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Using diffusion of innovation theory and sentiment analysis to analyze attitudes toward driving adoption by Saudi women

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A R T I C L E I N F O

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A B S T R A C T

Although several studies have used sentiment analysis to examine social media content, relatively few have complemented this work with sociological theories. This study employed the diffusion of innovation (DOI) framework to provide a deeper understanding of the recent debate on whether women in Saudi Arabia should be granted the right to drive. The outlook of proponents and opponents was considered by using detailed Arabic Twitter data. The sentiment analysis approach was used. The findings were analyzed on the basis of DOI stages, and the innovation–decision process demonstrated that 60% of Twitter users supported the governments' approval of women's right to drive and 40% either opposed the order or had a neutral opinion. The finding of our analysis suggests that Saudi society corresponds the DOI stages and exhibits the tendency to support the right of women to drive. This study contributes to DOI research, particularly concerning the use of social media for studying opinions on important unsettled social matters.

1. Introduction

Social media has become a significant part of the daily lives of many individuals and is the preferred platform for them to communicate with friends, access the latest news, and learn of diverse viewpoints [1]. The number of individuals creating a social media account is increasing daily, and popular platforms, such as Facebook and Twitter, have become part of the social fabric of many countries. Moreover, social media activity has recently become part of the mainstream news media. For example, many social media platforms provide news feeds on community events, where individuals express their opinions on new ideas or products. Notably, social media platforms reveal crucial important information on how societies interact with cultural changes in the information age. As a result, marketing firms and governments have been interested in this feedback and these comments on myriad topics [2]. Social media does not have boundaries; that is, there are no participating restrictions. In addition, fast adoption allows for quick decision-making with the help of large groups of individuals. Associating decisions "and [the] expansion process with the diffusion of innovation approach" is possible [3].

Diffusion of innovation (DOI) theory posits that communication has a strong effect on social change within a community. Diffusion, in this context, is defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system" [4]. Rogers's definition comprised four main elements: innovation, communication channels, time, and social system. We considered this definition as an appropriate social theory to discuss women driving concern in Saudi Arabia for the following reasons.

According to Rogers, who defined the first element of innovation, "An innovation is an idea, practice, or project that is perceived as new by an individual or other unit of adoption" (Rogers, 2003, p. 12). Individuals prefer to understand an innovation that is a new idea or an existing idea that is still new to society, because "innovation may have been invented a long time ago, but if individuals perceive it as new, then

Abbreviations: ARRF, Attribute-Relation File Format; CSS, Computational social science; DOI, Diffusion of innovation; ICT, Information and communications technology; MSA, Modern Standard Arabic; SVM, Support vector machine.

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it may still be an innovation for them" [5]. As was the case of women driving in Saudi Arabia, although the idea was suggested in 1990, it was not legal until 2018, and when it was legal, Saudi society viewed it as an innovation. Individuals usually do not adopt innovations unless they consider the comparative gains, ease or complication of use, and testing opportunities and discuss it with peers.

Moreover, innovations take time to be adopted even when their advantages are clear (i.e., several stages—knowledge, persuasion, and choice—are involved in the decision-making process for adopting or rejecting a new idea; [4]), allowing individuals to evaluate innovations [4]. The adoption of Saudi women driving analysis as we may think is more related to the three stages of the DOI process (knowledge, persuasion, and decision).

Rogers defined the second element of DOI definition as communication, which can be defined as "a process in which participants create and share information with one another to reach a mutual understanding" [5]. Moreover, Rogers stated, "A source is an individual or an institution that originates a message. A channel is the means by which a message gets from the source to the receiver" [4; p. 204]. Additionally, as stated by Ref. [2], "Communication channels geared toward followers and specific hashtags in Twitter platform." The channels can be any type of communication media and can nowadays be applied to social media, which, in our case, is Twitter, because tweets play a crucial role in the dissemination of local and national trends. Communication is usually between individuals who share similar views and attitudes, called homophily (e.g., the tendency of individuals to support others who use their preferred hashtags, even if they have never met), and innovation may be diffused across ties (i.e., weak or strong bonds between users) to influence followers and their attitudes [1]. Additionally, it includes communication among individuals who have different views or beliefs, called heterophily. These communication channels are applied in the knowledge stage [5]. In this study, we collected opinions on women driving in Saudi Arabia by using popular hashtags that supported (homophily) or were against (heterophily) this societal change. Therefore, each group could easily consider the other's viewpoints.

The third element of Rogers's theory is time. As stated in Chang [2]; Twitter is a real-time application, and tweets can be mapped by time. The duration of the debate in Saudi Arabia on women's legality was from 1990 until September 2017. At first, many individuals in this society disagreed, but over time, their attitudes have changed. From 1990 to 2000, religious scholars promoted the ban. Subsequently, individuals started discussing this topic publicly in their tweets, as Altoaimy [6] stated. In 2017, society was finally ready, and the government removed the ban on women driving. Our study will address this long-standing ban, which might affect attitude or actions in Saudi Arabia from computational social sciences analysis.

The social system is the last element in the diffusion process. Rogers (2003) defined the social system as "a set of interrelated units engaged in joint problem solving to accomplish a common goal" [5]. Additionally, in Chang [2]; a social system, comprising followers and the relationships among Twitter users, was considered a means to exchange information. In our case, the social system is a group of individuals expressing their opinions on Twitter to discuss the unsettle women driving matter in Saudi society. Moreover, to anticipate society's acceptance of this innovative action and to help predict who will accept this innovation (called adopters in the DOI), we attempted to analyze individuals' sentiment.

Saudi women's issues have been investigated in the context of social media. For example, Luppicini and Saleh [7] investigated the supporting role of social media for Saudi women who are divorced in terms of social, financial, emotional, and legal challenges. Their findings suggested that social media is a means of support for them. Additionally, Samargandi et al. [8] investigated the low female labor force participation in Saudi Arabia and how the Saudi government is beginning to empower women by granting them more of the rights that their male counterparts have. Our paper focused on a similar topic which is Saudi women driving.

In this study, we used sentiment analysis and Twitter to study and measure DOI on a trending topic in Saudi Arabia: the government's granting women the right to drive. According to our review of the literature, this research is one of the few to use DOI for analyzing Twitter posts, which has recently been recognized as a computational social science (CSS). CSS was defined by Wallach [9] as "the study of social phenomena using digitized information and computational and statistical methods."

In 2017, Saudi Arabia began to implement the "Vision of National Transition 2030" [10]. Significant changes were planned for individuals in many sectors of society, and women's empowerment was one of the essential objectives of the transition. To grant women a wider range of rights, King Salman bin Abdul-Aziz ordered in September 2017 that women would be granted the right to drive in Saudi Arabia. On June 24, 2018, women in Saudi Arabia gained full rights to obtain a driver's license. Since that day, Saudi Twitter users have created many hashtags in favor of and against the order. Because of the importance of the declaration, we aimed to identify Saudis' ratios of positive, negative, or neutral opinions on its implementation [11]. Next, to advance the understanding of Saudi society's acceptance of changes, we mapped these findings while applying DOI theory.

Our research attempted to accomplish the following objectives: (1) to conduct a study of the hybrid sentiment analysis approach by using Arabic Twitter data related to hashtags associated with Saudi women driving; (2) to compare the results obtained from different classification models used for sentiment analysis of Arabic data; (3) to obtain the ratio of supporting, opposing, and neutral opinions on granting women the right to drive in Saudi Arabia; and (4) to analyze the results from the DOI theory perspective and sociological point of view. In our analysis, we used machine-learning methods (classification techniques) to analyze the real-world data (in this case, tweets related to women driving) on Saudi society [9]. Furthermore, we implemented the theory-in and theory-out frameworks in our methodology, as presented by Radford and Joseph [12].

The study aimed to answer the following questions:

1 What hashtags were created to support or oppose women's right to drive in Saudi Arabia?
2 Did the Saudis' change their opinions on similar decisions after they were implemented?
3 Are there factors specific to women driving that lend themselves to an analysis by the DOI framework?

Section 2 of this article reviews related studies that have used Arabic data, sentiment analysis, and the DOI framework. Section 3 explains the methodology used and presents the evaluation of the classifiers by using different performance measures (precision, recall, accuracy, and the *F*-measure). Section 4 discusses the results of opinion prediction, including namely two subsections of explainability and theory building, and generalizability. We concluded the paper in section 5.

2. Literature review

In this section, we discuss research papers that have addressed sentiment analysis and Saudi women driving in social media.

2.1. Arabic sentiment analysis on twitter

Sentiment analysis is one approach to investigate individuals' written opinions. It relies on classifying written data into subjective classifications based on machine learning and natural language processing concepts [13]. This study used Arabic Twitter data to analyze the opinions of Saudi society on women driving. Twitter users in Saudi Arabia are the most active among those in all Arab countries [14], making twitter a reliable source of data for our research. Twitter provides an open medium for individuals to express their feelings and attitudes and is perhaps better considered as a notably breeding ground for productive social interaction. Therefore, such a medium (Twitter) necessitates analysis regarding substantial social changes in the culture and ruling of a conservative society such as Saudi. Analyzing Arabic language data is challenging [15] Because few tools are available for that purpose; thus, to obtain accurate results, we employed a hybrid sentiment analysis approach that relied on the machine learning of a Saudi dialect lexicon.

Qamar et al. [16] researched tweets related to Saudi telecommunication companies, namely STC, Zain, and Mobily. The researchers aimed to understand individuals' opinions on these companies and identify customers' needs by assessing their social media posts. They collected and analyzed 1331 tweets written in English. The tweets were classified into three groups (positive, negative, or neutral), and the classifications were based on Euclidean distance and cosine similarity. Their best results were obtained from the KNN algorithm, including an *F*-measure of 75.6%. As a result, they discovered the days and months in which users tweeted most often.

[17] designed an Arabic text classification for King Abdul-Aziz University students' opinions, to investigate the relationship between students and their tweets. Data were classified by using a support vector machine (SVM) and naïve Bayes (NB), with maximum accuracy obtained by using an SVM with the n-gram feature. The authors concluded that colloquial Arabic was more often used to provide feedback than Modern Standard Arabic (MSA) was.

Similarly [18], investigated sentiment analysis in Arabic reviews by using machine learning and considered sentiment analysis in Arabic text. Their dataset comprised 2591 tweets, and labeling was conducted by using crowdsourcing. The authors used SVM, NB, and KNN classifiers to detect polarity; the results demonstrated that the best precision was achieved with SVM.

Additionally [19], proposed the Detection of Arabic Sentiment Analysis Polarity method to analyze 5000 Arabic comments written in MSA or Arabic dialects on different social networks. Their data contained different forms of media (text, audio, image, and video). For the text, they used a new algorithm based on a mixture of term frequency and allocated weights from the lexicon's attributes to identify a term's quality. They found that the text-based opinions identified through their analysis were more accurate than those belonging to other media forms in their dataset.

In the same line of research [20], endeavored to discover the relationship between Saudi tweets written in standard and Gulf dialects and the Saudi market index. They gathered 3335 tweets from April 2015 to June 2015 from all shared parts of the Saudi stock market displayed on the Tadawul website.[1] They demonstrated that text pre-processing is the most important aspect of sentiment analysis classification for accuracy; the best result was achieved by using SVM [20].

In addition, Al-Twairesh et al. [21] built a corpus of tweets comprising MSA as well as Saudi dialect. The corpus comprised 17,573 tweets divided into four sentiment categories: positive, negative, neutral, and mixed. These tweets were manually annotated during the classification of the dataset.

Similarly [22], developed a lexicon tool that contained 1080 reviews from 72 social media websites. They focused on analyzing the polarity value, subjectivity, strength, and intensity of the reviews in their dataset. The tool depended on a manual lexicon.

Al-Hussaini et al. [23] analyzed restaurant reviews in Saudi Arabia that had been shared on Twitter. The authors used a lexicon-based approach to measure a reputation mark, for which they developed a Saudi dialect lexicon. In their analysis, they chose beta probability density functions to collect feedback from the lexicon for deriving reputation scores. The results demonstrated that this lexicon-based approach was efficient.

Studies [17,18], and [20] have indicated that the SVM algorithm is the most efficient method for sentiment analysis classifications. However, to attain the most accurate results, it is best to have more than two classes for sentiment analysis; thus, we used three classes: supporters, opposition, and neutrals. After the government decree granting women the right to drive, we started our project.

2.2. Saudi Women's right to drive

Several papers have discussed Saudi women's rights and Saudi Arabia's ban on women driving. Women driving in Saudi Arabia has long been debated and prohibited. The literature indicated that the only country in the world that forbade women from driving their cars was Saudi [24]. Some of these research papers have addressed the issue before removing the ban, and a few have conducted their investigations after it became legal.

Khalil et al. [25] addressed Saudi women's driving campaign from 1990 to 2018, to investigate the sociopolitical context of using digital media among the activists of this movement. The authors analyzed activists' collective and connective actions by using the theory of connective action. They conducted a case study of in-depth semistructured interviews of known prominent individuals in this movement. Next, the authors collected various media sources (YouTube videos and newspaper articles) from libraries and online search engines, and some tweets published in 2011 with the hashtag #women2drive. The authors used various codes and themes to ensure the results were valid and unified; their findings revealed that the activists' collective and connective actions were in their (the activists) organization and that they continued their efforts to promote this right (women2drive).

Along the same line, a study [24] discussed Saudi women driving by investigating the Western and local newspaper media coverage during the October 26 driving campaign in 2013. The Western side covered the ban from the perspective of human rights (supporter), without considering the culture and ruling aspects of the kingdoms, but the local coverage addressed the women driving matters from both support and opponent sides. The author recommended that the media address social movements from both sides to deliver and improve their accurate coverage of social activities.

Another study [26] addressed the Saudi #women2drive campaign on the basis of the civil society rules and functions in this Saudi women's movement. The authors demonstrated that civil society is a group of volunteer activists that organized unsettle matters in the society without having intended gain in terms of politics or economics. The authors illustrated the history of this campaign from 1990 until the removal of the ban in 2017. They discussed the use of social media by its activists to support this campaign. Their findings suggested that the social media campaign encouraged the government to grant women the right to drive.

The aforementioned papers of Alsulaiman [24]; Khalil et al. [25]; and Rijal and Khoirina [26] have discussed the rights of women to drive from the social science point of view. Alsulaiman [24]; Khalil et al. [25]; and Rijal and Khoirina [26] investigated the media coverage, conducted interviews, or studied the history of the women2drive campaign respectively. New approaches to study the content of social media posts are discussed next.

Almahmoud [27] presented a notable thesis on women drivers in Saudi Arabia. Although the author addressed this topic from the point of view of linguistic expression, not that of the content of the views gathered, her findings were intriguing. After collecting data from Twitter accounts associated with the "Women2Drive" campaign, she chose the 10 most active accounts with the hashtags #قيادة_26اكتوبر (translated as driving_October26) and #لا_لقيادة_السيارة (translated as No_for_womenDriving), and similar hashtags. In her analysis, she found two active groups: female social activists supporting the campaign and males opposing the campaign. Women wrote the most tweets written in

[1] https://www.tadawul.com.sa/wps/portal/tadawul/home/.

English on this topic, and the opposition's tweets were written in Arabic, because each group was targeting a different community and had different orientations. In addition, some individuals expressed their thoughts in Arabic by using the local Saudi Arabian dialect and concepts. Men who had a negative orientation toward the campaign tweeted more than the women did. Furthermore, the author found that an overly positive orientation was associated with women and that an overly negative orientation was associated with men. However, these results were based on a small sample of 10 active Twitter user accounts, for a limited time.

The research of Altoaimy [6] used the post-structural theories of gender theory to discuss the debate on women's right to drive in Saudi Arabia. She collected Twitter data from 2015, analyzed the tweets' contents by using a linguistic approach, and discovered several themes. The first theme indicated that individuals were discussing the ban openly and linking the ban to religious scholars. The second theme was the victimization of women, and movements against this phenomenon were attempting to advocate for additional rights for Saudi women, other than the right to drive. She discussed that for this theme, the tweets mentioned the word "driver," the burden of a driver's salary and expenses, and women's unsafe driving; additionally, they mentioned the rights of women to buy a car and drive it. The third theme was promoting women's independence, outside of the right to drive, and the corpus indicated that individuals were discussing more rights for women by stating "women are half of the society" and that their voices and contributions must be heard in the community without banning in their mobility. The tweets also stated that women should have the right to choose if they want to drive or hire a driver. The last theme reaffirmed the authority of the state. The tweets in this theme were directed to the king and expressed support for the right of Saudi women to drive; The analysis of the tweets indicated that society should respect the power of the authority to know what is best for individuals and not oppose the government's ruling. These tweets acknowledged that the Saudi government has been promoting women's rights in education, employment, and political participation and reforming many aspects to improve the life of Saudis.

Another study [28] collected Twitter data from 2012 to 2017 on the Saudi women's campaign by using the hashtag #women2drive from the first publicly discussed tweets in 2012, until the official announcement of granting women the right to drive in 2017. They collected many tweets, which required human annotation. To overcome the substantial amount of Twitter data, they sampled part of the tweets, and to manually label the data, they identified the stance of opinions and the gender. They found that more men than women were publicly discussing this topic on Twitter, and more notably, these male tweets were more favorable toward women driving than female tweets. Moreover, their findings indicated that the country of origin of the tweets was mostly Saudi Arabia, followed by the United States and Turkey. Their sample data addressed part of the social issue of women driving in terms of opinion, gender, and country.

Furthermore, AlSukhayri et al. [29] designed an ontology framework to link and transfer Saudi government data from various sources so that it would be accessible in RDF format. Their framework resulted in the Saudi Linked Open Government Data Cloud. Next, they applied their framework to women driving as a case study and ran several quires using the SPARQL endpoint from their data linked to women's right to drive. Some of their notable findings were as follows: the number of driving licenses issued increased after removing the ban on women driving, and the total number of employed females in Saudi increased compared with that the prior year, which eventually decreased the number of female job-seekers. As a result of allowing women to drive, the number of road accidents and traffic violations increased in the whole country. However, the number of traffic violations exceeded the number of accidents.

The aforementioned papers have used a Twitter corpus to discuss women's right to drive [6,27,28]. Almahmoud [27] and Altoaimy [6] have used a linguistics approach to assess Saudi women driving before removing the ban in 2015, and the study of Addawood [28] assessed before the ban and after removing it. However, Addawood [28] neither addressed the Saudi attitude after the order nor built classifiers to test their samples with other unlabeled tweets. Correspondingly [28], randomly selected a sample of tweets and then manually annotated for opinion and gender classification. What would have been notable is an analysis of the whole dataset by building one of the classification techniques, to gain more insights on individuals' opinions, especially after the order to grant women the right to drive.

According to the second author, who is specialized in Saudi society's sociology, the conservative Saudi culture usually takes time for new changes to occur until the whole community accepts and becomes something normal. Examples of this phenomenon are women attending schools and having satellite TV-dishes [6]. Sentiment analysis of Saudi's tweets is discussed in this paper.

2.3. Sentiment analysis

Sentiment analysis is the analysis of a piece of writing. In general, opinions are categorized as positive, negative, or neutral [30]. Sentiment analysis is also known as "opinion mining" (i.e., deriving an opinion or attitude). Initially, sentiment analysis was used to examine letters, emails, and post-crime criminal activities; it has also been used to study movie reviews, brand reviews, news, and blogs [31,32].

2.3.1. Lexicon-based approach

The lexicon-based approach uses a pre-existing dictionary where words are pre-tagged and text is converted to "tokens." New tokens are compared with words in the lexicon, and in the case of a positive match, the score is added to the calculated points for the input text. Next, the tweet's score is calculated on the basis of the average total words of the matched words in the tweets with the words in the dictionary. Subsequently, a label for the tweets is created on the basis of the score of the positive, negative, or natural categories. The limitation of this approach depends on the dictionary's size, which affects speed and accuracy [30,33].

2.3.2. Machine learning approach

This technique comprises five steps:

1. *Data collection*: Data are gathered from social networks.
2. *Pre-processing*: Data are cleaned by removing all hashtags, commas, spaces, emoticons, and non-English text.
3. *Training*: Collected and cleaned data are submitted to the algorithm for learning.
4. *Classification*: A classifier is applied to tweets/text for sentiment extraction.
5. *Results*: Results are derived in various forms, such as charts or graphs [30,33,34].

2.3.3. Hybrid approach

A hybrid approach can mimic the speed of the lexicon-based method and the accuracy of the machine learning approach [30,33]. The hybrid approach combines the machine learning approach and knowledge-based (lexicon) approach for polarity detection. This approach uses the high accuracy from machine learning and also the stability from the lexicon-based approach [35]. Therefore, we employed the hybrid approach for sentiment extraction or opinion mining of tweets.

We used the DOI framework to explore how Saudis behavior in their tweets toward women driving in the traditional Saudi society. This finding is important because it contributes to understanding how social attitudes toward culture change in terms of gender and sociocultural contexts through an open platform of social media usage. Furthermore, this study provides insights into empowering women's rights and participation, which has been forbidden in Saudi Arabia.

3. Methodology

This paper is methodologically innovative because it links social media attitudes with sociology theory (i.e., DOI theory). One exciting notion of Twitter is that users strategically express their opinions and impressions in a short text by using specific language, tones, and editing behaviors. This enabled our analysis to focus not only on the attitude of being (positive, negative, natural) but also on seeing the society changes through stages of popular sociology theory (i.e., DOI).

First, our study aimed to determine mainstream attitudes in Saudi Arabia on women driving. Twitter data revealed a broad range of supporting, opposing, and neutral opinions on the government granting women the right to drive in Saudi Arabia. Twitter has become a medium where users freely tweet their opinions. Before the government order, Aldayel and Azmi [36] and Altoaimy [6] claimed that the ban on women driving was openly discussed. Hence, when the government granted women the right to drive, the Saudis were expected to express their views on Twitter.

Second, our study addressed the social changes by using the DOI stages. As stated in Section 1, our choice of DOI is a suitable match with the DOI definition. Moreover, DOI theory has been the subject of many classic studies in marketing, economics, sociology, and information technology [4]. Innovation is central to society's evolution, and DOI uses a stage conception to analyze whether and how innovations are adopted: the character and factors associated with each stage reduce the complexity of analysis and help improve the findings produced [37]. Several studies have investigated DOI and social media [38]. For example, Koçak et al. [3] addressed social media in general, and Chang [2] studied hashtags to use on Twitter. Ma et al. [1] used the DOI framework to investigate factors that influence news sharing on social media platforms. Burgess and Paguio [37] examined the adoption of information and communications technology (ICT); a portion of the ICT analyzed was social media applications. Similarly, Burgess et al. [39] used DOI to examine social media adoption in five DOI stages among small businesses.

DOI comprises five stages, wherein an innovation is adopted and accepted by a community: "knowledge, persuasion, decision, implementation, and confirmation." *Knowledge* is when an innovation is seen by an individual; *persuasion* is when an individual forms positive or negative opinions about the new idea; *decision* is when an individual decides to adopt or reject the innovation; *implementation* is when an individual makes use the new idea and adopts it; and *confirmation* is when an individual looks for more support to solidify his decision regarding the innovation [3] (Fig. 1).

Our approach followed the model suggested and outlined by Radford and Joseph [12]; theories related to the machine learning approach, and the theory of out mapping the result of machine learning to the five stages of DOI and was inspired by the study by Burgess, Sellitto, Cox, Buultjens, & Bingley [39].

Fig. 2 presents our overall research methodology, where theory-in was mainly mapped to sentiment analysis, and theory-out was assigned to the DOI adoption stages.

3.1. Data gathering and exploration

The collected data for our study comprised Arabic tweets written in Saudi dialect. The data were collected by using R code and Twitter API [33] from September 26 to 30, 2017 (the week after the government granted women the right to drive). Seven Arabic hashtags active during that period were used to retrieve the tweets. R script was used to obtain many tweets so that valid results and insights could be derived.

Overall, 150,000 tweets were obtained, of which 30,000 used # (The king supports women driving) الملك-ينتصر-لقيادة-المرآه, the first active hashtag. In addition, 20,000 tweets were retrieved from each of the remaining seven hashtags (Table 1). We observed seven trending hashtags associated with women driving. These hashtags helped us analyze and understand individual and community attitudes toward this new direction for Saudi Arabia. However, tweets for active topics also often contain advertisements, repetition, or unwanted material. This phenomenon creates a substantial burden when obtaining and cleaning data, particularly when text is specifically written to express an opinion. In addition, the use of Arabic adds another challenge to pre-processing.

3.2. Data preparation and pre-processing

Data cleaning and pre-processing before text analysis is a critical step to obtain accurate results [20]. Fig. 3 presents the process used to prepare and build our model classification approach. For processing, we used Java code and Kutool [41], a data pre-processing plugin for Microsoft Excel.

The steps were as follows:

1. Eliminate all retweets from the collected data to retain the original tweets written by a user and avoid double counting.
2. Exclude tweets that included URLs or media, because they might contain unrelated material.
3. Remove broken lines, user names, punctuation marks, emoji, and hashtag names.
4. Normalize some tweets to gain a unified shape of the letters [21]. The set of letters that includes (أ, و, ي, ة) has many representations in Arabic. Therefore, we converted (إ, آ,أ) to (ا), (ى) to (ي), (ة) to (ه), and (ؤ,ئ) to (ء).
5. Split the text of the tweets into individual words in sequence (tokenization).

After cleaning and pre-processing, 14,777 tweets remained. Most were for #الشعب_يويد_قىاده_المراه, annotated as a positive hashtag. The lowest number of tweets was for #قىادة المرأة, considered a neutral hashtag.

3.3. Sentiment annotation

Data annotation, the core task of sentiment analysis, must be performed before the model-building phase, to train and test the classifier. Sentiment annotation is the process of annotating data according to sentiment [42]. In this study, we classified tweets into three categories: *positive* (support for women driving), *negative* (opposition to women driving), and *neutral* (neither support nor opposition for women driving). In addition, an *undefined* label was used for tweets without a clear meaning [21].

The annotation task was assigned to three individuals: two were the third and fourth authors of this paper. Guidelines for annotations were based on the work of Al-Twairesh et al. [21] and Cambria et al. [42]; because they extensively pre-processed Arabic tweets. Furthermore, we developed more guidelines after observing the Twitter data suitable for this study.

The labeling guidelines for annotators were as follows:

- *Sarcastic tweets*: A typical mix of positive and negative words that confused the classifier [33,47]. As a result, we labeled these tweets *unidentified* [42]; these types of tweets are beyond the scope of our research.

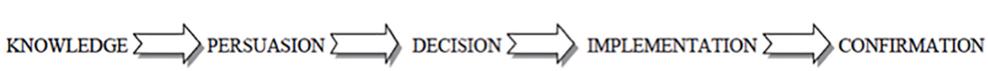

Fig. 1. Diffusion of innovation theory. From Degerli et al. [40].

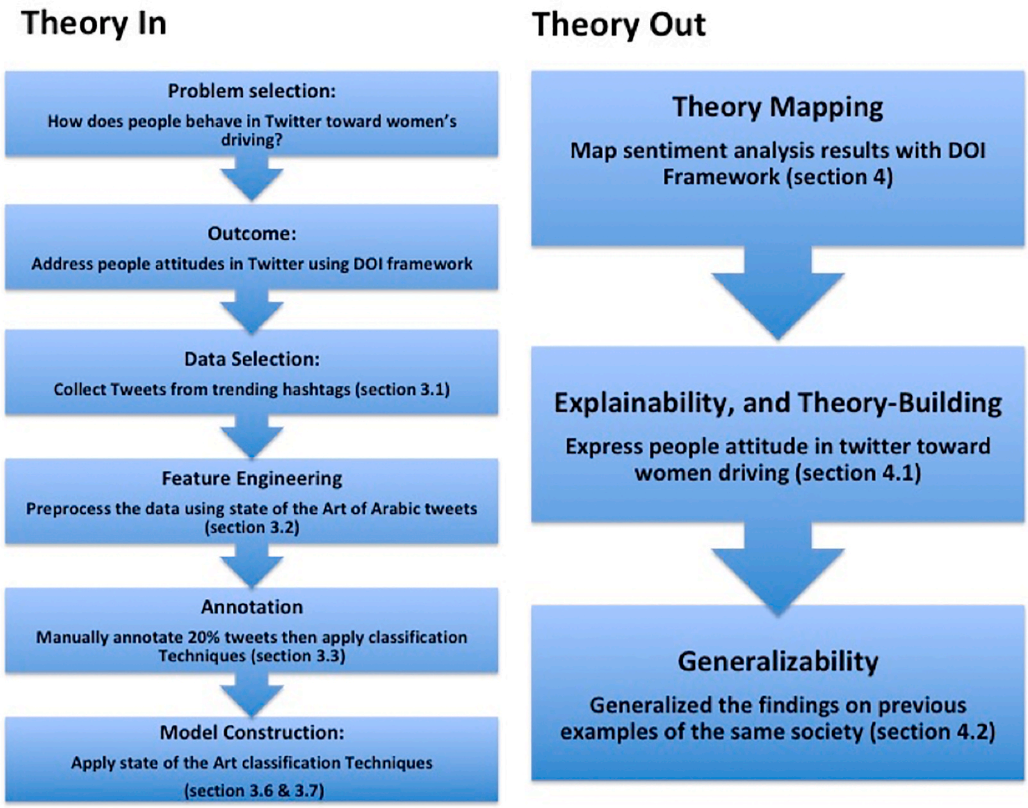

Fig. 2. Research methodology.

Table 1
Total number of tweets after cleaning and pre-processing.

#	Arabic hashtag	Opinion	English translation of hashtag	Collected tweets, *N*	Tweets after data cleaning, *n*
1	#-نحن-بنات-سلمان-لانريد-القيادة	Against	We are Salman's daughters; we refuse to drive	20,000	2470
2	#-الشعب-يرفض-قيادة-المرأة	Against	The nation refuses to allow women to drive	20,000	1289
3	#-الشعب-ضد-قيادة-المرأة	Against	The nation is against the freedom of women to drive	20,000	3634
4	#-الملك-ينتصر-لقيادة-المرأة	Support	The King supports the freedom of women to drive	30,000	1266
5	#-الشعب-يؤيد-قيادة-المرأة	Support	The nation supports the freedom of women to drive	20,000	4629
6	#-قيادة-المرأة	Natural	Women driving	20,000	489
7	#-السماح-لقيادة-المرأة-للسيارة	Natural	Women are allowed to drive cars	20,000	1000
Total				150,000	14,777

- *News tweets*: News was identified as neutral [21].
- *Perspectives*: Sentiment based on the writer's, not the annotator's, opinion [21].
- *Ambiguity*: If the tweet was unclear, it was labeled *unidentified* [21].
- *One-word tweets*: Sentiment for one-word tweets depended on the hashtag; all one-word tweets were annotated as unidentified.

The amount of data collected was large; hence, we annotated a sample comprising 20% of the total tweets (2955 tweets). We used these data to train classifiers by using labeled data to build an accurate classification model and predict and label the remainder of our dataset. To prepare the sample, we randomly selected 20% of the tweets associated with each hashtag. First, two of the annotators annotated all the tweets. Next, they met with the third annotator to decide on the sentiments related to the tweets. Table 2 presents the number of tweets selected for each hashtag.

After manual annotation, of all the tweets, 45.5% were positive tweets, 33% were negative tweets, 8.56% were neutral tweets, and 13.98% were undefined tweets. Table 3 presents the final results of the annotation.

3.4. Hybrid sentiment analysis approach

We used a hybrid sentiment analysis approach that combines the lexicon-based and machine learning methods. Because our corpus mainly contained Arabic text, we used AraSenTi-Lexicon developed by Al-Twairesh et al. [15]: it contains 225,303 Arabic words and phrases and their polarities in two merged lexicons, namely, the Liu lexicon [43] and the MPQA lexicon [44]. We also used the AraSenti-PMI package generated from the AraSenTi-Tweet Corpus, a Saudi dialect lexicon.

We applied the hybrid approach in 2 steps; the first step was by using the lexicons in the feature selection stage to identify more features that can enhance the accuracy of the final results. The second step was by feeding the training data after the feature selection process to different machine learning classifiers, which approved their efficiency in the literature (SVM, Naïve Bayes, IBK). Then, we classified the rest of the data (testing data) by the best classifier to detect Saudi society's

Fig. 3. Process used to prepare and build the model classification used in this study.

Table 2
Number of tweets selected from each hashtag for annotation.

English translation of hashtag	No. of tweets selected for annotations
# We are Salman's daughters; we refuse to drive	494
# The nation refuses to allow women to drive	257
# The nation is against the freedom of women to drive	727
# The King supports the freedom of women to drive	253
# The nation supports the freedom of women to drive	926
# Women driving	98
# Women are allowed to drive cars	200

Table 3
Final results of the annotation.

Class	Results	Ratio
Positive	1314	44.47%
Negative	975	32.99%
Neutral	253	8.56%
Undefined	413	13.98%
All	2955	100%

opinions regarding women's driving decisions.

During pre-processing, the data were not stemmed (the process of removing prefixes and suffixes to obtain root words). The use of AraSenTi-Lexicon, which contains words and phrases written in Saudi dialect, obviated the need to perform stemming and allowed us to match the words in our data with lexicon words [15]. Notably, our tokenization words matched with lexicon words. The second part of our hybrid approach used a machine learning methodology to build a classifier model to predict the sentiments of the remaining corpus.

3.5. *Feature selection*

Annotated data were prepared in an Attribute-Relation File Format (ARRF) file [44]. We wrote a Java code to build our ARRF file based on AraSenTi-Lexicon, which was split into three files (AraSenti-PMI, MPQA_ar, and bingliu_ar) to identify more features of the data.

The following are the features of our ARRF file:

- Tweet-TXT string contains the tweet text.
- Tweet-Length contains the number of words in each tweet.
- Has-Negation indicates whether the tweet contains a negation word, based on a list of negation words identified in the lexicons identified. The value for this attribute is either *yes* or *no*.
- Has-Positive-Word indicates whether the tweet has a positive word, based on the AraSenti-PMI lexicon file. The value is either *yes* or *no*.
- Has-Negative-Word indicates whether the tweet has a negative word, based on the AraSenti-PMI lexicon file. The value is either *yes* or *no*.
- Has-Positive-MPQA indicates whether the tweet has a positive word, based on the MPQA_ar lexicon file. The value is either *yes* or *no*.
- Has-Negative-MPQA indicates whether the tweet has a negative word, based on the MPQA_ar lexicon file. The value is either *yes* or *no*.
- Has-Positive-Liu indicates whether the tweet has a positive word, based on MPQA_ar. The value is either *yes* or *no*.
- Has-Negative-Liu indicates whether the tweet has a negative word, based on MPQA_ar. The value is either *yes* or *no*.
- PositiveWordCount: the sum of identified positive words in a sentence.
- NegativeWordCount: the sum of identified negative words in a sentence.
- Sentiment: the sentiment of each tweet: positive, negative, or neutral.

In this first part of our research, we have extracted features of tweets by using a lexicon approach; next, we used them as input features for the machine learning approach, as explained in the next subsection.

3.6. *Predictive model training and building*

The classification model used for this study was built by using WEKA software, a well-known data-mining tool [44]. As previously mentioned in the literature review [15,36,45], the SVM classifier is generally acknowledged as the best technique for sentiment analysis. The SVM algorithm represents text as points in space, to differentiate between classes with a clear margin. The core idea is to find the best hyperplane suited to separate document vectors in one class from vectors in other classes [18].

We trained the SVM classifier on our data with 10-fold cross-validation for testing. The SVM predictive model achieved a high, acceptable accuracy of 76.48%. The obtained true recognition rates for sentiment were 80.4% for positive, 65.3% for negative, and 99.2% for neutral. Neutral classification had the highest precision and recall for the three classifiers despite it having the least amount of tweets.

3.7. *Evaluation*

In this subsection, we compare the different measures of accuracy, precision, recall, and *F*-measure. *Accuracy* refers to the properly classified sentiment ratio; *precision* shows the proportion of correctly classified positive instances of all positive predictions; *recall* is the percentage of true positives with respect to the entire positive prediction; and *F-measure* provides the equal weight of precision and recall. These measures were calculated as follows [34,48]:

$$Accuracy = \frac{(TP + TN)}{(P + N)} \tag{1}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

where P is the number of positive records, N is the number of negative records, TP is the number of records correctly classified as positive, TN is the number of records correctly classified as negative, and FN is the number of records misclassified as negative [34].

$$F - measure = \frac{(2 * \text{Precision} \ * \ \text{Recall})}{(\text{Precision} \ + \ \text{Recall})} \tag{4}$$

We applied different classifier techniques to our dataset, including SVM, NB, and IBK. NB is a probabilistic classifier that uses Bayes's theorem [46]; IBK categorizes objects on the basis of their surrounding environment [46]. All models were built by using 10-fold cross-validation. Table 4 presents the calculated evaluation measures obtained for three classifiers.

In addition to having the highest *F*-measure results, SVM achieved the highest overall accuracy among the techniques. The SVM model of annotations for 20% of the trained data was applied to the remainder of our corpus, to predict the class label for each tweet. The remainder of the dataset (11,822 tweets) was prepared as an ARRF file with the same features as the annotated data file. In addition, we followed the same methodology reported in Section 3.5. Table 5 presents the predictive results.

The prediction process did not obtain neutral classifications, despite this category having the highest recognition rate. Predictive sentiments included positive and negative tweets; 69% of the predictive data were classified as positive tweets and 31% as negative tweets. This result might be because there were few neutral classifications that were not as obvious to the classifiers. Nonetheless, the neutral class did not offer substantive information for the analysis of individuals' opinions toward granting women Saudi Arabia the right to drive.

4. Results and discussion

Our research contributes to the body of sentiment analysis of individuals' opinions when governments issue new rulings. It anticipated individuals' attitudes toward new innovation in terms of adoption or rejection. Moreover, the practical significance of our study is linking Twitter sentiment analysis with DOI adoption stages, called CSS. Our analysis will help guide the Saudi government to anticipate the spread of further innovations and plan for the acceptance rate of any new idea. Our result will also help analyze the reaction of a conservative society when experiencing a new cultural change and might help similar societies predict individuals' reactions when significant changes are introduced into the culture.

Our dataset contained 14,777 tweets. During the annotation process, we discarded 413 tweets annotated as undefined sentiments, resulting in 14,364 tweets. We calculated the final results for each sentiment by combining the annotated data results with the predictive data results. Table 6 presents the final classification results for all tweets.

The results achieved 76% accuracy, with positive opinion classifications forming 60.6% of the collected data. Notably, 1.8% of tweets offered neutral opinions and was identified during the annotation process. Negative opinions represented the remaining tweets (37.6% of our dataset).

Researchers have applied DOI theory with social media. For example, Koçak et al. [3] compared the five stages of DOI with the decision, approval, and expansion processes associated with social media usage. The authors argued that individuals first learn how to use social media and exchange information (the knowledge stage) and then decide to use social media and become more psychologically involved in relating to and communicating with others (the persuasion stage). By registering their user name with a social media service, individuals decide to participate in a new communication medium (the decision stage), and by interacting with others, they become part of a group and feel satisfied with the medium (the implementation stage). If individuals feel that their privacy has been compromised, they can abandon or accept this idea (the confirmation stage). Using this staging system, the authors mapped in detail the social media usage into DOI stages. The studies by Burgess and Paguio [37] and Burgess et al. [39] have employed semistructured interviews and analyses using Rogers's principles. They have classified business owners' adoption of social media (Facebook, Twitter, and YouTube) into DOI stages. For example, for Twitter, the authors reported on the number of users who did not know enough about Twitter as (the knowledge stage) to be persuaded of its benefits (the persuasion stage). Next, they reported the number of users who decided to adopt (the decision stage).

Also, the authors reported users' opinion of being unsure of its effectiveness or wasting their time (the implementation stage); finally, in the confirmation stage, they reported users' views on the usefulness of Twitter.

On the basis of the aforementioned papers [37,39] that classified the adoption of business owners into DOI five stages, we used a similar approach. However, instead of mapping the interviewed results, we based our data analysis on Twitter by employing a hybrid approach (lexicon and machine learning) in DOI stages. In the next paragraph, we present our results based on Rogers's framework [4].

Table 7 shows Rogers's classifications in different stages for supporters of the governmental order.

Knowledge: The Saudis already knew about this topic. Women drove publicly in 1990 to protest for their right to drive, and subsequently, the ruling of banning women to drive was established in the kingdom. The ban was accepted by society because when women drive, they interact with unrelated male relatives. At that time, in the closed society of Saudi Arabia, a woman driving was considered having a shameful social practice. Later, the #women2drive movement was addressed in social media by groups of activists using various means to make their voices heard [6]. In 2008, Saudi women signed a petition and sent it to their leader (King Abdullah) to allow them to drive. In 2011, advocates re-launched the #women2drive campaign. This campaign used social media sites such as YouTube, Facebook, and Twitter to spread their messages, gain support, and defy this ban [26]. Hence, the prior acts were not successful because Saudi society was not ready. Therefore, in

Table 4
Comparison of sentiment analysis classifiers.

Classifier	Accuracy	Class	Precision	Recall	*F*-measure
SVM	76.48	Positive	75.7	80.4	76.3
		Negative	71.1	65.3	
		Neutral	100	99.2	
Naïve Bayes	70.26	Positive	68.6	79	69.7
		Negative	64.3	51.8	
		Neutral	99.6	96	
IBK	62.39	Positive	66.6	66.2	62.8
		Negative	53	61.1	
		Neutral	91.1	62.4	

Table 5
Prediction results.

Predictive Class	Results	Ratio
Positive	7400 tweets	69%
Negative	4422 tweets	31%
All	11,822 tweets	100%

Table 6
Final classification results for all tweets.

Sentiment	Results	Ratio
Positive	8714	60.6%
Negative	5397	37.6%
Neutral	253	1.8%
All	14,364	100%

Table 7
Stages of adoption for supporters.

Knowledge	Persuasion	Decision	Implementation	Confirmation
No data	Two hashtags translated as #Individuals support women driving #The king won for women's right to drive	4629 (approval) 1266 (approval)	• Strong desire to drive • The right to drive → 60.6% (approved)	No data yet

this stage (Knowledge), almost everyone in the society knew about it, and discussing it further was pointless. Saudi society knew about women banned from driving and accepted it. Saudi society is very conservative, and its members do not easily accept changes unless they take their time and witness how others react to these new changes [6].

Although many individuals were aware of the government order permitting women to drive, they did not take it seriously because women had been banned from driving for decades. As a result, there was little motivation to uncover further details. As stated by Rogers [4]; "Media channels are more significant at the knowledge stage."

Persuasion: After the government lifted the ban and permitted women to drive, two hashtags were created to persuade individuals to support this innovation. Moreover, the words used in the hashtags implied sentiments of victory and happiness, and the old hashtags created in 2011 "#women2drive" were used again in 2017. These hashtags became slogans [25]. As stated by Koçak et al. [3]; in this stage, individuals cope with feelings associated with a new idea, and in the case of Saudi society was more toward joy and success.

Decision: In this stage, individuals attempted to publicize their opinion by using hashtags that supported the women's movement [4]. The tweets written on this topic (5895 tweets in less than one week) demonstrated substantial support for the governmental order. The high degree of participation (i.e., 40% of unique contributions) indicated that Saudi society was eager to move forward on this right for women. Moreover, some tweets spoke directly to the king and asked him to grant women more of rights that men have [6].

Implementation: During this stage, the decision is put into action [3]. In our case, individuals approved a course of action by expressing their support through written tweets. Notably, one user wrote, "We started to train our mother on driving her car to enable managing her own driving business." This tweet was written by a woman's sons, indicating that even men were excited about the change and exhibiting tendencies to quickly adopt the order, implemented in July 2018. Moreover, additional positive tweets were posted [28]. Additionally, as indicated in Altoaimy [6]; the tweets were from more supporters of this ruling and blamed the ban on the men and the religious authority.

Confirmation: During this stage, a decision has been made, and individuals seek support and reinforcement to complete adoption or change their mind and reject the innovation. However, because the collected and pre-processed tweets were posted before the order was implemented, we will analyze the effect after the order in further research.

Table 8 presents the stages of adoption of the opponents of the order.

Knowledge: As stated in the support stage, Saudi society is aware of this topic.

Persuasion: In this stage, three hashtags were developed to re-emphasize prior opinions and demonstrate the disadvantages of allowing women to drive (e.g., how it would cause problems such as car accidents and stress). Negative tones and pejorative words were used to convey these messages [3]. Notably, as stated in Ref. [28], the tweets against women driving were mostly by women who claimed that driving is men's responsibility. Moreover, some who opposed women driving stated that it might harm the duties of men and the balance between men and women in society. Furthermore, opposers view the limits placed on women driving as "a balance between the rights and duties of men and women as prescribed by Islam and necessary to uphold honor and family values" [6].

Decision: Posters highlighted the opposition to the movement and expressed unfavorable attitudes [3]. In less than a week, 7393 tweets were posted by the opponents, with 50% unique participation. We posit that this group comprised the old generations who opposed granting women rights to protect them and that this group believed in the responsibility of a male guardian to manage and protect their females.

Implementation: We conclude from the written text that individuals used threatening phrases against this new idea. One poster wrote, "Avoiding perversion is favored and then brings benefits. Women's driving is a perverse act. God bless whoever tweeted to oppose women's driving." Although opposing tweets formed approximately 50% of the total participation for the three active hashtags, sentiment analysis revealed approximately 37.6% accuracy. Opponent sentiment of only 37.6% could be due to the supporters of the order using opponent hashtags to encourage women to drive and attempt to persuade the opposition of the benefits of granting women the right to drive. This may have caused the accuracy to decrease from 50% to 37.6%, illustrating the value of sentiment analysis (i.e., not considering only the total number of tweets with a specific hashtag). It also reveals the value of text mining in gathering sentiments.

Confirmation: There was little information on this new act in Saudi society when we collected the data. Therefore, we must collect and analyze its effects on Saudi families specifically and Saudi society in general. This is will be the topic of our next research endeavor.

Table 9 presents data for individuals with a neutral stance toward adoption.

Knowledge: This group waits for society to form a popular opinion and offers no decision.

Persuasion: In this stage, individuals attempt not to rush to a decision. However, after the government order, they expressed their opinion by using two neutral hashtags that did not correspond with the hashtags of either the supporters or the opponents.

Decision: Individuals tend to read what others have written and respond in a manner that expresses their indifference to the topic. Some participants wait and see what others express. The amount of these tweets formed approximately 10% of the total tweets.

Implementation: These users' tweets indicate that they were passive about the order. For example, one user wrote, "I did not agree or disagree because I do not care. I have someone to take care of my needs. I do not want to add more responsibilities on my shoulders plus I fear car's driving." Neutral tweets formed approximately 10% of the total participation of people tweeting for the two active hashtags; text tokenization and lexicon matching of the neutral words demonstrated an approximate 1.8% accuracy, which indicates that participants might be more likely to be supportive than neutral.

Confirmation: According to the second author, an expert in Saudi

Table 8
Stages of rejection for opponents.

Knowledge	Persuasion	Decision	Implementation	Confirmation
No data	Three hashtags translated as #Individuals against women driving #Individuals reject women driving #We are the daughters of Salman and don't want to drive	3634 (opposition) 1289 (opposition) 2470 (opposition)	-Avoiding perversion is favored versus bringing benefits -Women's driving is a perverse act → 37.6% (opposed)	No data

Table 9
Stages of acceptance for neutral adoption.

Knowledge	Persuasion	Decision	Implementation	Confirmation
No data	Two hashtags translated as #Women are allowed to drive #Women driving	1000 (neutral) 489 (neutral)	-Scare to drive -Don't care -From our machine learning →1.8% (neutral)	No data

sociology, this group will be the last to adopt. However, further investigation is necessary after women start driving.

4.1. Explainability and theory building

We attempted to answer our research questions by mapping the sentiment analysis results to the DOI dissemination process that addresses individual opinions regarding explainability outputs. We observed that most individuals could be classified into Rogers's [4] stages of persuasion, decision, and implementation. For the most part, opinions in this study were geared toward acceptance of the government order. The findings suggest that Saudi society is typically in the implementation stage (60% supporter accuracy). Furthermore, the majority of supporters' words eventually advance to the confirmation stage. The supporters were perhaps exposed to the social benefits of women driving in other countries. These supporters share "common meanings, a mutual subcultural language, and are alike in personal and social characteristics" [4]. Moreover, the supporters' tweets were more cognizant of the relative benefits for women, family, and society [4].

By contrast, the opponents reached the implementation stage, wherein they voiced their disapproval of granting women the right to drive. Furthermore, they focused on the disadvantages that women might experience while driving (e.g., accidents). Opponents tended to not be in the knowledge stage, because they did not consider that government preparation would ease the transition (e.g., establishing driving schools for women and training policewomen).

For individuals with neutral opinions, we speculate that their opinions will gradually change as the benefits and positive outcomes of the decree start to materialize.

4.2. Generalizability

Individuals often adapt slowly to new ideas, with little traction occurring until social and economic benefits become evident. For example, Saudi Arabia prohibited television satellite dishes when they first became available, but today, they are used in almost every household. Similarly, the mobile phone camera was censored upon its initial release. Consequently, we anticipated that the right of women to drive in Saudi Arabia would become acceptable to subsequent generations. Furthermore, acceptance of women driving for current generation would indicate an ease of acceptance of new cultural changes among conservatives in society, especially among those in Arab regions.

Our research linked sentiment analysis with one of the sociology theories: DOI theory. According to our review of the literature, we think our study is the first to be conducted on society while using a Twitter data source. Our approach was not designed to assess society's attitude on this topic or similar topics. Nevertheless, our approach advance beyond that aim because the order granting women the right to drive is the first ruling of many promised societal changes; this form of analysis advances this paper from an assessment of social media communication to that of CSS.

The second part of this research will be to study what occurred after the ruling was implemented. We also want to study the characteristics of the early adaptors because we know that members of any society will have different opinions on innovations. Therefore, all members of Saudi society will not adopt women driving at the same time or react in the same manner because individuals have various priorities, opportunities, and conditions. We would like to predict how to expand this innovation among Saudi individuals and to anticipate similar reactions when similar rulings are introduced to Arab regions.

The limitation of our study is that not many studies have used social media analysis in the context of sociology theory. We hope this new approach of CSS will be the starting point for further research.

5. Conclusion

This study adds to the literature by conducting sentiment analysis of Arabic social media. We used Rogers's [4] innovation–decision process to demonstrate the utility of social system theory in social media analysis. In addition, the use of Rogers's stages allowed us to understand issues that affected societal perceptions of the right of women to drive. Our research merged technical and theoretical aspects of Rogers's framework, to analyze the benefits to society. Regarding the technical contribution of the article, 150,000 tweets from seven active hashtags were collected over a short time, providing a description of societal opinion at the beginning of a major initiative. The high number of supporters was not surprising because of the long-standing debate on the right of women to drive. Moreover, most individuals were determined to remain in the implementation stage in their acceptance of the initiative.

This study's results are similar to those of [6,27,28] studies that indicated that Saudi society would gradually accept and support women's rights. Consequently, we visited Twitter's trending hashtags on June 24, 2018, after women started driving and all of the posted tweets were positive. Our second research paper will conduct a survey and semistructured interview, and new findings will be analyzed.

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