resource	Context	Healthcare Roles	Hospital Department/ Place	Patient Problem	Healthcare Facilities/ Medication
1	Awful hospital I felt that there were a few doctors and nurses who care Once you DEMAND they speak with you, but the majority did not. Rudest staff I have come across in any hospital. Disgraceful place. To those who do care use your voice to be honest about your colleagues and have a real conversation about improving hospitals for everyone involved	Awful hospital I felt that there were a few doctors and nurses who care	Patient Care	Doctors Nurses	Lack of Care	Doctors Nurses			
		Once you DEMAND they speak with you, but the majority did not	Communication with Patient	Doctors Nurses	Impoliteness of communication	Doctors Nurses			
		Rudest staff I have come across in any hospital.	Communication with Patient	Staff	Impoliteness of communication	Staff			
		Disgraceful place.	Patient Care	Staff	Lack of Care	Staff			
2	I was sent home with a toe fracture given advice that I would be back to normal in two weeks. I had no x-ray scan, no physiotherapy. Also, nobody gave my any further advice in case something went wrong, and I had no review	I was sent home with a toe fracture given advice that I would be back to normal in two weeks.	Patient Treatment	Staff	Discharge Note	Staff		Toe fracture	
		I had no x-ray scan, no physiotherapy.	Patient Treatment	Staff	Discharge Note	Staff			x-ray scan physiotherapy
		Also, nobody gave my any further advice in case something went wrong, and I had no review	Communication/Information Exchange with Patient	Staff	Lack of medication information	Staff			
3	AE was filthy as were the toilets. We were left waiting for 5 hours with no information and nobody to talk to not even administration staff. Reception was empty for more than an hour. We were not the only ones to leave on the night	AE was filthy as were the toilets.	Service management	Emergency area	Dirty in the rooms	Staff	Emergency		
		We were left waiting for 5 hours with no information and nobody to talk to not even administration staff.	Communication/Information Exchange with Patient	Administrative staff	Long waiting time Patient(s) left in corridor(s)	Administrative staff	Emergency		
		Reception was empty for more than an hour.	Service management	Doctors	Patient left alone	Doctors	Reception		
		We were not the only ones to leave on the night	Service management	Staff	NIGHT time	Staff	Emergency		
4	Appalling. No explanation given. Numerous attempts to talk to doctors hindered by nurses. Incredibly unprofessional. Poor care not thorough and very uncaring	Appalling	Communication Information Exchange with Patient	Doctors Nurses	Lack of Care	Doctors Nurses			
		No explanation given	Communication Information Exchange with Patient		Lack of explanation Communication gap	Doctors Nurses			
		Numerous attempts to talk to doctors hindered by nurses.	Communication Information Exchange with Patient		Impoliteness of communication	Doctors Nurses			
		Incredibly unprofessional	Patient Care		Lack of professionalism	Doctors Nurses			
		Poor care not thorough and very uncaring	Patient Care		Low care	Doctors Nurses			

and extracting all possible knowledge (in accordance with the principles of grouping accepted by the authors). In the Conceptual Framework, it is proposed to use the results of such studies as one of the options of expert knowledge for matching and evaluation of the results of negative healthcare event coding.

TABLE 12. ***(Continued)*** **Full Results Of Semantic Patterns-Level Coding Stage.**

#	Text of Comment	Units of information	ARC⁺			ARC⁺ enriched Context			
			Activity	Resource	Context	Healthcare Roles	Hospital Department/ Place	Patient Problem	Healthcare Facilities/ Medication
5	Dirty and chaotic. Twenty hours on a trolley with 3 fractures, a head injury and pneumonia. Patient 76 years old. Equipment mostly old and not clean. Patronizing doctors. No explanations and limited English. Would never go near this place again	Dirty and chaotic.	Cleanliness of the premises	Staff Ward area	Dirty in the rooms	Staff	Emergency		
		Twenty hours on a trolley with 3 fractures, a head injury and pneumonia.	Patient Care	Staff	Long waiting time Patient left on trolley Limited/poor resource in hospital	Staff	Emergency	Head injury Pneumonia	Trolley
		Patient 76 years old.	Patient Care	Staff	Elderly patient	Staff	Emergency		
		Equipment mostly old and not clean.	Service management	Staff	Old equipment	Staff	Emergency		Equipment
		No explanations and limited English	Communication Information Exchange with Patient	Doctors	Limited English Communication gap	Doctors	Emergency		
		Would never go near this place again	Service management	Staff	Low care	Staff	Emergency		
6	Went in as had a miscarriage and was treated appallingly. No after care, no follow up and numerous mistakes made.	Went in as had a miscarriage and was treated appallingly.	Patient Treatment	Staff	Miscarriage	Staff			
		No after care, no follow up and numerous mistakes made.	Patient Treatment	Staff	No after care No follow up Staff mistakes	Staff			
7	We travelled almost 60 miles every day to see my father in this hospital. We did this for three weeks. One day we traveled to Waterford but just as we were about to enter the hospital my father phoned us on another patient's phone to say he was in our local hospital in Wexford. The hospital had never phoned us to say he was moved	We travelled almost 60 miles every day to see my father in this hospital.	Relatives-related Care (Communication/Information Exchange)	Staff	Lack of information about changing the hospital location	Staff			
		We did this for three weeks.	Relatives-related Care (Communication/Information Exchange)	Staff	Lack of information about changing the hospital location	Staff			
		One day we traveled to Waterford but just as we were about to enter the hospital my father phoned us on another patient's phone to say he was in our local hospital in Wexford. The hospital had never phoned us to say he was moved	Relatives-related Care (Communication/Information Exchange)	Staff	Lack of information about changing the hospital location	Staff			
8	The nurses here are just brilliant in maternity pediatrics and AE and without wee them the hospital would fall apart. The consultants on the other hand apart from a select few I have found brutal. They either seem completely clueless or just couldn't care less.	The consultants on the other hand apart from a select few I have found brutal.	Patient Care	Consultants	Consultants clueless and brutality	Consultants	Maternity pediatrics Emergency		
		They either seem completely clueless or just couldn't care less.	Patient Care	Consultants	Consultants insufficient procedures and practices	Doctors Nurses			
9	Check-in delay. MRI delay. Sedation didn't work. Consultant on leave. Nurse unhelpful. Doctor pleasant. No given appointment for MRI. Told back on the waiting list after over seven hours in the hospital.	Check-in delay.	Patient Treatment	Administrative staff	Delay in admission	Administrative staff	Admission		
		MRI delay.	Patient Treatment	Administrative staff	MRI Delay	Administrative staff	Admission		MRI
		Sedation didn't work.	Patient Treatment	Doctors	Low care	Doctors	Admission		Sedation
		Consultant on leave.	Patient Treatment	Consultants	Low care	Consultants	Admission		
		Nurse unhelpful.	Communication with Patient	Nurses	Nurse unhelpful	Nurses	Admission		
		No given appointment for MRI.	Service management	Administrative staff	No MRI appointment	Administrative staff	Admission		MRI
		Told back on the waiting list after over seven hours in the hospital.	Service management	Administrative staff	Back on waiting list with no procedures	Administrative staff	Admission	Back on waiting list with no procedures	
10	The doctor i saw in AE was rude and arrogant while treating my wife. We were sent home back in the next day as the bloods now showed a problem. The lack of professionalism caused great stress for us during our initial visit. And we were never given an apology.	The doctor i saw in AE was rude and arrogant while treating my wife.	Communication with Patient	Doctors	Doctors insufficient procedures and practices	Doctors	Emergency		
		We were sent home back in the next day as the bloods now showed a problem.	Communication/Information Exchange with Patient	Doctors	Patient initial visit	Doctors	Emergency	Bloods	
		The lack of professionalism caused great stress for us during our initial visit.	Communication/Information Exchange with Patient	Doctors	Stressed patient	Doctors	Emergency		

To structure knowledge about the degree of negative healthcare event criticality, the authors propose (1) to categorize the Intensity markers according to four Reasons and (2) form a separate group of additional amplifiers for the degree of negative healthcare event criticality, consisting of trigger words describing the frequency of the healthcare

TABLE 12. ***(Continued)*** **Full Results Of Semantic Patterns-Level Coding Stage.**

#	Text of Comment	Units of information	ARC⁺			ARC⁺ enriched Context			
			Activity	Resource	Context	Healthcare Roles	Hospital Department/ Place	Patient Problem	Healthcare Facilities/ Medication
		And we were never given an apology.	Communication with Patient	Doctors	Impoliteness of communication	Doctors	Emergency		
11	The patient developed an allergy after a few days, and we found it quite difficult to get readmitted for observation. There was only one doctor on duty at the weekend on the relevant floor. Surely more staff should have been on duty.	The patient developed an allergy after a few days and we found it quite difficult to get readmitted for observation.	Service management	Doctors	Observation Difficult to get admission	Doctors	Admission	Allergy	
		There was only one doctor on duty at the weekend on the relevant floor.	Service management	Administrative staff	Weekend Only one doctor on duty	Administrative staff			
12	Sad but true. In my experience, if you have excellent insurance you will get appointments and care. If not, they will refer you to appointments that will never happen.	Sad but true.	Service management	Administrative staff	Appointments Outpatient	Administrative staff			
		In my experience, if you have excellent insurance you will get appointments and care.	Service management	Administrative staff	Problems of lack of insurance	Administrative staff		Insurance	
		If not, they will refer you to appointments that will never happen.	Service management	Administrative staff	Appointment and violation	Administrative staff			
13	My consultant and his team of doctors were absolutely amazing. So kind and considerate very approachable. Nurses in OPD were lovely and caring. My only fault was with the care assistants I came across who were rude and lazy	My only fault was with the care assistants I came across who were rude and lazy	Patient care	Doctors Consultants Nurses	Care assistants rude and lazy	Doctors Consultants Nurses			
14	Poor follow up care after surgery. Couldn't get in touch with relevant staff member. Staff on the ward rude. Poor communication between teams and with family. Overall disappointed	Poor follow up care after surgery.	Patient care	Staff	Poor follow up care after surgery	Staff	Surgery		
		Couldn't get in touch with relevant staff member.	Communication/Information Exchange between Health Professionals	Staff	Lack of professionalism	Staff	Surgery		
		Staff on the ward rude.	Communication with Patient	Staff	Impoliteness of communication	Staff	Ward		
		Poor communication between teams and with family	Relatives-related Care (Communication/Information Exchange)	Staff	Communication gap between teams and with family	Staff	Surgery		
		Overall disappointed	All (Care, treatment)	Staff	No patient care	Staff	Surgery		
15	Consultant was a nice man but overworked and never sent test results to my GP. Asked for follow-up appointment but declined so went to another hospital	Consultant was a nice man but overworked and never sent test results to my GP.	Communication/Information Exchange between Health Professionals	Consultants	Consultant overworked Test No information passed on to GP	Consultants			
		Asked for follow-up appointment but declined so went to another hospital	Service management	Staff	Admission/Appointment Cancelled	Staff			
16	Very disappointed with my overall stay experience in Letterkenny University Hospital. There is a serious shortage of medical staff resulting in a lack of personal care.	Very disappointed with my overall stay experience in Letterkenny University Hospital.	Service management	Staff	Patient with bad experience No patient care	Staff			
		There is a serious shortage of medical staff resulting in a lack of personal care.	Patient care	Staff	No patient care	Staff			
17	Son waiting since 11am to be put on a drip. Didn't get it for nearly 24 hours. Felt we were forgotten about. Every other parent on the ward was given a mattress. Nobody bothered coming near me even to give a pillow	Son waiting since 11am to be put on a drip.	Patient care	Nurses Drip/ IV/ Cannula	Long waiting time	Nurses	Ward		Drip
		Didn't get it for nearly 24 hours	Patient care	Nurses	Long waiting time	Nurses	Ward		Drip
		Felt we were forgotten about.	Patient care	Staff	No patient care	Nurses	Ward		
		Every other parent on the ward was given a mattress.	Providing facilities	Staff Mattress Pillow	No patient care	Nurses	Ward		Mattress
		Nobody bothered coming near me even to give a pillow	Providing facilities	Staff	No patient care	Staff	Ward		Pillow

NE, related information, consequences and patient's opinion (sentiment). The authors [90] also use categories of factors that influence patient satisfaction (Patient Characteristics, Structure, and Processes). However, these factors are proposed to be applied to the categorization of the results of pre-structured customer responses. Thus, the approach of our

TABLE 12. ***(Continued)*** **Full Results Of Semantic Patterns-Level Coding Stage.**

#	Text of Comment	Units of information	ARC⁺ Activity	ARC⁺ Resource	ARC⁺ Context	ARC⁺ enriched Context: Healthcare Roles	Hospital Department/ Place	Patient Problem	Healthcare Facilities/ Medication
18	We waited 11 hours in the emergency department and could not manage to get any doctor examination. We checked many times and nurses kept putting drunk people in front of the queue. The worst hospital I've ever seen	We waited 11 hours in the Emergency Department and could not manage to get any doctor examination	Patient care	Staff	Doctor examination Long waiting time Patient got no examination	Doctors	Emergency		Doctor examination
		We checked many times and nurses kept putting drunk people in front of the queue.	Patient care	Nurses	Drunks are put first in the queue	Nurses	Emergency		
		The worst hospital I've ever seen	Patient care	Staff	No patient care	Staff	Emergency		
19	Consultant not interested. Not examined by consultant or CNS despite complications CNS was rude. Communication poor. Practice below what expected. Radiotherapists top class.	Consultant not interested.	Patient Treatment	Consultants	Consultants insufficient procedures and practices	Consultants			
		Not examined by consultant or CNS despite complications CNS was rude.	Patient Treatment	Consultants	Patient got no examination	Consultants			
		Communication poor.	Communication/Information Exchange with Patient	Consultants	Communication gap	Consultants			
		Practice below what expected.	Patient Treatment	Consultants	Consultants insufficient procedures and practices	Consultants			
20	The doctor I saw was one of the rudest doctors I have ever encountered. He didn't even look me in the eye on introduction or shake hands. This is a man receiving a lot of money for a 10-minute consultation he needs to learn manners. Impossible to describe his rudeness	The doctor I saw was one of the rudest doctors I have ever encountered.	Communication with Patient	Doctors	Impoliteness of communication	Doctors			
		He didn't even look me in the eye on introduction or shake hands.	Patient care	Doctors	Doctors insufficient procedures and practices	Doctors			
		This is a man receiving a lot of money for a 10-minute consultation he needs to learn manners.	Patient care	Doctors	Money Doctor's short expensive visit	Doctors			
		Impossible to describe his rudeness	Communication with Patient	Doctors	Impoliteness of communication	Doctors			

TABLE 13. **Full Results Of Semantic Intensity Coding Stage.**

	Units of information	Activity	Intensity Markers: Healthcare Issues REASONS: Professional	Inter-Personal	Service quality: Timeliness	Service quality: Reliability	Technical	Expanded AMPLIFIERS: Frequency	Consequences	Opinion (sentiment)	Related Information: Prior facts	Age	Time of day
1	Awful hospital I felt that there were a few doctors and nurses who care	Patient Care	Few doctors and nurses who care							Awful			
	Once you DEMAND they speak with you, but the majority did not .	Communication with Patient		Majority did not speak				Care once you DEMAND		DEMAND did not			
	Rudest staff I have come across in any hospital.	Communication with Patient				Across in any hospital				Rudest			
	Disgraceful place	Patient Care								Disgraceful			
2	I had no x-ray scan, no physiotherapy	Patient Treatment				No x-ray scan No physiotherapy							
	Also, nobody gave my any further advice in case something went wrong, and I had no review	Communication/Information Exchange with Patient	No review Nobody gave advice										

Conceptual Framework structures the nature of the negative healthcare event providing opportunities to assess the degree of negative healthcare event criticality from the point of view of causes, which are present in the free-text patient comments with different frequency and intensity. In addition, consideration of Contextual dimensions (Hospital

TABLE 13. ***(Continued)*** **Full Results Of Semantic Intensity Coding Stage.**

	Units of information	Activity	Intensity Markers										
			Healthcare Issues REASONS					Expanded AMPLIFIERS					
					Service quality						Related Information		
			Professional	Inter-Personal	Timeliness	Reliability	Technical	Frequency	Consequences	Opinion (sentiment)	Prior facts	Age	Time of day
3	AE was filthy as were the toilets	Service management								filthy			
	We were left waiting for 5 hours with no information and nobody to talk to not even administration staff	Communication/Information Exchange with Patient	No information	Nobody to talk Not even administration staff talk	5 hours waiting								
	Reception was empty for more than an hour	Service management			An hour Reception was empty					empty			
	We were not the only ones to leave on the night	Service management						not the only ones to leave					night
4	Appalling	Communication Information Exchange with Patient								Appalling			
	No explanation given	Communication Information Exchange with Patient	No explanation										
	Numerous attempts to talk to doctors hindered by nurses	Communication Information Exchange with Patient						Numerous attempts to talk		hindered			
	Incredibly unprofessional	Patient Care								Incredibly unprofessional			
	Poor care not thorough and very uncaring	Patient Care								Poor very uncaring			
5	Dirty and chaotic	Cleanliness of the premises								Dirty chaotic			
	Twenty hours on a trolley with 3 fractures, a head injury and pneumonia.	Patient Care			Twenty hours waiting								
	Patient 76 years old.	Patient Care										76 years old	
	Equipment mostly old and not clean	Service management					Equipment mostly old not clean						
	No explanations and limited English	Communication Information Exchange with Patient	No explanations Limited English										
	Would never go near this place again	Service management								Would never go			
6	Went in as had a miscarriage and was treated appallingly	Patient Treatment								appallingly			
	No after care, no follow up and numerous mistakes made.	Patient Care				No after care No follow up		Numerous mistakes					
7	We travelled almost 60 miles every day to see my father in this hospital.	Relatives-related Care (Communication/Information Exchange)									60 miles every day		
	We did this for three weeks.	Relatives-related Care (Communication/Information Exchange									three weeks		

Department / Place, Patient Health Problem, Health Care Facilities / Medication and Actors) provides an opportunity to reveal the presence of causal relationships between the conditions in which the patient was in, the context of the described negative healthcare event and the degree of criticality of this event.

TABLE 13. *(Continued)* **Full Results Of Semantic Intensity Coding Stage.**

	Units of information	Activity	Intensity Markers										
			Healthcare Issues REASONS					Expanded AMPLIFIERS					
					Service quality						Related Information		
			Professional	Inter-Personal	Timeliness	Reliability	Technical	Frequency	Consequences	Opinion (sentiment)	Prior facts	Age	Time of day
	The hospital had never phoned us to say he was moved	Relatives-related Care (Communication/Information Exchange						Never phoned					
8	The consultants on the other hand apart from a select few I have found brutal	Patient Care		apart from a select few I have found						brutal			
	They either seem completely clueless or just couldn't care less	Patient Care	completely clueless			just couldn't care less							
9	Check-in delay	Patient Treatment								Check-in delay			
	MRI delay	Patient Treatment								MRI delay			
	Sedation didn't work	Patient Treatment								Sedation didn't work			
	Consultant on leave	Patient Treatment				Consultant on leave							
	Nurse unhelpful	Communication with Patient								Nurse unhelpful			
	No given appointment for MRI	Service management				No given appointment							
	Told back on the waiting list after over seven hours in the hospital.	Service management			seven hours in the hospital								
10	The doctor I saw in AE was rude and arrogant while treating my wife	Communication with Patient								rude and arrogant			
	We were sent home back in the next day as the bloods now showed a problem	Communication/Information Exchange with Patient			only to be called back in the next day								
	The lack of professionalism caused great stress for us during our initial visit	Communication/Information Exchange with Patient							caused great stress	The lack of professionalism			
	And we were never given an apology	Communication with Patient						Never given an apology					
11	The patient developed an allergy after a few days and we found it quite difficult to get readmitted for observation	Service management				quite difficult to get readmitted					developed an allergy after a few days		
	There was only one doctor on duty at the weekend on the relevant floor	Service management				only one doctor on duty							week end
12	Sad but true	Service management								Sad			
	If not, they will refer you to appointments that will never happen	Service management						appointments never happen					
13	My only fault was with the care assistants I came across who were rude and lazy	Patient care				Only fault was with the care assistants				rude lazy			
14	Poor follow up care after surgery	Patient care								Poor			
	Couldn't get in touch with relevant staff member	Communication/Information Exchange between Health Professionals								Couldn't get in touch			

It should also be noted that the Conceptual Framework presented in the article has several *Limitations* that the authors intend to eliminate in *Future work* described in detail below.

The first and obvious limitation of the proposed concept is the absence of algorithms for its practical implementation using NLP and Machine Learning tools.

TABLE 13. ***(Continued)*** **Full Results Of Semantic Intensity Coding Stage.**

			Intensity Markers										
			Healthcare Issues REASONS					Expanded AMPLIFIERS					
					Service quality						Related Information		
	Units of information	Activity	Professional	Inter-Personal	Timeliness	Reliability	Technical	Frequency	Consequences	Opinion (sentiment)	Prior facts	Age	Time of day
	Staff on the ward rude	Communication with Patient								rude			
	Poor communication between teams and with family	Relatives-related Care (Communication/Information Exchange)								Poor communication			
	Overall disappointed	All (Care, treatment)				Overall				disappointed			
15	Consultant was a nice man but overworked and never sent test results to my GP	Service management Communication/Information Exchange between Health Professionals						Never sent test results		overworked			
	Asked for follow-up appointment but declined so went to another hospital	Service management								declined			
16	Very disappointed with my overall stay experience in Letterkenny University Hospital	Service management				Overall				Very disappointed			
	There is a serious shortage of medical staff resulting in a lack of personal care	Patient care				Serious shortage							
17	Son waiting since 11am to be put on a drip	Patient care			since 11am								
	Didn't get it for nearly 24 hours.	Patient care			nearly 24 hours					Didn't get			
	Felt we were forgotten about.	Patient care								were forgotten			
	Nobody bothered coming near me even to give a pillow	Providing facilities	Nobody bothered coming near me										
18	We waited 11 hours in the emergency department and could not manage to get any doctor examination	Patient care			waited 11 hours	to get any examination				could not manage			
	We checked many times and nurses kept putting drunk people in front of the queue	Patient care						many times					
	The worst hospital I've ever seen	Patient care								worst			
19	Consultant not interested	Patient Treatment	Not interested										
	Not examined by consultant or CNS despite complications CNS was rude	Patient Treatment	Not examined							rude			
	Communication poor	Communication/Information Exchange with Patient								Poor			
	Practice below what expected.	Patient Treatment								below what expected			
20	The doctor I saw was one of the rudest doctors I have ever encountered	Communication with Patient	one of the rudest							rudest			
	He didn't even look me in the eye on introduction or shake hands	Patient care				didn't even look							
	This is a man receiving a lot of money for a 10-minute consultation he needs to learn manners	Patient care			10-minute consultation								
	Impossible to describe his rudeness	Communication with Patient								Impossible to describe his rudeness			

This limitation is planned to be implemented first. The presented level of concept development was justified and planned by the authors since at the first stage of research it was necessary to develop, test and refine the theoretical aspects of the proposed approach. After this stage and organization of the workshop with the participation of patients

TABLE 14. The Results Of Intensity-Level Scaling Stage.

Intensity marker		Intensity level	Low		Medium				High										
		Scale	0.2		0.3	0.4		0.5	0.6	0.7		0.8		0.9	1				
Healthcare issue		Professional	Limited						Few			No	Not	One of	Completely	Nobody			
Healthcare issue		*Context examples*	English, interest, explanation						doctors and nurses who care			review, information, explanation	interested, examined, tested, consulted	rudest, clueless	clueless, rude	coming, help, care, treat, test, examine, gave advice			
Healthcare issue		Inter-Personal			Apart from a select few				Not even					Majority	Nobody				
Healthcare issue		*Context examples*			doctors (nurses, consultants) I have found				administration staff talk					did not speak	to talk				
Healthcare issue	Service quality Reasons	Timeliness	10-minute	in the next day	since 11am	An hour		more than an hour				5 hours			seven hours, 11 hours, twenty hours, nearly 24 hours				
Healthcare issue	Service quality Reasons	*Context examples*	consultation	only to be called back, informed	waiting	Reception was empty		waiting, do not help				waiting			in the hospital, waiting				
Healthcare issue	Service quality Reasons	Reliability	Quite difficult					On leave, Across in any	No given	only one		didn't even			to get any	No	Serious	Only fault	Overall
Healthcare issue	Service quality Reasons	*Context examples*	to get readmitted, consultation	hospital				Consultant	appointment	doctor on duty		look			examination	x-ray scan, physiotherapy, after care, follow up	shortage	was with the care assistants	disappointed
Healthcare issue		Technical						mostly old	not clean										
Healthcare issue		*Context examples*						Equipment	Equipment										
Expanded Amplifiers		Frequency				Once	Not the only ones			Numerous	Many times				Never				
Expanded Amplifiers		*Context examples*				Care once you DEMAND	to leave			attempts to talk	nurses kept putting drunk people				given an apology, happen appointments, sent test results, phoned, help, examine				
Expanded Amplifiers		Consequences										great stress							
Expanded Amplifiers		Opinion (sentiment)			Arrogant, very	unhelpful, rude			rudest, lazy, worst, below what expected most	filthy, overworked, very disappointed, didn't get		empty, poor, overall disappointed, declined, were forgotten, could not manage		brutal, couldn't care less	appalling, Incredibly, uncaring, appallingly, didn't work				
Expanded Amplifiers	Related Information	Prior facts	60 miles, every day, three weeks, after a few days																
Expanded Amplifiers	Related Information	Age										76 years old							
Expanded Amplifiers	Related Information	Time of day										night, weekend							

TABLE 15. The Intermediate Results Of Intensity Index Calculating.

Activity-Context Patterns by Roles						Intensity markers												Intensity index	Normalized Intensity index
Activities	Context by Roles					Additional Amplifiers						Professional Reasons	Inter-Personal Reasons	Service quality Reasons		Technical Reasons			
	Doctors	Nurses	Consultant	Administrative staff	All medical staff	Frequency	Opinion (sentiment)	Prior facts	Age	Time of day	Consequences			Reliability	Timeliness				
Communication with Patient	Impoliteness of communication					Once	DEMAND						Majority					1.5	0.79
Communication with Patient					Impoliteness of communication		Rudest							Across in any				1	0.53
Communication with Patient		Staff unhelpful					unhelpful											0.4	0.21

and doctors for the evolution of the results of applying this approach to a random comments sample, the authors plan to perform the selection and development of algorithms for automated extraction and recognition of knowledge in accordance with the proposed structure.

Since the developed Conceptual Framework is based on the definition of the negative healthcare event concept as "adverse events (incidents), decision and circumstances that are part of patient experience and reported as resulting in or/and having the potential for physical, emotional,

TABLE 15. ***(Continued)*** **The Intermediate Results Of Intensity Index Calculating.**

Activity-Context Patterns by Roles						Intensity markers												
	Context by Roles					Additional Amplifiers								Service quality Reasons				
Activities	Doctors	Nurses	Consultant	Administrative staff	All medical staff	Frequency	Opinion (sentiment)	Prior facts	Age	Time of day	Consequences	Professional Reasons	Inter-Personal Reasons	Reliability	Timeliness	Technical Reasons	Intensity index	Normalized Intensity index
Communication with Patient	Doctors insufficient procedures and practices						rude										0.4	0.21
Communication with Patient	Doctors insufficient procedures and practices						arrogant										0.3	0.16
Communication with Patient	Impoliteness of communication					Never											1	0.53
Communication with Patient					Impoliteness of communication		rude										0.4	0.21
Communication with Patient	Impoliteness of communication						Rudest					One of					1.4	0.74
Communication with Patient	Impoliteness of communication						Impossible to describe										0.7	0.37
Communication with Patient	Impoliteness of communication						rude										0.4	0.21
Communication /Information Exchange between Health Professionals					Lack of professionalism		couldnt get in touch										0.6	0.32
Communication /Information Exchange between Health Professionals			Lack of medication information			Never											1	0.53
Communication /Information Exchange with Patient					Lack of medication information							No					0.8	0.42
Communication /Information Exchange with Patient					Lack of medication information							Nobody					1	0.53
Communication /Information Exchange with Patient				Communication exchange gap								No	Nobody				1.8	0.95
Communication /Information Exchange with Patient	Communication exchange gap											No					0.8	0.42
Communication /Information Exchange with Patient	Communication exchange gap					Numerous	hindered										1.4	0.74
Communication /Information Exchange with Patient					Communication exchange gap							No					0.8	0.42
Communication /Information Exchange with Patient					Limited English							Limited					0.2	0.11
Communication /Information Exchange with Patient					Communication exchange gap		appalling										1	0.53
Communication /Information Exchange with Patient				Communication exchange gap									Not even				0.6	0.32
Communication /Information Exchange with Patient	Communication exchange gap														in the next day		0.2	0.11
Communication /Information Exchange with Patient	Lack of professionalism						Lack				great stress						1.5	0.79
Communication /Information Exchange with Patient			Communication exchange gap				poor										0.8	0.42
Patient Care	Lack of Care	Lack of Care					Awful					Few					0.8	0.42
Patient Care					Lack of Care		Disgraceful										0.6	0.32

TABLE 15. ***(Continued)*** **The Intermediate Results Of Intensity Index Calculating.**

Activity-Context Patterns by Roles						Intensity markers												
	Context by Roles					Additional Amplifiers								Service quality Reasons				
Activities	Doctors	Nurses	Consultant	Administrative staff	All medical staff	Frequency	Opinion (sentiment)	Prior facts	Age	Time of day	Consequences	Professional Reasons	Inter-Personal Reasons	Reliability	Timeliness	Technical Reasons	Intensity index	Normalized Intensity index
Patient Care	Lack of professi onalism	Lack of professi onalism					Incredibly										1	0.53
Patient Care	Lack of Care	Lack of Care					poor										0.8	0.42
Patient Care	Lack of Care	Lack of Care					very uncaring										0.9	0.47
Patient Care					Lack of Care										Twe nty hours		1	0.53
Patient Care					Elderly patient				76 ye ar s ol d								0.8	0.42
Patient Care					Lack of Care		poor										0.8	0.42
Patient Care					Lack of Care		were forgotten										0.8	0.42
Patient Care		Long waiting time				Man y times											0.9	0.47
Patient Care					Lack of Care		worst										0.5	0.26
Patient Care	Lack of professi onalism													didnt even			0.8	0.42
Patient Care	Lack of Care														10- minu te		0.2	0.11
Patient Care			Staff rudenes s				brutal						Apart from a select few				1.2	0.63
Patient Care			Staff rudenes s									Comp letely		coul dn't care less			1.9	1.00
Patient Care	Staff rudenes s	Staff rudenes s	Staff rudenes s				rude							Only fault			1.4	0.74
Patient Care	Staff rudenes s	Staff rudenes s	Staff rudenes s				lazy										0.5	0.26
Patient Care					Lack of Care		serious shortage										0.7	0.37
Patient Care		Long waiting time													since 11am		0.3	0.16
Patient Care		Long waiting time					didn't get								nearl y 24 hours		1.7	0.89
Patient Care					No patient care		overall disappointe d										0.8	0.42
Patient Care					Long waiting time		could not manage								11 hours		1.8	0.95
Patient Care					Lack of Care							Nobo dy					1	0.53
Patient Treatment					Discharge Note									No			1	0.53
Patient Treatment					Discharge Note									No			1	0.53
Patient Treatment					Low quality of treatment		appalling										1	0.53
Patient Treatment					Low quality of treatment									No			1	0.53
Patient Treatment					Low quality of treatment	Num erous								No			1.7	0.89
Patient Treatment				Delay in admission			delay										0.7	0.37
Patient Treatment				MRI Delay			delay										0.7	0.37
Patient Treatment	Low quality of treatme nt						didn't get										0.7	0.37
Patient Treatment			Low quality of treatme nt											On leave			0.5	0.26
Patient Treatment			Lack of professi onalism									Not					0.8	0.42
Patient Treatment			Low quality of treatme nt				rude					Not					1.2	0.63
Patient Treatment			Lack of professi onalism				below what expected										0.5	0.26
Relatives-related Care (Communicatio n/Information Exchange)					Lack of informatio n			60 miles									0.2	0.11
Relatives-related Care (Communicatio n/Information Exchange)					Lack of informatio n			every day									0.2	0.11

TABLE 15. *(Continued)* **The Intermediate Results Of Intensity Index Calculating.**

Activity-Context Patterns by Roles						Intensity markers												
	Context by Roles					Additional Amplifiers								Service quality Reasons				
Activities	Doctors	Nurses	Consultant	Administrative staff	All medical staff	Frequency	Opinion (sentiment)	Prior facts	Age	Time of day	Consequences	Professional Reasons	Inter-Personal Reasons	Reliability	Timeliness	Technical Reasons	Intensity index	Normalized Intensity index
Relatives-related Care (Communication/Information Exchange)					Lack of information			three weeks									0.2	0.11
Relatives-related Care (Communication/Information Exchange)					Lack of information	Never											1	0.53
Relatives-related Care (Communication/Information Exchange)					Lack of information		poor										0.8	0.42
Service management	Delays in service							after a few days						Quite difficult			0.4	0.21
Service management				Lack of personal						weekend				only one			1.5	0.79
Service management				Low quality of service			Sad										0.7	0.37
Service management					Dirty in the rooms		filthy										0.7	0.37
Service management	Delays in service						empty								An hour		1.2	0.63
Service management					NIGHT time	Not the only ones				night							1.2	0.63
Service management				Low quality of care in Public hospitals		Never											1	0.53
Service management					Admission/Appointment Cancelled		declined										0.8	0.42
Service management					Low quality of service		very disappointed										0.7	0.37
Service management					Old equipment											mostly old	0.5	0.26
Service management					Old equipment											not clean	0.6	0.32
Service management					Low quality of service		Would never go										0.9	0.47
Service management				Admission/Appointment Cancelled										No given			0.6	0.32
Service management				Delays in service											seven hours		1	0.53
Service management					Dirty in the rooms		dirty										0.6	0.32
Service management					Dirty in the rooms		chaotic										0.6	0.32

TABLE 16. **The Final Results Of Criticality Index Calculating.**

Activity-Context Patterns		Criticality Indicators by Roles					Criticality Index	Importance Index	Healthcare issue Urgency
Activities	Context	Doctors	Nurses	Consultant	Administrative staff	All medical staff			
Communication/Information Exchange with Patient	Communication exchange gap	1.26	0.00	0.42	1.26	0.95	3.89	2	3
Communication/Information Exchange with Patient	Limited English	0.00	0.00	0.00	0.00	0.11	0.11	17	28
Communication/Information Exchange with Patient	Lack of professionalism	0.79	0.00	0.00	0.00	0.00	0.79	17	14
Communication/Information Exchange with Patient	Lack of medication information	0.00	0.00	0.00	0.00	0.95	0.95	11	13
Communication with Patient	Impoliteness of communication	2.63	0.00	0.00	0.00	0.74	3.37	4	4
Communication with Patient	Staff unhelpful	0.00	0.21	0.00	0.00	0.00	0.21	17	27

psychological or financial harmful for the him'', presented in this article version of Conceptual Framework allows to measure the level of ''seriousness of the anticipated negative consequences'', using only facts and emotions perceived and expressed by patients as a source of knowledge. Thus, the basis for the formation of a rating of criticality and

TABLE 16. ***(Continued)*** **The Final Results Of Criticality Index Calculating.**

Activity-Context Patterns		Criticality Indicators by Roles					Criticality Index	Importance Index	Healthcare issue Urgency
Activities	**Context**	**Doctors**	**Nurses**	**Consultant**	**Administrative staff**	**All medical staff**			
Communication with Patient	Doctors insufficient procedures and practices	0.37	0.00	0.00	0.00	0.00	**0.37**	11	**23**
Communication/Information Exchange between Health Professionals	Lack of medication information	0.00	0.00	0.53	0.00	0.00	**0.53**	17	**20**
Communication/Information Exchange between Health Professionals	Lack of professionalism	0.00	0.00	0.00	0.00	0.32	**0.32**	17	**26**
Patient Care	Lack of Care	1.42	1.32	0.00	0.00	2.84	**5.58**	1	**1**
Patient Care	Lack of professionalism	0.95	0.53	0.00	0.00	0.00	**1.47**	7	**7**
Patient Care	Long waiting time	0.00	1.53	0.00	0.00	0.00	**1.53**	7	**6**
Patient Care	Elderly patient	0.00	0.00	0.00	0.00	0.42	**0.42**	17	**22**
Patient Care	Staff rudeness	1.00	1.00	2.63	0.00	0.00	**4.63**	2	**2**
Patient Treatment	Discharge Note	0.00	0.00	0.00	0.00	1.05	**1.05**	11	**11**
Patient Treatment	Low quality of treatment	0.37	0.00	0.89	0.00	1.95	**3.21**	5	**5**
Patient Treatment	Delay in admission	0.00	0.00	0.00	0.37	0.00	**0.37**	17	**24**
Patient Treatment	MRI Delay	0.00	0.00	0.00	0.37	0.00	**0.37**	17	**24**
Patient Treatment	Lack of professionalism	0.00	0.00	0.68	0.00	0.00	**0.68**	11	**17**
Relatives-related Care (Communication/Information Exchange)	Lack of information	0.00	0.00	0.00	0.00	1.26	**1.26**	6	**9**
Service management	Delays in service	0.84	0.00	0.00	0.53	0.00	**1.37**	7	**8**
Service management	Lack of personal	0.00	0.00	0.00	0.79	0.00	**0.79**	17	**14**
Service management	Low quality of service	0.00	0.00	0.00	0.37	0.84	**1.21**	7	**10**
Service management	Dirty in the rooms	0.00	0.00	0.00	0.00	1.00	**1.00**	17	**12**
Service management	NIGHT time	0.00	0.00	0.00	0.00	0.63	**0.63**	17	**18**
Service management	Low quality of care in Public hospitals	0.00	0.00	0.00	0.53	0.00	**0.53**	17	**20**
Service management	Admission/Appointment Cancelled	0.00	0.00	0.00	0.32	0.42	**0.74**	11	**16**
Service management	Old equipment	0.00	0.00	0.00	0.00	0.58	**0.58**	11	**19**
Service management	Dirty in the rooms	0.00	0.00	0.00	0.00	1.00	**1.00**	17	**12**

TABLE 17. **Example Of Detailed Context-Mechanism-Outcome Configuration For Arc+ Enrich Conceptual Framework.**

Comment	CMO configuration								
	Context					Mechanisms		Outcomes	
Dirty and chaotic. Twenty hours on a trolley with 3 fractures, a head injury and pneumonia. Patient 76 years old. Equipment mostly old and not clean. Patronizing doctors. No explanations and limited English. Would never go near this place again	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Patient Care	*Criticality value*	**1.53**
		Prior facts	-	*Hospital Department/Place*	Emergency				
		Age	76 years old	*Patient Health Problem*	Head injury, Pneumonia				
		Time of day		*Healthcare Facilities/ Medication*	Trolley				
	Circumstances	Long waiting time							
		Patient left on trolley							
	Actors	Staff							
Disgraceful place. I was sent home with a toe fracture given advice that I would be back to normal in two weeks. I had no x-ray scan, no physiotherapy. Also, nobody gave my any further advice in case something went wrong, and I had no review	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Patient Care	*Criticality value*	**0.6**
		Prior facts	-	*Hospital Department/Place*	-				
		Age	-	*Patient Health Problem*	Toe fracture				
		Time of day	-	*Healthcare Facilities/ Medication*	x-ray scan physiotherapy				
	Circumstances	Low quality of care							
	Actors	Staff							

urgency of problems in this stage of Conceptual Framework development is the information: (1) about the presence of specific marker containing knowledge on various degrees and aspects of negative healthcare event criticality in the comments and (2) about the specific consequences that occurred and are described by the patient in the comments. However, at the next stage of research, the authors plan to introduce the second dimension of seriousness of the anticipated negative consequences taking into account professionally sound causal relationships of the healthcare

TABLE 17. ***(Continued)*** **Example Of Detailed Context-Mechanism-Outcome Configuration For Arc+ Enrich Conceptual Framework.**

Comment	CMO configuration								
	Context					Mechanisms		Outcomes	
Son waiting since 11am to be put on a drip. Didn't get it for nearly 24 hours. Felt we were forgotten about. Every other parent on the ward was given a mattress. Nobody bothered coming near me even to give a pillow	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Patient Care	*Criticality value*	**1.20**
		Prior facts	Sent home	*Hospital Department/Place*	Ward				
		Age	-	*Patient Health Problem*	-				
		Time of day	-	*Healthcare Facilities/ Medication*	Drip				
	Circumstances	Very long waiting time							
		No patient care							
	Actors	Nurses							
Dirty and chaotic. Twenty hours on a trolley with 3 fractures, a head injury and pneumonia. Patient 76 years old. Equipment mostly old and not clean. Patronizing doctors. No explanations and limited English. Would never go near this place again	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Communication/Information Exchange with Patient	*Criticality value*	**1.30**
		Prior facts	-	*Hospital Department/Place*	Emergency				
		Age	76 years old	*Patient Health Problem*	Head injury, Pneumonia				
		Time of day	-	*Healthcare Facilities/ Medication*	Trolley				
	Circumstances	No explanations							
		Limited English							
	Actors	Staff							
Disgraceful place. I was sent home with a toe fracture given advice that I would be back to normal in two weeks. I had no x-ray scan, no physiotherapy. Also, nobody gave my any further advice in case something went wrong, and I had no review	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Communication/Information Exchange with Patient	*Criticality value*	**1.29**
		Prior facts	-	*Hospital Department/Place*	-				
		Age	-	*Patient Health Problem*	Toe fracture				
		Time of day	-	*Healthcare Facilities/ Medication*	x-ray scan physiotherapy				
	Circumstances	Lack of medication information (review, advice)							
	Actors	Staff							
Dirty and chaotic. Twenty hours on a trolley with 3 fractures, a head injury and pneumonia. Patient 76 years old. Equipment mostly old and not clean. Patronizing doctors. No explanations and limited English. Would never go near this place again	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Service management	*Criticality value*	**1.99**
		Prior facts	-	*Hospital Department/Place*	Emergency				
		Age	76 years old	*Patient Health Problem*	Head injury, Pneumonia				
		Time of day	-	*Healthcare Facilities/ Medication*	Trolley				
	Circumstances	Limited/poor resource in hospital							
		Dirty in the rooms							
		Equipment mostly old and not clean							
	Actors	Staff							
Disgraceful place. I was sent home with a toe fracture given advice that I would be back to normal in two weeks. I had no x-ray scan, no physiotherapy. Also, nobody gave my any further advice in case something went wrong, and I had no review	*Personal situation*	*Individual*		*Healthcare*		*Activity*	Patient Treatment	*Criticality value*	**1.80**
		Prior facts	-	*Hospital Department/Place*	-				
		Age	-	*Patient Health Problem*	Toe fracture				
		Time of day	-	*Healthcare Facilities/ Medication*	x-ray scan physiotherapy				
	Circumstances	Discharge Note							
	Actors	Staff							

Event and its consequences, for example, the consequences of poor lighting in the ward for patients in the department of Eye Diseases treatment, long waiting time for a doctor in the Emergency with certain diagnoses, etc. This information can be obtained from expert doctors by conducting interviews/workshops using pre-prepared templates of Context-mechanism-outcome dependencies.

Due to the fact that the results of the patient experience analysis conducted using the proposed Conceptual Framework should serve as a basis for solving the problems existing in the field of healthcare, in the next stages of the study, the authors plan to address the problems of causal relationships between (1) existing problems, (2) factors influencing the occurrence of this problem and (3) the necessary management solutions to eliminate this problem. This stage of research is also planned to be carried out using a triangular approach, namely: extracting knowledge from existing comments, studying sources of literature on methods of decision-making in the field of healthcare, and conducting interviews with healthcare workers. This direction of research should increase the effectiveness of the practical application of the proposed concept, since it will allow forming a comprehensive vision of the problem – from its nature and degree of criticality (taking into account both the patient's experience and doctors' knowledge of the degree of seriousness of the problems) to the decision-making tools to ameliorate existing problems.

VIII. CONCLUSION

In this paper, we presented a novel Conceptual Framework and method for identifying the degree of criticality of a negative healthcare event based on the patient's experience, perceived and expressed in a free-text format.

Regarding the scientific contributions of the research, we claim that we have provided: (1) a way to measure the scale and importance of a negative healthcare event by its

Criticality for the patient; (2) a richer structure of the ARC framework by the contextual dimensions, NE; (3) an opportunity to reveal the presence of causal relationships between the conditions in which the patient was in, the context of the described negative experience and the degree of criticality of this event.

Our immediate future work will rely on the foundation established in this article to develop named entity extraction models that will automatically extract or identify the relevant markers from free-text describing negative healthcare experience to compute the criticality index.

APPENDIX

The list of attached Appendixes:

Appendix I. (See Table 10.)
Appendix II. (See Table 11.)
Appendix III. (See Table 12.)
Appendix IV. (See Table 13.)
Appendix V. (See Table 14.)
Appendix VI. (See Table 15.)
Appendix VII. (See Table 16.)
Appendix VIII. (See Table 17.)

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