Deciphering Medical Errors: What Matters for Patients on Social Media

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Abstract

This study investigates medical errors, germane to patient safety, from the patient's perspective. We analyzed social media data, Twitter posts, about patients' perspective on their medical experiences, which have been rarely translated into a systemic and rigorous research result. Employing a combined-research method, the qualitative content analysis and the analytical automatic categorization of text data, we analyzed 1,806 tweet entries during four and half years, from December 2017 to June 2022. We identified the categories and consequences of medical errors, critical from the patient's perspective. The common medical errors include ignorance, misdiagnosis, negligence, and medication errors. The manifested consequences of medical errors include medical complications, death, and paralyzed/disabled. The study emphasizes the importance of patient's experience in complementing other error reporting systems and mechanisms, that have been utilized by healthcare professionals for establishing more meaningful recommendations for reducing medical errors.

Keywords: Medical Errors, Social Media, Patient Safety, Content Analysis, Analytics.

1. Introduction

Medical errors are the leading cause of death in healthcare settings (Wallis et al., 2019) with as many as 98 thousand to 251 thousand hospitalized patients die in the United States every year from medical errors and such errors result in billions of dollars in financial losses (Pereira-Lima et al., 2019). Medical errors and patient safety have also been major challenges for the healthcare systems around the world (Schwappach, 2014) especially during the pandemic (Hay-David et al., 2020). Healthcare professionals strive to provide quality care and improve patient safety (Wallis et al., 2019). Patient safety is related to means of avoiding medical errors and the associated significant negative effect to patients (Sultana et al., 2018), despite the fact that some of these errors are difficult to avoid (Wallis et al., 2019).

Much progress has been made in healthcare research on medical errors and provided pragmatic recommendations. Nevertheless, the medical errors continue to plague the healthcare system, particularly patient's wellbeing and health. As the healthcare system is complex and composed of multiple stakeholders, networks and evolving technologies, the search for solutions needs a fresh look. Indeed, understanding, preventing, and reducing medical errors requires inputs from different stakeholders, particularly the patients, (Nakhasi et al., 2012), where patients can report safety-related problems that are related to their care (Armitage et al., 2018). This is the lever that we explore the patient's perspective on medical errors. We intentionally chose to use the data from a social media platform, where patients and their families can voluntarily and directly access, express, and publicly share their experiences.

Characterizing the extent of medical errors is considered the first step to address these errors (Lind et al., 2020). Such characterization requires understating different factors involved in the production of the medical error, which are directly related to the task, environment, process, and individuals (Pipino & Lee, 2011). Medical errors are often collected through error-reporting systems, which are considered critical components of healthcare systems (Nakhasi et al., 2019). However, these data-driven solutions do not effectively involve patients as well as other parties as part of the process for reporting and collecting information about medical errors (Nakhasi et al., 2019; Xie et al., 2017).

Recently, there has been a growing discussion about how the public share opinions about medical conditions and treatment experiences on social media platforms, such as Twitter (Bardhan et al., 2020). Such shared information and experiences are required to

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improve patient-centered healthcare (Xie et al., 2017). Comments and sentiments in discussion forums have been used for medical error monitoring and drug safety surveillance (Bardhan et al., 2020). Accordingly, social media is one important source of information that could help complement our understanding of medical errors and patient safety while at the same time involve patients, family members, relatives, and the public (Nakhasi et al., 2019). The approaches (Lind et al., 2020; Silva et al., 2019; Cooper et al., 2018; Singh et al., 2013) for identifying medical errors and establishing medical errors taxonomies and classifications are based on randomized controlled trial of computer and paper reporting methods (Dovey et al., 2002), a de-facto standard approach (Silva et al., 2019), systematic literature review (Cooper et al., 2018; Elder & Dovey, 2002), review of medical records, medical documents, incidents reports, and cases (Keselman & Smith, 2012; Kopec et al., 2004; Kuo et al., 2008; M. a. B. Makeham et al., 2008; Rosser et al., 2005; Singh et al., 2013; Tran & Johnson, 2010), comparative analysis of existing errors (Taib et al., 2011), interviews (Buetow et al., 2009; Hakimzada et al., 2008), and ethnographic observation (Hakimzada et al., 2008).

Social media platforms, such as Twitter, are becoming increasingly important platforms for sharing health-related information. Such platforms are becoming a place where patients voice their experiences (L. McDonald et al., 2019). Yet, a small percentage of such information is currently used to improve the quality of care and patient safety (Xie et al., 2017). Few studies have attempted to address medical errors and patient safety by analyzing social media content (Nakhasi et al., 2012, 2019).

In summary, the existing literature has benefitted from understanding medical errors from various perspectives, using various research methods and data sets, and yielded useful insights. Such studies have shown that social media data can be a valuable source of information about medical errors from the patient's perspective (Nakhasi et al., 2019). In addition, big-data approaches for analyzing social media data can help advance the field of patient safety and medical errors (Xie et al., 2017). Furthermore, analysis of social media data for the identification of medical errors can help health care systems and providers to identify such patients and communicate with them about their experiences with medical errors (Nakhasi et al., 2019). Medical errors, however, continue to plaque the healthcare system, particularly patients. To understand the evidence of medical errors and their consequences at a deeper level, the direct and up-close experience of many patients and the systemic analysis are critical. The use of social media to investigate medical errors and patient safety (Nakhasi et al., 2012, 2019) renewed the attention to medical errors, and the untapped direct experience by a large number of patients.

These studies, however, were limited in terms of the number of social media posts that were analyzed, thus limiting the generalizability of the findings. For example, Nakhasi et al., (2012) have analyzed a total of 770 tweets, while Nakhasi et al., (2019) analyzed a total of 1006 tweets; where both studies considered any geographic area in the data collection process. In addition, some of these studies analyzed only self-identified negative experiences with healthcare providers and ignored the voice of the patients' families and friends. Furthermore, these studies adopted a manual approach to analyzing social media data, which limits leveraging the large-scale data on social media platforms, and, thus, limits the publicly reproduceable opportunities for future research to endorse or refute their findings.

This paper aims to fill the gap in research as illustrated above and provide insights on medical errors based on capturing first-hand experience, directly from the patients, their families, and friends. We analyzed social media data to explicate the experiential evidence, and identify what the patients consider as medical errors, consequences as voiced and reported voluntarily by the patients, key healthcare stakeholders. This first-hand reported experience can complement other error reporting systems and mechanisms that have been utilized by healthcare professionals for establishing more meaningful recommendations for reducing medical errors. The paper contributes to research and practice in three ways. *First*, the study captures and exploits the large-scale, volunteered data from social media, which represent the critical and experiential evidence from the patient's perspective. *Second*, employing a combined-research method benefits from the more comprehensive and in-depth qualitative content analysis; while gaining from the more systemic and rigorous analysis of longitudinal large-scale data sets, exploiting the analytical power of the automatic categorization method. *Finally*, the study provides an example of future research into medical errors and patient safety with a critically framed and rigorous analysis and provides important input to healthcare practice for considering more focused and meaningful recommendations that can affect and impact patients directly.

2. Background and related work

Medical errors encompass various different classifications and taxonomies (Silva et al., 2019;

Cooper et al., 2018; Singh et al., 2013; Rosser et al., 2005; Dovey et al., 2002). Silva et al., (2019) developed a taxonomy for medical errors that consists of generic use errors types and medical device use errors types, where the medical device use errors types were further classified into mistakes, slips, lapses, and shortcut errors. While Cooper et al., (2018) developed a new system for classifying harm severity. For example, a qualitative study by Rosser et al., (2005), categories of medical errors were mainly related to administrative failures, investigation failures, treatment delivery lapses, miscommunication, payment systems problems, error in the execution of a clinical task, wrong treatment decision, and wrong diagnosis. Singh et al., (2013) have determined the disease and diagnostic method involved in confirmed medical errors cases.

Buetow et al., (2009) developed a three-level patient errors taxonomy, with the first level consists of two main groups, namely action errors and mental errors. Other errors classifications and taxonomies reported in the literature consist of errors of identification (Hakimzada et al., 2008), medication errors including prescription, administration, documentation, and dispensing errors (Kuo et al., 2008). Another classification by Steele et al., (2006) consists of optical prescriptions, communication, administrative, appointments, equipment, clinical and other. Zhang et al., (2004) taxonomy consists of slips and mistakes at the execution level and evaluation level, while Kopec et al., (2004) taxonomy consists of human and structure/process errors, where human errors could be diagnostic, medication, clerical procedure, and treatment procedure errors. Table 1 summarizes the common types of medical errors.

Table 1. Summary of Common Medical Error Types

Medical Error Type	Reference
Administrative related	Tran & Johnson, (2010), Kuo et al., (2008), Steele et al., (2006), Rosser et al., (2005), Elder & Dovey, (2002), & Dovey et al., (2002)
Lapses	Silva et al., (2019) & Dovey et al., (2002)
Communication related	Tran & Johnson, (2010), Dovey et al., (2002), Makeham et al., (2008), Steele et al., (2006), Rosser et al., (2005), Rubin, (2003), & Elder & Dovey, (2002)
Knowledge and skills related	Tran & Johnson, (2010), Buetow et al., (2009), Makeham et al., (2002), & Rosser et al., (2005)
Medication and prescription errors	Keselman & Smith, (2012), Kuo et al., (2008), & Rosser et al., (2005)
Treatment errors	Makeham et al., (2008), Rosser et al., (2005), Rosser et al., (2005), Kopec et al., (2004), & Kopec et al., (2003)
Diagnosis errors	Singh et al., (2013), Makeham et al., (2008), Rosser et al., (2005), Kopec et al., (2004), Dovey et al., (2002), Kopec et al., (2003)
Clerical procedures errors	Kopec et al., (2004) & Kopec et al., (2003)
Process errors	Tran & Johnson, (2010), Rosser et al., (2005), & Elder & Dovey, (2002)

Brunsberg et al., (2019) studied the association between the rates of medical errors and physicians' depression and burnout and showed that depression was significantly associated with medical errors. Another study by Pereira-Lima et al., (2019) has systematically analyzed relevant literature related to medical errors and physician depression symptoms and found that the overall relative risk for medical errors increases with depression.

Harris & Peeples, (2015) analyzed whether demographic and system variables are considered predictors of higher risks of death by analyzing data from closed medical malpractice lawsuits. Finally, Kaissi et al., (2007) analyzed whether organizational culture and structure, and their fit have any effects on medical errors among medical practitioners.

A limited number of studies have utilized social media data to analyze public opinion about medical errors and patient safety. Nakhasi et al., (2019) have utilized Twitter as a source to analyze patients' perspective about medical errors. Data collected from Twitter related to patient safety was manually analyzed. Results showed that patients and family members were the ones reporting the errors. Errors reported were mainly procedural errors, medication errors, diagnostic errors, and surgical errors. A small percentage of tweets stated that patients and family members are planning to pursue a malpractice litigation. In another study, Nakhasi et al., (2012) analyzed Twitter data to identify medical errors, who caused them, as well as who reported the errors. Most of the errors were self-reported, while others were reported by family members, friends, colleagues, another patient, a medical provider, or an unknown source. Procedural errors and medication errors were the most frequently reported errors. Physicians, nurses, and surgeon were the most frequent error source.

A limited number of studies utilized social media data to better understand medical errors. Also, none of the existing studies utilized social media content to identify medical errors consequences. Finally, the current study utilized a mixed method approach compared to existing one that mainly relied on manual analysis, which is not efficient for large scale data analysis. Accordingly, this study attempts to utilize social media content to provide an overview of the public perception about medical errors which could complement information exists in error reporting system by providing a public perspective about medical errors and help better design processes and procedures that can help reduce medical errors.

We posit that the patients' experience and reports are likely to further illustrate the reality and scope of the issues related to communication, medication, treatments, and diagnosis (See Table 1), which patients directly observe and experience the impact. The analysis from this study can provide expanded insights into these categories. For example, non-communication or being ignored by doctors or nurses can be devastating to a patient; while the background process, system and data glitches and poor handoffs behind the scenes may not be caught by the patients directly. Patients will experience the consequences of possibly the majority if not all categories of medical errors, however. Among the topical categories identified in the literature (See Table 1), administrative and clerical procedures, process errors, knowledge and skill sets, and lapses are unlikely to be the major issues that patients notice directly, while they impact the patients.

3. Research Design and Methodology

Figure 1 showed the methodology followed in order to determine medical error types and consequences from Twitter data.

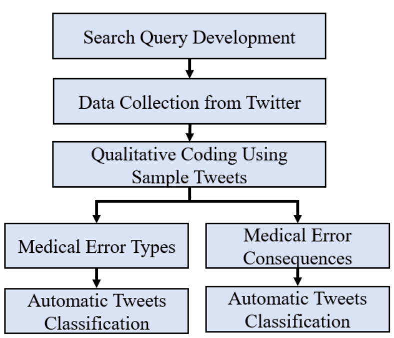

Figure 1. Research methodology

Twitter data was collected using a query developed based on existing literature as shown in figure 2. Tweets were collected from Brandwatch based on the criteria of having a combination of three words, with two of three keywords occurring near each other in the tweet based on the "NEAR/0f" criterion. Another set of keywords was excluded in order to reduce the number of irrelevant tweets.

((physician* OR doctor* OR nurse* OR surgeon* OR pharmacist) NEAR/0f (error* OR mistak* OR malpractic* OR disregard OR neglig* OR "messed up" OR fail OR ignor* OR messed OR "screwed up" OR "made a mistake" OR "was wrong" OR "gave me the wrong" OR misdiag* OR improper OR delay* OR "doesn't work" OR incorrect OR worse OR miss* OR damage OR destro* OR ruin* OR break OR broke OR hurt OR harm OR unprofessional OR inaccurate OR careless OR fault* OR untrue OR weakness)) AND (I OR my OR mine OR her OR hers OR his) AND (medica* OR health* OR well*) AND -(RT OR http* OR bill OR tobacco OR obesity OR alcohol OR suicide OR "drunk dnvang" OR poisoning OR accidents OR claim OR insurance)

Figure 2. Search Query

A total of 1,806 tweets, posted by users in the United States, were collected between December 2017 and Jun 2022. The timeframe was selected based on the current capabilities of Brandwatch, which give access to all data available through the system.

Qualitative data analysis has been used due to its ability to understand a phenomenon from the participants' point of view (Anderson & Aydin, 2005) and help making sure that results are grounded in the collected and analyzed data (Kelle, 2007). In order to identify medical errors and consequences from Twitter data, a random sample of tweets were selected for manual analysis using a quasi-randomization process (Cochran, 1946). In order to make sure that results are valid, reliable, and consistent, we have established inter-rater reliability to avoid any bias in the analysis process and making sure that researchers will end up with similar results. To do so, a random sample of 400 tweets were selected from the collected tweets and manually coded by two researchers. The qualitative analysis process consists of two researchers independently reading through the sample data and assign the appropriate type of medical error and consequences.

Once medical errors types and consequences are identified from the sample data using manual analysis, two separate classifiers, one for medical errors types and another for medical error consequences, were created in Brandwatch using the ReadMe algorithm developed by Hopkins and King (2010). The ReadMe algorithm attempts to focus on broad categorization of the entire set of tweets. The algorithm is also practical when researchers attempt to show how a set of tweets spread across different categories and provide unbiased text classification when compared to known classification techniques (Hopkins & King, 2010).

In general, the ReadMe algorithm does not focus on increasing the percent of tweets correctly classified into different categories but emphasizes social science goals which are mainly concerned with broad categorization of the tweets (Hopkins & King, 2010).

In this study, we trained two instances of the ReadMe algorithm to classify tweets into different medical errors and consequences categories by manually coding sample tweets into each predefined medical error type and consequence obtained from manual coding and used the trained models to classify the remaining tweets. In order to ensure that the models were trained properly and avoid any bias in the training process, a random sample of 60 tweets were manually labeled by two researchers. 30 tweets for medical error types, and another 30 tweets for medical error consequences.

4. Findings

Our analysis yielded (1) four categories of medical errors, and (2) three categories of the consequences of the medical errors: (1) Misdiagnosis, Ignorance, Medical Negligence, and Medication Errors; and (2) Medical Complications, Death, and Disability. The categories found are related to the actions and phenomena primarily based on the direct interaction with the patients and providers. Other factors, such as, process, knowledge, and background clerical errors were not expressed directly by the patients, in part, due to the fact that the patients may not have full access to, thus, the knowledge of such information. This notion might also be stemming from the commonly-held patient's belief that the providers will do no harm to patients and will be responsible for shielding against possible near-misses, handoff errors, clerical and process errors that involves data and information systems, standard protocols, and human resource management. These errors should have been caught and resolved by the providers in general before they affect the patients, based on the patients' perspective. Specifically, we observed that several medical errors that the existing literature identified, such as, administrative, knowledge and skills, process and clerical errors were not reported by the patients from the social media we studied. Below, we illustrate the detailed findings.

The search query returned a total of 1,806 tweets posted by 1,699 unique authors. Among those who shared their gender identity, 422 authors (45%) were males, and 507 authors (55%) were females.

Given the scope of the study, we have analyzed emotion in the tweets with respect to four categories, namely, anger, disgust, fear, and sadness. If no emotion is found, the mention will not be classified (*Emotions*, 2022). As shown in figure 3, the emotion analysis results show that 558 tweets (38%) were reflecting anger emotion, 394 tweets (27%) were reflecting sadness emotion, 342 tweets (23%) reflecting disgust emotion, and 169 tweets (12%) reflecting fear emotion. Overall, emotion analysis results reflect, in general, users' outrage about medical errors.

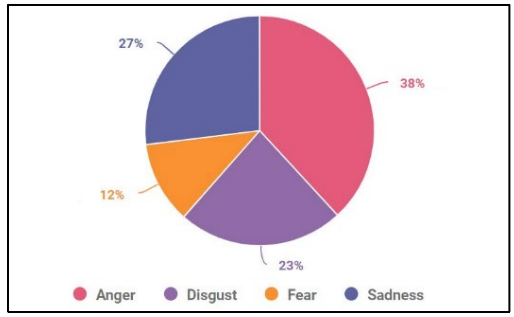

Figure 3. Emotion Analysis for Tweets

Figure 4 shows a word cloud for the tweets used in the manual analysis process to identify medical errors and medical errors consequences.

The separate manual qualitative analysis for medical errors and medical consequences results in Cohen's Kappa statistics of 91% and 93% for each analysis respectively, which reflects almost perfect agreement among the two raters among different raters (Landis & Koch, 1977).

Figure 4. Word Cloud for Tweets used Qualitative Analysis

Qualitative analysis using manual coding for the identification of medical errors from the tweets resulted in the identification of 4 main categories that reflect common errors by medical professionals and healthcare providers. The analysis yielded four categories, including *ignorance*, *misdiagnosis*, *negligence*, and *medication* errors.

Qualitative analysis using manual coding for the identification of medical errors consequences from the tweets resulted in the identification of 3 high level categories that reflect what medical errors could cause to patients. These categories included *medical complications*, *death*, and *paralyzed/disabled*.

To train the two ReadMe classifiers for medical errors and medical consequences, a sample of tweets were labeled by two researchers using the predefined categories. The process resulted in a Cohen's Kappa statistic of 83% for the medical errors classifier sample and 80% for the medical consequences classifier sample, which reflects substantial agreement, and almost perfect agreement among the two raters (Landis & Koch, 1977), respectively.

The medical errors classifier was able to identify 1,001 relevant errors tweets, while the medical error consequence classifier was able to identify 1,510 relevant consequences tweets. The relevant reviews were classified by the corresponding classifiers into the identified medical errors categories and medical errors consequences categories from the manual coding analysis.

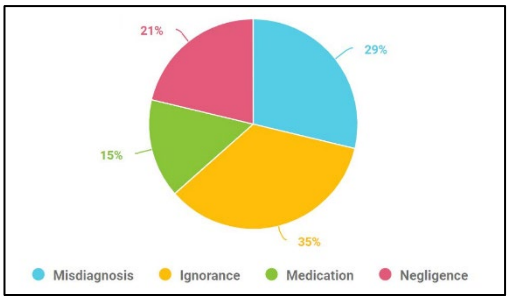

Figure 5. Distribution of Medical Errors per Category

The ReadMe classifier for the medical errors was able to categorize 1,001 tweets (55.5%) out of the 1,806 tweets into the four different medical errors categories. As shown in figure 5, there were 358 tweets related to ignorance (35%), 269 tweets related to misdiagnosis (29%), 219 tweets related to negligence (21%), and 157 tweets related to medication (15%). Appendix A shows example tweets for each category.

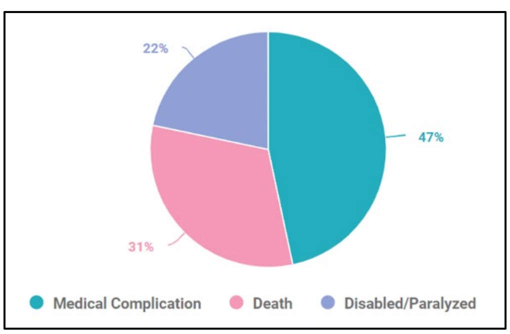

Figure 6. Distribution of Medical Errors Consequences per Category

The ReadMe classifier for the medical errors' consequences was able to categorize 1,521 tweets (84.2%) out of the 1,806 tweets into the three different medical errors consequences categories. As shown in figure 6, there were 710 tweets related to medical complications (47%), 481 tweets related to death (31%), and 330 tweets related to paralyzed/disabled (22%). Appendix B shows example tweets for each category.

5. Discussion

Data collection and analysis showed that social media platforms, such as Twitter, could be used as a source of information about medical errors and patient safety with respect to medical errors consequences, particularly experienced directly by patients and care taking families. The results showed that the medical errors discussed by the public focused on misdiagnosis, ignorance, negligence, and medication errors. Most expressed statements introduced here are the patients' direct experience with the medical providers such as doctors, nurses, and pharmacists. Patients and family members express publicly about the consequences of their negative experiences with the medical providers, by telling their stories about what led to the unexpected, terrible, and extremely damaging medical conditions for themselves or family members. As is the case, they do focus on what they experience and observe directly and may not include or understand the information related to the possible root conditions and the background contextual situations or information that the patients often do not have accessibility to read or observe.

Nevertheless, as patients are the key stakeholder group in the patient-centered healthcare system, analyzing and understanding the patients' story on the patient's experience will be the critical step towards deciphering medical errors, patient safety, and finding ways to prevent and reduce them.

Misdiagnosis occurs when the healthcare provider fails to correctly diagnose the patients and being mistakenly diagnosed as a different condition that the patient does not exhibit. Diagnosis errors could be related to delayed diagnosis, missed diagnosis, and wrong diagnosis (Kopec et al., 2004). Diagnostic errors could occur based on many different reasons: these include but not limited to lack of diagnostic testing (Zhang et al., 2016), healthcare professional inexperience and/or overconfidence (K. McDonald et al., 2013), fragmentation of care (Laugaland et al., 2011), lack of time with patients (Walsh et al., 2018), and lack of or delayed follow up (Singh et al., 2014).

Ignorance is another key issue that could lead to medical errors and usually happened when healthcare professionals such as physicians and nurses do not listen to the patient, ignoring a patient's comments, requests, and communications, ignoring the stated symptoms, or did not take the stated symptoms seriously. According to the collected tweets, some of the cases reporting ignorance by the healthcare professional were also related to patients' race.

Medical negligence is a type of medical errors that occurs when the medical professional fail to provide the adequate and proper care to the patient and fails to apply proper safeguards or measures, resulting in harm to patients (Kapur, 2022).

Medication errors are one of the widely discussed errors by the public as well as in the literature. These errors could be related to many aspects of the medication, such as incorrect medication, incorrect dose and refill issues, and drug interactions. A number of tweets reported issues related to patients being prescribed the ***wrong medication*** by the healthcare providers.

Incorrect dose was another issue reported by the tweets where some patients stated that the healthcare provider had administered an insufficient dose of medication or administrated or prescribed a dose that is more than the normal or known recommendations. Incorrect supply of medication is also reported when patients do not receive the correct dosage of specific prescription.

Drug interaction was another issue reported under medication errors where patients ended up having complications and allergic reactions because of a change in the ways a drug acts because of other factors.

The results showed that medical errors could lead to three main categories of consequences as expressed by the public. The medical consequences include: medical complications, death, and disabled/paralyzed.

Medical errors could lead to different kinds of ***medical complications***. A medical complication refers to any undesirable event or consequences that result from a disease, health condition, treatment, or therapy (Fahmy, 2019). Medical complications also include any "unexpected deviation from a normal treatment outcome" (Jokstad, 2019). Given that no comprehensive and agreed-upon taxonomies of medical complications are available, we considered any undesirable outcome of the diagnosis and treatment process as a medical complication except the cases of death and when the patient becomes disabled. Based on the manual analysis of tweets, medical errors could lead to different medical complications including but not limited to heart attacks and strokes, viral infections, damage to the patient body, such as, damage to hands and nerve damage, rapid weight gain, hearing issues, weakening the immune system, ruptured colon, decreases sensation, allergic reaction, bleeding, throwing up, and vomiting.

Medical errors are considered the third leading cause of ***death*** in the United States (Hay-David et al., 2020). With many of such medical errors happen less frequently, such errors could lead to "accelerate impending death" or even shorten life of patients (Kim et al., 2020). Medical errors cause more deaths compared to breast cancer, AIDS, and traffic accidents in the United States (Oyekanmi, 2018).

Medical errors in the United States increase ***disability*** among patients population and decrease confidence in care delivery (Pham et al., 2011).Regardless of the significant effort by care providers, medical errors still lead to a significant number of disabilities (Ologunde et al., 2022). According to the manual analysis of tweets, medical errors could lead to complete disability, permanent paralysis, losing ability to walk, and paraplegia.

6. Conclusion

In this study we explored the potential of social media data, Twitter data from patients and their families, as a useful source for identifying categories and consequences of medical errors. Using qualitative analysis and automatic categorization, we identified four generic medical errors categories, namely, medication, negligence, ignorance, and diagnosis errors. We also identified three generic groups of harms that medical errors could cause, namely, death, disability/paralyzed, and medical complications.

This research is not without any limitations. First, the query developed was not able to completely filter irrelevant posts, where these posts were eliminated using the custom ReadMe classifier. Second, the tweets were classified as they were reported by patients, family members, relatives, and the public without taking into consideration whether they are able to differentiate between these errors, for example differentiate between errors due to malpractice and negligence. Third, when it comes to the collected data, there is no proof of the real source or contributor of the tweets. Fourth, our scope is limited to patient-generated data, and not including the objective stored data from healthcare records. Fifth, data was collected using a custom query, as a result, the sample might not be representative of the overall population and could represent the most extreme cases of medical errors. As such, for this stage of the study, we did not interview the patients and other stakeholders in person, which could have triangulated the data we used. Nevertheless, this study represents the patient's perspective as our intended focus.

This research also provides specific and broad implications for future research and practice. In practice, this study calls for more effective understanding and utilization of patients' experience, not only in the hospital rooms and floors, but also for revising and establishing the overall governance recommendations for standard protocols, processes, systems, and performance evaluation schemes. Patient's voice will dramatically increase as the access to social media from the public is becoming easier and diverse. Specifically, with pervasive use of data-intensive artificial intelligence algorithms, the frequently-reported category by the patients for medical errors, ignorance, can be incorporated into an AI-assisted alert system. Among the several categories, the ignorance category stood out as a surprise at first to the authors. For example, the patients intensely complained that some providers (doctors and nurses) simply and repeatedly "ignored" patient's communications and complaints. The complaints, which are the feedback and request from the patients, can be incorporated into actionable alert systems (Choi et. al., 2018). The providers can treat the patient's communication as an informative alert, that can be manifested potentially into one of the consequences of the medical errors that the patients reported on the social media: death.

In research, further interdisciplinary studies can further examine the relationships between the patient's complaints and the associated topic areas broadly in two avenues. Managerially, studies can focus on the healthcare management system's governance mechanisms, processes, and overall performance. Technically, advanced text and process mining algorithms can be developed to reveal the paths and relationships between the complaints and the eventual consequences. To triangulate the data from different sources, objective health care records can be integrated to form a larger pool of data for this type of study. This future study can prove, refute, or augment this paper's findings that are solely based on the patients' perspective.

Today's healthcare systems operate based on the complex structure of a highly-professional division of labor, relying on each segment's professional performance. At the center of it, indeed, are the patients. How best and truthfully understand and transform the patient's communication into the care of patients should be a renewed focus for future study and practice of the patient-centered, evidence-based healthcare system. This study provides one small step towards the goal we all aspire to be a part of.

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Appendix A: Medical Errors Categories and Example Tweets

Misdiagnosis	“I had two physicians fail me. One misdiagnosed a condition, causing continued severe pain. The second failed to anticipate an anomaly in my anatomy, causing a surgery to fail”, and “I have had more than my share of issues with doctors misdiagnosing me and performing unnecessary procedures. I ended up with a chronic illness as a direct result of one unnecessary procedure, on top of the issue with my vision as a result of medication.”
Ignorance	“My doctor ignores my tachycardia followed by syncope due to under treated pain”, and “I’ve noticed that so many doctors ignore most anything I have to say about my own symptoms or medical history”
Medical negligence	“my nephew passed away at 3 days old because of nurse negligence”; “my healthcare is crappy now and I was injured by a doctor’s negligence”; and “I was born with health nightmares caused by doctor’s negligence.”
Medication errors (wrong Medication)	“almost perfect agreement among the two raters”, “I was mistakenly given a stomach medication with a 5% misoprostol infusion”; and “In the hospital the nurses gave me the wrong medication I went in a coma”.
Medication errors (incorrect dose)	“my mom had 13 seizures back-to-back, and the doctors screwed up and gave her an overdose to get her out of the seizures and she stayed in medically induced coma”, and “my doctor made a mistake and sent in a 1-week supply of a medication instead of 1 month”.
Medication errors (drug interaction)	“one of the nurses gave me the wrong medication, I got an allergic reaction, felt like ants were crawling over my body”, and “that’s what they did to me. Prescribed a medication I am deadly allergic to. It's all over my records but the Dr and the pharmacist missed it.”

Appendix B: Medical Errors Consequences and Example Tweets

Medical complications	“doctor screwed up my immune system with 38 years of antibiotics and other drugs that were eventually labeled black box”; and “doctors ruined my life with the medications they gave me without testing for any other conditions ... I developed permanent nerve damage because of a vitamin B deficiency no one ever tested for until it was too late.”
Death	“doctor malpractice was the reason my wife passed away”; and “my mother was not allowed to see her primary physician, so the hospital assigned a temporary doctor over Zoom. That doctor miss diagnosed her, gave her the wrong medications which killed her.”
Disability	“my mother had cancer and was left paraplegic by a doctor's negligence”; and “I am permanently disabled because of doctors ignoring their due diligence.”