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**Scientific Abstract - Violence Mitigation in Emergency Rooms Using Real-Time Sensors, Load, and Heuristics-Based Actuators**

Violence in emergency rooms (ER) is prevalent, severe, and costly. Such violence usually includes verbal violence that can be escalated to physical violence as well. There are different ways to cope with such cases, most of them tackle violence after its occurrence and thus far none utilized real time data to identify, intervene and predict instances of violence.

Thus, the overarching goal of this work is to establish a holistic framework to mitigate violence that merges real-time audio, video and location data with ER information, and harness data science techniques to *identify* violence in real-time, aiming at *intervene* while violence occurs and furthermore *predict* these instances to prevent them on time.

**Keywords:** Violence; Verbal Violence; Identification; Intervention; Prediction; Data science; Emergency room

# SCIENTIFIC BACKGROUND

## Violence at healthcare staff

Violence directed at healthcare staff is prevalent and is on the rise (Du at al.,2020). Those working in medical occupations were found to be at high risk of being a target of violence at work compare to other occupations (Gates, 2004; Gates et al., 2006; Speroni et al.,2014). Focusing on healthcare it was reported that Emergency nurses have been exposed to greater number of violent incidents (Speroni et al.,2014) perpetrated mostly by patients and visitors (Gates et al., 2006). Indeed studies have pinpointed emergency departments as high risk sets for violence against healthcare staff (Anglin et al.,1994; Foust et al., 1993; Gates et al., 2006 ; Gerberich et al., 2004; Kowalenko et al., 2005).

Violence can take many forms. A recent review (Mento, et al., 2020) found that ERs are, among other selected departments, prone to verbal abuse, psychological violence, physical assault, and sexual abuse. Still, data shows that most of these occurrences are verbal (Gerberich et al., 2004).

The negative impact of verbal violence at work has received growing scholarly attention in recent years. (Hodgins et al., 2014; McCord et al. .2018; Yang et al., 2014). Indeed, verbal violence at work is associated with psychological distress, burnout, anxiety, depression, and general reduced wellbeing (Schilpzand, De Pater & Erez, 2016). The impact of violence goes beyond individuals as employees who experience violence undergo decreasing service performance, and they might harm their customers (Park & Kim, 2020). In a hospital setting these decreases in productivity are translated to reduced quality of treatment to patients (Hutton et al., 2008). In their recent seminal review Mento, et al., (2020) found that lack of information, insufficient personnel and equipment, and communication breakdowns increase the risk of violent behaviour that is mainly perpetrated by patients and other visitors.

Existing tools to *identify* violence (Schilpzand, De Pater & Erez, 2016, Wilson and Holmvall 2013) has few shortcomings all which can be dealt by utilizing data science capabilities:

1. They are subjective
2. There is a time gap between the abusive act and the data collection. This issue might also impact the ability to intervene effectively.
3. They rely on targets' memory - They all lean on the frequency or sense of extensiveness of the occurrence as perceived and recalled retrospectively, by the target (Schilpzand, De Pater & Erez, 2016) and thus the identification of verbal violence, is biased. Indeed, in their seminal review, the authors called for utilizing implicit measures that "do not rely on introspection or participants' accurate and full awareness of how or why they feel, think, react, or behave in a certain way" (p. S64-S65). Thus far, their call was not answered.

With respect to *intervention* processes, the existing intervention programs are very limited in number (Howard, & Embree, 2020). They are all retrospective, and the impact of most was graded as low (Hodgins et al., 2014). Additionally they all overlook the potential escalation of violence. The broad literature on verbal violence indicates that verbal violence can develop into physical violence (Andersson and Pearson, 1999). Thus, identification of minor instances of violence (such as uncivil behaviour from patients, visitors or staff) should be identified before they are escalated to enhance the ability to intervene on time before the verbal instance of violence becomes physical. Previous studies showed that various types of factors are involved in the process of escalation, such as patient behavior, hospital conditions, waiting times and others (Shafran et al.,2017), Thus, various types of data should be collected in order to intervene and prevent escalation.

With respect to prediction, studies indicated that contextual stressors which reflect an imbalance between job demands and available resources to deal with these demands (Lazarus & Folkman, 1984), constitute emotional and behavioural responses that might be counterproductive (Roberts et al. 2011). Indeed, Oyeleye et al. (2013) found that stress is related to conflict. In the same route, Roberts et al. (2011) managed to show that stress leads to the perpetration of incivility a specific form of verbal violence. As different stressors exist in various settings, scholars focused on specific work environments to identify stressors which depends on the specific setting. Focusing on healthcare, in their recent seminal review Mento, et al., (2020) found that lack of information, insufficient personnel and equipment, and communication breakdowns increase the risk of violent behaviour that is mainly perpetrated by patients and other visitors. Indeed insufficient personnel is expected to lead to a mismatch between patient expectations and the reality of the services offered, which in turn was shown to be related to violence against nurses (Nowrouzi-Kia et al.,2019). These findings were also supported by (Spelten, et al., 2020) who found that family members visiting emergency departments could become violent if they feel frustrated, stressful, helpless, or entitled.

Thus far, no research focused on a longitudinal learning of risk factors that excelerate violence perpetrated by patients and their relatives (Mento, et al., 2020), in order to enable an ongoing prediction of l violence overtime.

Taking together thus far , to the best of our knowledge, there was no utilization of technology and data science that allows the following mitigation components:

1. *Identify* violence occurrences based on realtime data
2. *Intervene* in real-time
3. *Predict* violence through data collection overtime

Thus, in order to overcome the challenges presented above, the overarching goal of the current research is to collect realtime data on verbal violence incidents focusing on engagements between the medical staff and the visitors in ER nurse station and intervene in realtime in incidents of verbal violence.

Concerning the third challange, the data collected overtime will help predicting incidents of verbal violence as a basis for future prevention that is beyond the scope of the current research.

As far as we know, there is no existing platform that gathers data from multiple sources including real-time data and provides data analysis and predictive insights on violence at healthcare staff.

## Using Data Science Techniques to Measure Violence

We establish a Violence Mitigation Information System that is based on a multiple-source data engine that provides analytics and insights. We use a machine learning model, that includes collection, preparation and learning phases as shown in Figure 1.



Figure 1: The Machine learning Model

The diversity of data sources and data types is considered. Once all data types are collected, the data fusion sub-stage is performed. *Data fusion* is the ability to combine multiple data sources into an integrated source, to increase the accuracy and consistency of the information system. The data sources are varied and based on streaming sensors' data: videos and images from security cameras, decibel gauge, voice recordings, infra-red images, and textual information.

The processes of data collection and data fusion are important preprocessing procedures to ensure high level of data quality (Ben Ami, 2019). Effective pre-processing methodology involves field extraction, significant attribute selection, data selection, and data cleaning (Kaur et al., 2019). The focus is on data selection strategies which limit the size of the stored training data by different inclusion, exclusion, and further dataset manipulation criteria (Krell et al., 2017) (Hatzi et al., 2014). Therefore, once the data is collected, it is customized, cleaned, and approved for the next stages. All the stages have been described in detail in Ben Ami, 2019:

(1) Cleaning 🡪 (2) Integration 🡪 (3) Reduction 🡪 (4) Transformation & Discretization

As part of the data preparation, additional stages are implemented as follows. Over-fitting, outliers, high dimensionality of the database (Dunham, 2003, p. 15), distinguishing between nominal and numerical attributes data objects from within the specific data mining models (Han et al., 2011, p.40), all immediately affect the results and cause data distortion. This part of the procedure is based on *attribute selection and pattern evaluation* (Han et al., 2011, p. 336, 224, 40, 264).

Data mining models are a set of tools that enables the exploration of descriptive and predictive approaches for real time use. Such models can describe deep, wide, tangible, and intangible data aspects and patterns, and specific data behavior arguments (Dunham, 2003) (Awad et al., 2009). The importance of data mining techniques and their application has been described clearly in Sivakumar et al., 2015. Machine learning techniques are completely appropriate for applications and explorations where sensors, image (and voice) processing techniques are included (Zhang et al., 2016) (Pan et al., 2018). The strongest justification for machine learning for this work, is its ability to generate a *learning cycle* from within the system.

Our approach is to use existing models in the areas of voice recognition, face recognition, and behavior analysis. We note that we already have few possible strategic partners, which should contribute their existing technical environments for our work. Thus, we need to make customizations and adaptation of current tech systems into our work, rather than developing them from scratch. This will reduce the total effort and will enable us to generate deliverables with relatively short timeline.

# Research Objective and Expected Significance

**2.1 Research Objectives**

The overarching goal of this work is twofold:

1. Develop an objective measurement tool to *identify* violence at healthcare staff
2. Extend the measurement tool with an *intervention* loopback component that can:
   1. Enact *immediate intervention* mechanisms that provide loopback data for learning.
   2. Identify patterns of contextual precursors to *predict* future violence.

**2.2** **Expected significance**

The scientific contribution relates to the ability to identify and extract violence occurrences at healthcare staff out of sensors data that is merged with the medical center data, and develop a set of heuristics that foster interventions in nearly real-time and possible prediction and prevention in the long term.

The practical contribution relates to the social benefits of the innovative technology for ERs that among others, include increasing the safety of the medical staff and customers by mitigating violence in real-time.

The aforementioned objectives, once attained, represent a novel approach to the identification and intervention of violence and a potential to predict violence before it takes place. The solutions proposed can bridge the gap between the existing shortcomings in identification and intervention of violence and enable better mitigation of such costly and prevalent phenomenon which must be mitigated.

# Methodology and Data: Detailed Description of the Proposed Research

## Detailed Description of the Research

### Background - The Poriya Medical Center

The Emergency Medicine Department also called Emergency Room (ER) in the Poriya medical center is designed to provide treatment for patients with urgent medical problems at all times, while providing life-saving treatments, evaluations, and primary diagnosis and treatment. The Department, led by Dr. Eran Tal-Or (PI in this proposal), handles some 60,000 patients a year and has 32 beds. Patients present problems from a variety of fields: internal cardiology, surgery, pediatrics and orthopedics, and Covid-19.

There are between 1,500-2,000 cases of light and severe trauma per month, and, approximately 350 cases per year are treated in trauma rooms, while some patients are hospitalized in the hospital's various departments, while others are transferred to other hospitals. The Department's staff works tirelessly to provide high-quality, professional medical and nursing treatment while maintaining the dignity of the patient and their family.

In this work, we focus on violence mitigation using advanced technology while measuring the ER load and studying its effect on violence specifically in the area of the Nurse Station in the ER which was identified by the medical center as the primary destination for violence occurrences. The technology will allow us to identify violence in real-time and intervene as much as possible in nearly real-time.

We note that data collection in this work aim at identifying violence in general, thus enabling the analysis of variety of violence manifestations and inner relationships.

## Method

The primary proposition of the current project leans on the shortcomings in the study of violence. Thus far there was no evidence found for the utilization of technology in identifying, intervening and prediction of violence which is studied retrospectively. Through a longitudinal design and by utilizing data science technology, this study aims to gather and analyze data over time from different sources in the ER nurse station in Poria medical center. The nurse station location was chosen as it serves as a main interface between medical staff and visitors (patients and escorts) where violence evidently occurs. A longitudinal design will allow us to analyse patterns over time and learning the context of violence and its change and impact over time. Furthermore, it will enable us to focus on the most relevant i.e., more prevalence over time , antecedents of violence.

Specifically, we intend to develop the RoboTreat[[1]](#footnote-1) technology that is composed of three main components as follows:

1. Integration of the relevant sensing devices for data collection and transmission. These devices include audio sensors, cameras, location systems, communication modules.
2. Cloud-based data engine that merges the multiple data and enable developing a learning data model.
3. Actuation mechanisms for intervention and prevention.

Practically, the inputs are based on Internet of Things (IoT) sensors (Dachyar et al., 2020), which collect several possible stimuli at the same time: sounds, facial features, movements, gestures, temperatures, and images. Thus, the data analysis process can identify and recognize mistreatment in nearly real-time, at the time when events happen. On the other hand, the intervention process, which is part of our entire system flow, depends on pre-defined assumptions and learned assumptions. The pre-defined assumptions should be cast into the system, as "what-if rules", like typical decision support system structure (Meyers, 2019). Thus, the cycle of stimuli and action should be relatively simple. The ability of the machine learning system to analyze differentiations should be utilized to generate additional learned sets of behaviors (Sui, 2015). These should be adopted by the system after human experts' diagnosis that will be performed in collaboration with the Poriya ER experts.

**3.3. Time table**

In accordance with the program outlined above, the planned timetable in this research is aimed to deploy the RoboTreat technology in the Poriya ER and use real time data as well as hospital data and ER load to identify verbal violence and provide heuristics-based actuating mechanisms.

We plan to deploy the project across three years.

* The first year is divided into two parts. In the first part we plan to set up the sensors and required equipment, the data interface, and the conceptual data mining models and run a short pilot. In the second half of the first year we plan to start data collection and validate real-time and static data as well as Provide insights on violence identification and crowdedness measures
* The second-year plan should examine the results of our first-year pilot and expand it into much wide platform: conceptually and technically. Thus, the dynamic and static data should be integrated into one merged model, and expand our abilities to identify verbal violence and other violence behaviors, based on real-time cameras and sensors.
* The third-year plan should be focused on additional data mining and artificial intelligence algorithm, which should be activated on the same format of the second year. The main purpose is to enable comparative analysis of and between the different models, to increase the accuracy and the preciseness of the entire software-based system. This is mainly important to leverage the machine-learning performances. The last stage of this year should be focused on reflection of our research activities on both areas: social and technical.

**3.4 Preliminary Results**

For almost three years the first PI was investigating different aspects of verbal violence in the Poriya hospital and its costly consequences. As part of the research a mixed-method design was utilized. 487 medical staff members (half of the medical staff) filled in validated questionnaires and 45 interviews were conducted with medical staff from various disciplines (nurses, doctors, logistics, etc.). Results indicated that 40% of the workers mentioned that they don't feel protected. Additionally, family members (visitors) and patients perpetrate 25% of the verbal violence instances. It was agreed with the hospital management that violence should be dealt as part of the organizational strategy as it impacts the quality of work life of employees, the ethical climate of the hospital and eventually its performance.

**3.5 Research Infrastructure**

The *current project* is conducted under the auspice of Kinneret Academic College. The college has a well-established engineering school equipped with top technology and suitable infrastructure hich can support the project. Additionally, the college established an innovation center that is a potential source for different technical experts per need. Additionally, the PI’s expertise in the above-mentioned methodologies, foregrounded in various previous projects, will be complemented by Dror ben Ami who is a key expert Dror has more than 20 years of experience as senior programmer and CTO (Hitech companies) in expert systems (ES) development and decision support system(DSS). Those were mainly based on data mining and artificial intelligence models. In the last five years, Dror was also involved in machine learning practical R&D projects, as private advisor and as entrepreneur. His two last big projects on machine learning were: (1) for OECD country: analysis of web users' behavior; (2) mines detection by means of machine learning techniques. All these projects required wide knowledge and implementation competencies in big data systems, as well as wide mathematical background (image processing, optimization math models). Additionally, the third PI is the manager of the ER at the poriya hospital. As one of the PI’s in the proposal he can contribute to the project due to his extensive experience in data science and his vast experience and familiarity with challenges of the ER.

Additionally, research assistants at the rank of MA students and PhD will be employed for various tasks. B.A students will be employed per hour on specific tasks related to the project.

**3.6 Expected Significance, Pitfalls and Alternative Routes to Desired Results**

Due to the well-established relations with the Poriya center, and specifically the partnership with the ER manager and poriya’s management, the extensive knowledge of the first PI in the study of verbal violence and the extensive knowledge of the second PR in data science project management, we are positive that the project will be successful and achieve its goals. Additionally, we decided to focus on the nurse station in order to reduce the number of intervening factors and to have a better control over the different aspects of the project. The project is expected to add significantly to our knowledge of identifying mitigating and prediction of violence in healthcare. Although we can expect challenges in establishing the data ongoing infrastructure and the model for innovative intervening analysis, we are positive that our well-planned project can succeed reach its goals.

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1. Term we choose to describe the integrated nature of the project which is based on technology that is used to mitigate a social challenge [↑](#footnote-ref-1)