Exploring an In-house Online Reputation Monitoring Implementation

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Abstract. Today, our online reputation can be developed through subjective opinions communication by netizen on social media. Online reputation especially for business entities can affect in many aspects such as sales and customer loyalty. Due to high amount of social data (e.g. comments), the manual approach in monitoring subjective opinions towards our brands, products or name is no longer relevant. Therefore, entities either organizations or individuals should monitor their online reputation using social media analytics tools such as sentiment analysis to mitigate reputation attack. However, Online Reputation Monitoring (ORMo) is yet a common practice where most practitioners are large corporations. Outsourcing is a good option but entities must allocate some costs which a burden for most small and medium entities. Thus, implementing social media analytics in-house ORMo by entities is a reasonable option. However, the guideline to implement in-house ORMo is still not well explored including what are the needed features in an ORMo tool. Therefore, this research attempts to explore on how to implement an in-house ORMo at affordable cost but reliable. In achieving the objective, this research involved four stages of investigations which are needs assessment of ORMo tool features, prototype development, simulation and expert survey for validation. This research found that in-house ORMo can be implemented at minimal cost using existing resources and the accuracy can be improved by updating the collection of words with its sentiment polarity. The results of this research can be the basis for an in-house ORMo tool implementation and for reviewing the existing ORMo tool.

1. Introduction
Social media today is the most preferred channel for creating and sharing subjective opinions towards entities such as product, brand, organization and individual. This creates an online reputation for entities which helps to increase visibility of their products or brands. At this point, Online Reputation Management (ORM) is the practice to mitigate reputation attack, which is divided into three stages before attack, during attack and after attack. This research focuses on before attack which is a proactive measure that we call online reputation monitoring (ORMo). Many entities have implemented ORMo manually like handling a personal social media account. This approach is time consuming and not systematic especially for entities that reached high visibility or in trending where too many subjective opinions received. Therefore, ORMo implementation is more appropriate using social media analytics approach where textual data were extracted, cleaned and analyzed with certain methods and
tools. However, this approach incurs additional resources especially costs and skills. Therefore, many large and high-income entities implemented ORMo by outsourcing it to ORM providers. However, that option is not friendly to most small and medium entities. This research attempts to explore on how an in-house ORMo implementation can be made at affordable cost but still produce reliable sentiment analysis. This research involved four main stages which are; Stage One: Need Assessment of in-house ORMo tool, Stage Two: Prototype Development, Stage Three: Simulation of the Developed ORMo Prototype, and Stage Four: Validation with Expert survey on the Identified Features. From the needs assessment of stage one, ten features were identified which are i) informative visualized reports (IVR), ii) useful monitoring and classification (UMC) iii) intelligent iv) reliable v) time-saving vi) cost-effective vii) user friendly viii) systematic ix) decision support and x) big data capable (BDC). Further in stage two, the identified features were materialized into an ORMo tool prototype that was developed in Microsoft Excel platform and used Lexicon-Based Sentiment Analysis. This is to allow for simulation and validation of all the needed features which were attempted to be available in the prototype. In stage three, an ORMo process was simulated using the prototype using four different real datasets (textual comments) from Facebook. The sentiment analysis results from the simulations were recorded based on comparison with human annotated comments. Finally, in stage four, the materialized identified features were reviewed by selected experts to evaluate the identified features and further improvements. This research discovered that in-house ORMo is implementable at minimal cost using existing resources like a spreadsheet software but still produce a reliable sentiment analysis for business decisions. The identified needed features can be used as a guideline or the general requirements for an in-house ORMo tool development as well as for reviewing of existing ORMo tool used by entities. The outcome of the research will be extended with the development of methodological framework for in-house ORMo to guide that researchers and practitioners in implementing ORMo by themselves.

This paper is organized as follows. In the next section, some information about the topic are provided to guide in understanding the existing knowledge about the research. Further, the research methodology is explained in section three and then the results are described in section four. In section five, the discussion of the results and conclusion of the research are presented, and finally future work is presented in section six.

2. Background

2.1. Online Reputation Management (ORM)
Reputation is defined as what influences people to think, feel and talk about us the way they do [18]. “Online Reputation Management (ORM) is the act of monitoring, addressing or mitigating SERPs (search engine result pages) or mentions in online media and Web content” [1]. ORM is a new element of public image for entities especially organization that makes their presence on the Internet. However, those who are not presence on the Internet can also have online reputation when the public create subjective opinion with mentioning our identity with certain adjectives [2]. In [3], online reputation management is dived into three stages of reputation attack. First stage is called before attack which is more on preventive measure before any reputation attack. The second stage is called during attack which refers to the management of reputation during the attack such as action needed to be taken. The third stage of ORM is after attack. This is about the handling after an entity’s reputation had been attacked and the involved entity wants to rebuild its reputation from the damages. As mentioned, this research focuses on the first stage which is online reputation monitoring which is a proactive stage before our online reputation is being attacked.

2.2. Online Reputation Monitoring (ORMo)
In this research, ORMo is a task of screening on what people are talking about certain organizations, persons, products or entities on social media [4]. While ORM is the entire reputation management which
is mentioned above, ORMo is the first stage of ORM which is before reputation attack. The monitoring is based on sentiment analysis which can help entities to make business decisions such as sales and marketing strategy and risk management [5]. The report of ORMo usually prepared with visualization to provide better understanding and interpretation. The source of ORMo can be from search engine or from social media contents [6]. The process of ORMo normally follows social media analytics process as described in the following sub-section.

2.3. Social Media Analytics
According to [7], social media analytics (SMA) is defined as process of “developing and evaluating informatics tools to collect, monitor, analyze, summarize, and visualize social media data”. The common purpose of social media analytics (SMA) in commercial organization is to support marketing and customer service processes by mining customers’ sentiment or sentiment analysis. In SMA, among of the processes are data extraction or scrap, data cleaning, analysis and interpretation and decision making [4]. ORMo is one of the common purposes of SMA. In ORMo, SMA process involved are extracting social media contents such as text to predict the polarity of the content. One tool to obtain the predicted feedback from cumulative opinions by customers or consumers is sentiment analysis. Finally, the results of sentiment analysis are presented in visualized report to allow quick understanding so that interpretation and appropriate action can be taken.

2.4. Sentiment Analysis
Sentiment analysis (SA) is an automatic process in mining attitudes, opinions and emotion from text, speech, tweets and the like through Natural Language Processing [8]. In Social Media Analytics (SMA), SA is the common tool used for content analysis. It also called are opinion mining and appraisal extraction. Businesses can use SA to understand consumer’s emotion towards their brand or company or signature products and services whether they are accepted positively or negatively on the Internet SA is a classification problem where opinionated texts will be categorized as “positive” or “negative” or “neutral” using either lexicon-based or machine learning algorithm [9]. Lexicon-Based Sentiment Analysis (LBSA) is a method that matches texts to be analyzed with a collection of lexical or dictionary which have predefined sentiment polarity either positive or negative [10]. The challenge of this method is to prepare the dictionary before it can produce the sentiment analysis, however, this method is flexible to any language standard and style. Meanwhile, machine learning is more advance as it uses either trained or untrained datasets where it requires suitable algorithms to work on its own either with supervised or non-supervised learning. Various classification methods can be used in this supervised machine learning approach such as decision tree, linear classifiers, rule-based classifiers and probabilistic classifiers.

3. Research Methodology
This research is used a combination of qualitative and quantitative method to achieve the research goal to identify the needed features for in-house ORMo tool. This research involved four main phases which are: Stage 1: Need Assessment of in-house ORMo tool, Stage 2: Materialization of Identified Needs, Stage 3: Simulation of the Developed ORMo Prototype, and Stage 4: Validation with Expert survey of the Identified Features.

3.1. Stage 1. Needs Assessments of in-house ORMo tool
This research started with the dentification of the needed features of an in-house ORMo tool based on current practices. In the stage one, a need assessment was conducted to identify the entity’s needs in ORMo tool. A need assessment model introduced by [11] was followed where three phases involved;(i) pre-assessment, (ii) assessment and (iii) post-assessment. Pre-assessment is the preparation phase of the assessment such as what to assess and who will be involved. For the assessment phase, we have decided to assess on the features of ORMo tool based on current practices and challenge that entities are facing.
The entities that involved in the assessment are divided into two type which are organization and individual. For organization, the key person of business organization, government department and non-profit organization (NGO). Meanwhile for individual, the individuals are from business owner, politician and celebrity. In the second phase of the needs assessment, a total of six persons were selected for semi-structured interviews. Further, the transcribed interviews then were analyzed using inductive content analysis (ICA) method to elicit the needed features of an ORMo tool as shown in Figure 1 below.

### 3.1.1 Inductive Content Analysis (ICA).
According to [12] ICA includes open coding, creating categories and abstraction. Open coding means writing notes and headings while reading the text (e.g. interview transcript). The text is carefully read through again as well as the headings are written down repeatedly as needed in the margins to describe every aspect of the content. From the margins, headings are collected to become a coding sheets and then categories are generated freely in this stage. In this research we used a qualitative data analysis software called Atlas.ti version 7 to perform ICA process. After open coding is done, the lists of categories are grouped under higher order headings. This is to reduce the number of categories by eliminating similar or dissimilar into broader higher order categories. The objective of developing categories is to bring means of describing phenomenon and to improve understanding as well as knowledge in the subject. In developing categories using ICA, we need to decide based on interpretation for which things to put under similar category [13]. The final step of ICA is abstraction, where a general description of the research topic is formulated through generating categories. Each of the category is named using content-characteristic words. Similar sub-categories and categories are grouped together as categories and categories are grouped as main categories. The process of abstraction continues as long as they are relevant and possible. In Atlas.ti, this process is performed by ‘code family’ function and it can be supported with network diagram. At this stage, we have concluded ten features as described Results section below.

![Figure 1](image_url) Inductive Content Analysis Process by [12].

In the third phase of Witkin’s Needs Assessment Model (post-assessment) a prioritization will be made and then action plan will be designed. In this research, we let the prioritization to be made by the experts during the evaluation of prototype. Thus, in the action plan, we attempted to materialize all implementable features in a prototype first and followed by the prioritization (importance) of the features during expert survey.

### 3.1.2 Stage 2. Prototype Development.
As drawn in the action plan of post-assessment, we have developed a prototype of ORMo using Microsoft Excel 2016. We have attempted to fulfill all the needed features as finalized in the previous stage of the research. We used Lexicon-Based Sentiment Analysis (LBSA) as the method for sentiment analysis. In LBSA, we need to prepare of collection of words or lexical with its sentiment polarity that we call Sentiment Dictionary in the prototype. Due to the varsity of natural language constraints, we have developed a Malay Language dictionary based on political theme for this research. This means that collection of words in the dictionary are normally used in political news topic. When this paper is written, 3,628 words have been included in the dictionary with the sentiment polarity. The sentiment polarity for each word were annotated by three different high skilled Malay Language users. And most of the classification for certain words by the annotators will be taken as the sentiment polarity of the word. LBSA has many advantages in this research including cost and reliability. For instance, due to the different standards and forms used by netizens today, we can include and define sentiment polarity of any new word in the dictionary with its sentiment polarity. For example, “merempit”, the word is a trending Malay word that refers to illegal motorcycle racing (negative polarity) which is found in the standard Malay Language dictionary with different meaning.
which is hit something with rattan wood. But since the word is widely used by netizen with negative sentiment, we can add it into our sentiment dictionary for the contextual meaning. This is to allow the sentiment analysis to produce more reliable results which is one of the critical features of ORMo tool.

3.1.3. Term Counting Method. In term of the sentiment polarity classification, term counting method is used for the prototype. This simple method introduced by [14] and it was employed in the number of works such as [15-17]. Although it is not as effective and advanced as machine learning methods such as Support Vector Machine (SVM), term counting has its own advantage over machine learning. [14] suggested term counting term counting method can be easily modified to use valence shifters which is difficult on machine learning in a way that makes it clear if the improvement in the results caused by the use. Valence shifters are those terms that can change the semantic orientation of another term or terms that can shift a positive term to negative and vice versa. For example, terms like not, never, nobody. In ORMoS prototype, the valence shifting can be done by defining terms in the Sentiment Dictionary Module.

3.2. Stage 3. Simulation of ORMo Using the Developed Prototype
To evaluate the defined features, we have conducted several simulations of ORMo using the prototype with four different real datasets. We have extracted Facebook comments for two sets of political themed news, one about product and one about celebrity. The first two sets of data were used to test the tool with political themed texts (code named DSN and Rafizi) as the dictionary developed is more to political. However, another two sets of data were used to see the performance of how if the other theme of content is used which product (MyVi) and Neelofa (celebrity). The sentiment polarity of all datasets was annotated manually by three different persons who are high skilled user of Malay Language such as librarian, insurance copywriter and a lecturer. The majority classification from the three annotators is taken as the correct sentiment polarity for each comment. Due to low collection of lexical in the dictionary (3,628), many cells are empty as the attempt to match the given datasets of with the dictionary was failed. Thus, the tool cannot classify the sentiment polarity as no weight can be calculated. Thus, in the results we removed the empty cells to only count the matched comments and named the process as null control. The results are shown as in Table 1. In the table, Total True and Total False means the number matched sentiment polarity definition of sentences with human annotation.

3.3. Stage 4. Validation with Expert Survey
Further, in the final stage of the research, we have validated the identified and materialized features of ORMo tool with five experts from different fields such as academic, industry and government to review the identified features. Five questions were asked including suggestion for improvement.

4. Results
The objective of the research is to identify the needed features by entities in ORMo tool. The research undergone several stages before finalizing the needed features. As a result of needs assessment stage from phase one of the research. Ten features were finalized from inductive content analysis at phase two of needs assessment. Features in this context means the characteristic of ORMo tool including capability, functionality and quality of the ORMo tool. The features are; (1) Informative Visualized Report (IVR) (2) Useful Monitoring and Classification (UMC) (3) Decision Making Support (DMS) (4) Systematic (5) Big Data Capable (BDC) (6) Cost-Effective (7) Time Saving (8) Intelligent (9) User Friendly (10) Reliable. A prototype was developed using Microsoft Excel to validate the features through simulation and expert survey. Table 1 below shows the results of sentiment analysis simulation where the prototype predicted more than 50% accuracy with DSN 87%, Rafizi 53% and Neelofa 80% after null control for political news and celebrity datasets of Facebook comments. There is a substantial difference of accuracy results between two political datasets of DSN and Rafizi about 34%. Based on the textual comments, netizen put more lengthy comments compared to DSN dataset. This due to the topic of the news for Rafizi is rather new and unclear compared to DSN regarding a decision had been made.
However, for product dataset (MyVi) the prototype unable to predict more than 50% accuracy which is most probably due to limited lexical related to automotive. This shows that our testing dictionary which is political themed can also be used for celebrity domain, most probably due to common terminologies related to human. However, the dictionary seems unsuitable for product domain (MyVi) such as automotive where only 43% accuracy. As per described in research methodology, the accuracy validation is based on term counting method where the majority.

Table 1. Results of Simulation with Different Datasets.

| Dataset | Type | Null Control | Total Comments | Total True | Total False | Total Null | Accuracy Percentage |
|---------|------|--------------|----------------|------------|-------------|-------------|---------------------|
| DSN     | Political News | Before       | 1000           | 379        | 620         | 564         | 38%                 |
|         |                   | After        | 436            | 379        | 56          | 564         | 87%                 |
| Rafizi  | Political News | Before       | 508            | 161        | 345         | 207         | 32%                 |
|         |                   | After        | 301            | 161        | 138         | 207         | 53%                 |
| MyVi    | Product          | Before       | 420            | 37         | 382         | 334         | 9%                  |
|         |                   | After        | 86             | 37         | 48          | 334         | 43%                 |
| Neelofa | Celebrity       | Before       | 916            | 200        | 614         | 667         | 22%                 |
|         |                   | After        | 249            | 200        | 53          | 667         | 80%                 |

In term of expert survey, four questions were asked (excluding suggestions for improvement) to define the rating of the identified features. The results are based on the frequency of the rating among experts. Firstly, for the most visible feature in the prototype, experts voted for IVR and reliable while BDC is the least visible. Further in question two, experts provided that the most important feature among the ten is intelligent while user friendly is the least important. This is the prioritization stage that we have decided to let expert to define after the needs assessment stage three. In term of strongest feature, majority of the expert chose IVR followed by UMC and BDC is the least strength. Finally, it was discovered that BDC, IVR, UMC and DMS are all the urgent features to be improved. Although it was ranked at number two in the second question, this survey shows that the IVR and UMC are among the most important features. IVR is where the output of ORMo which normally appears in the dashboard of ORMo tool. Meanwhile, UMC is another critical feature which is referred to sentiment analysis with LBSA. BDC seems to be the less popular feature as the platform itself (Microsoft Excel) doesn’t support big data especially locally extracted data. Another surprising result is on question two where experts do not treat cost-effective as the most important feature. However, we can anticipate that they are not aware of the actual cost of ORMo and more concern on the functionality of the tool.

5. Discussion and Conclusion
This research discovered ten needed features of ORMo tool for in-house implementation. The features are materialized in a prototype based on Microsoft Excel 2016 using LBSA. However, not all features are implementable such big data capable BDC. But the tool successfully follows the social media analytic process. This research does not intended to showcase an intelligent tool to be compared with existing ORMo tool especially those developed using machine learning, but this research attempt to explore how to implement an in-house ORMo so that any size of entities can have a control of online reputation without spending much costs. This research discovered that ORMo can be implemented at minimal cost with intermediary level of IT skill. This is because the prototype can be developed in Microsoft Excel 2016 where most organization used the spreadsheet software. Furthermore, as entity can implement ORMo by themselves, issues on information privacy can be controlled as they do not depend on vendor. In term of reliability, more words needed to be included in the sentiment dictionary to improve the accuracy and reliability of the sentiment analysis report. For example, dataset DSN and dataset Rafizi are both in political themed comments on an online news post. But DSN dataset has higher accuracy at 87% after null control compared with Rafizi dataset only 53%. This is because comments
on DSN is more straightforward and mostly the same meaning that support in the former Prime Minister of Malaysia resignation of his post from his leading party. However, for Rafizi dataset the comments are longer and deeper with some sarcastic words which are not available in the sentiment analysis dictionary. This is among of the limitations of our ORMo tool.

This research has achieved its objective to identify the critical features of ORMo tool through four stages of research including needs assessment, prototype development, simulation and expert survey for validation. It is shown that ORMo can be implemented at minimal cost using existing resources such as spreadsheet software and the same staff who know spreadsheet software. Although lower cost, we still can get acceptable reliability of the results. Entities especially small and medium sized or even individual can shift from manual ORMo to this doable semi-automated ORMo. The features can contribute in the development of in-house ORMo implementation or evaluation of existing ORMo tool used

6. Future Work
In extending this research, we are developing a methodological framework for in-house ORMo implementation based on this research as guideline for practitioners and researchers. Perhaps, sample of entities can be selected to test out the methodological framework.

7. References
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