Application No. 1916/21

PI Names: Yariv Itzkovich, Yael Dubinsky, Eran Talor

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

**Abstract**

Violence in emergency rooms (ER) is prevalent, severe, and costly. It usually takes the form of verbal violence but can escalate to physical violence. Most of the methods for coping with this focus on violence after its occurrence, and so far there has been no use of real-time data to identify, intervene in, or 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. It will harness data science techniques to *identify* violence in real time in order to *intervene* while violence is taking place and to *predict* cases of violence with a view to preventing them.

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

# Scientific Background

## Violence Directed at Healthcare Staff

Violence directed at healthcare staff is prevalent and on the increase (Du at al. 2020). Those working in medical occupations are at high risk of being a target of violence at work compared to other occupations (Gates 2004; Gates et al. 2006; Speroni et al. 2014). In the healthcare field, it is reported that nurses in emergency departments are exposed to greater numbers of violent incidents than other staff (Speroni et al. 2014), and that these incidents are mostly perpetrated by patients and visitors (Gates et al. 2006). Indeed, studies have pinpointed emergency departments as high-risk settings for violence against healthcare staff (Anglin et al. 1994; Foust and Rhee 1993; Gates et al. 2006; Gerberich et al. 2004; Kowalenko et al. 2005). Violence can take many forms, and a recent review (Mento et al. 2020) found that emergency rooms (ERs) are particularly likely to be settings for verbal abuse, psychological violence, physical assault, and sexual abuse. However, data suggest that most occurrences of violence are verbal (Gerberich et al. 2004).

The negative impact of verbal violence at work has received increasing scholarly attention in recent years (Hodgins et al. 2014; McCord et al. 2018; Yang et al. 2014). Verbal violence at work is associated with psychological distress, burnout, anxiety, depression, and reduced well-being in general (Schilpzand et al. 2016). The impact of violence goes beyond individuals, as the service performance of employees who experience violence is adversely affected, to the extent that they may harm their customers (Park and Kim 2020). In a hospital setting, such decreases in productivity translate into lower quality treatment for 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 behavior, which is mainly perpetrated by patients and other visitors.

Existing tools to *identify* violence (Schilpzand et al. 2016; Wilson and Holmvall 2013) have a number of shortcomings, all which can be dealt by using the capabilities of data science:

1. They are subjective.
2. There is a time gap between the abusive act and the data collection, and this impacts the ability to intervene effectively.
3. They rely on the memory of the targets. In that identification of verbal violence depends on the target’s perception and retrospective recall of the frequency or severity of the occurrence, it is often biased. In their important review, Schilpzand et al. (2016) called for the use of 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” (2016, pp. S64–S65). So far, their call has gone unanswered.

With respect to *intervention* processes, existing intervention programs are scarce (Howard and Embree 2020). All are retrospective, and the impact of most has been graded as low (Hodgins et al. 2014). Moreover, they overlook the potential escalation of violence, despite the consensus in the literature that verbal violence can develop into physical violence (Andersson and Pearson 1999). Thus, minor instances of violence (such as uncivil behavior from patients, visitors, or staff) should be identified before any escalation takes place, facilitating timely intervention that prevents verbal violence from becoming physical. Previous studies have shown that various factors are involved in the process of escalation, such as patient behavior, hospital conditions, and waiting times (Shafran et al. 2017), Thus, various types of data should be collected in order to intervene and prevent escalation.

With respect to prediction, studies have indicated that contextual stressors which reflect an imbalance between job demands and the resources available to deal with those demands (Lazarus and Folkman 1984) constitute emotional and behavioral responses that may be counterproductive (Roberts et al. 2011). Indeed, Oyeleye et al. (2013) found that stress is related to conflict, and Roberts et al. (2011) demonstrated that stress leads to the perpetration of incivility, a specific form of verbal violence. As different stressors exist in various settings, scholars have focused on identifying those that depend on specific work environments. In a healthcare setting, the recent seminal review of Mento et al. (2020) found that lack of information, insufficient personnel and equipment, and communication breakdowns increase the risk of violent behavior, which is mainly perpetrated by patients and other visitors. Insufficient personnel, in particular, is expected to lead to a mismatch between patient expectations and the reality of the services offered, which has been shown to be related to violence against nurses (Nowrouzi-Kia et al. 2019). These findings were corroborated by Spelten et al. (2020), who observed that family members visiting an ER could become violent if they felt frustrated, stressed, helpless, or entitled.

Although longitudinal studies of risk factors that accelerate violence perpetrated by patients and their relatives (Mento et al. 2020) would enable better prediction of violence over time, so far there have been no such studies. In fact, to the best of our knowledge, there has been no use of the technology and data science that would facilitate the following components of violent mitigation:

1. *identifying* occurrences of violence using real-time data;
2. *intervening* in real time; and
3. *predicting* violence through data collection over time.

To address the first two points, the overarching goal of the current research is to collect real-time data on verbal violence incidents focusing on engagements between medical staff and visitors in an ER nurse station so as to intervene in real time in incidents of verbal violence. Concerning the third point, the data collected over time will help in predicting incidents of verbal violence as a basis for future prevention (although this lies beyond the scope of the current research).

To the best of our knowledge, there is no existing platform that gathers data from multiple sources, including real-time data, and provides data analysis and predictive insights into violence targeted at healthcare staff.

## Using Data Science Techniques to Measure Violence

We will establish a violence mitigation information system based on a multiple-source data engine that provides analytics and insights. Our machine learning model will include collection, preparation, and learning phases (Figure 1).



**Fig. 1** The machine learning model

The diversity of data sources and data types is thus taken into account. Once all data types have been collected, a data fusion substage will be performed. *Data fusion* is the combination of multiple data sources into an integrated source to increase the accuracy and consistency of the information system. In this case, the data sources are varied and based on streaming sensor data: videos and images from security cameras, decibel gauges, voice recordings, infrared images, and textual information.

Data collection and data fusion are important preprocessing procedures for ensuring high-quality data (Ben Ami 2019). Effective preprocessing methodology involves field extraction, selection of significant attributes, data selection, and data cleaning (Kaur and Garg 2019). The focus is on data selection strategies that limit the size of the stored training data by applying different criteria for inclusion, exclusion, and further dataset manipulation (Hatzi et al. 2014; Krell et al. 2017). Therefore, once the data are collected, they will be customized, cleaned, and approved for the next stages. The process, which has been described in detail by Ben Ami (2019), can be summarized as follows:

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

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

Data mining models are a set of tools that enable the exploration of descriptive and predictive approaches for real-time use. Such models can describe deep, wide, tangible, and intangible data aspects and patterns, as well as specific data behavior arguments (Awad et al. 2009; Dunham 2003). The importance of data mining techniques and their application has been argued for convincingly by Sivakumar et al. (2015), and machine learning techniques are entirely appropriate for applications and explorations where sensors and image- and voice-processing techniques are used (Pan et al. 2018; Zhang and Du 2016). The strongest justification for the use of machine learning in this study 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 already have a number of strategic partners who could contribute their technical environments to our work. Thus, rather than developing tech systems from scratch, we anticipate being able to customize and adapt existing systems to fit our research. This will reduce the total effort and enable us to generate deliverables in a relatively short time.

# Research Objectives and Expected Significance

## 2.1 Research Objectives

The overarching goal of this work is twofold:

1. to develop an objective measurement tool to *identify* violence targeted at healthcare staff; and
2. to extend the measurement tool with an *intervention* loopback component that can

(a) enact *immediate intervention* mechanisms that provide loopback data for learning, and

(b) identify patterns of contextual precursors to *predict* future violence.

## 2.2 Expected Significance

The scientific contribution of this work relates to the ability to identify and extract occurrences of violence targeted at healthcare staff from sensor data merged with medical center data, and to use the information to develop a set of heuristics that foster real-time interventions and enable prediction and prevention in the long term. The practical contribution relates to the social benefits of innovative technology for ERs, including increasing the safety of medical staff and customers by mitigating violence in real time.

Achieving the research objectives will represent a novel approach to identification of and intervention in violence, offering the potential to predict violence before it takes place. The solutions proposed will address shortcomings in current approaches to identifying and intervening in violence and will enable better mitigation of this prevalent and costly phenomenon.

# Methodology and Data: Detailed Description of the Proposed Research

## Research Setting

The Emergency Medicine Department or ER in Poriya Medical Center aims to provide treatment at all times for patients with urgent medical problems, including life-saving treatments, evaluations, and primary diagnosis and treatment. The ER, which is led by Dr. Eran Tal-Or (the PI in this proposal), handles some 60,000 patients a year and has 32 beds. Patients present with problems in a range of fields, including internal cardiology, surgery, pediatrics and orthopedics, and Covid-19. There are between 1,500 and 2,000 cases of light and severe trauma per month, and approximately 350 cases per year are treated in trauma rooms. Some patients go on to be admitted to other departments in the same hospital, while others are transferred to different hospitals. The ER’s staff works tirelessly to provide high-quality, professional medical and nursing treatment while maintaining the dignity of patients and their families.

In this study, we will focus on violence mitigation using advanced technology while measuring the ER load and studying its effect on violence in the area of the ER nurse station, which has been identified by the medical center as the primary location for occurrences of violence. The technology will allow us to identify violence in real time and to intervene almost in real time. We note that the data collection in this work aims to identify violence in general, thereby facilitating the analysis of a variety of manifestations of violence and their relationships to one another.

## Research Methods

The primary proposition of the current project draws on shortcomings in previous studies of violence. There is no evidence relating to the use of technology in identifying, intervening in, and predicting violence, which has so far been studied only retrospectively. By means of a longitudinal design and the use of data science technology, this study will gather and analyze data over time from different sources in the ER nurse station in Poriya Medical Center. This location has been chosen because it serves as a main interface between medical staff and visitors (patients and escorts), and violence occurs there. The longitudinal design will allow us to analyze patterns over time, learning the context of violence and how it changes and impacts over time. It will also enable us to focus on the most relevant antecedents of violence (i.e. those that are most prevalent over time).

Specifically, we intend to develop the RoboTreat[[1]](#footnote-1) technology, which consists of the following three main components:

1. integration of the relevant sensing devices for data collection and transmission, including audio sensors, cameras, location systems, and communication modules;
2. a cloud-based data engine that merges multiple data and allows a learning model to be developed; and
3. actuation mechanisms for intervention and prevention.

The inputs are derived from Internet of Things (IoT) sensors (Dachyar and Pertiwi 2020), which collect several stimuli at the same time: sounds, facial features, movements, gestures, temperatures, and images. Thus, our data analysis process will identify and recognize mistreatment almost in real time, as events unfold. The intervention process, which is part of our system flow, depends on predefined and learned assumptions. The predefined assumptions will be built into the system in the form of “what-if rules,” as in a typical decision support system structure (Meyers 2019). Thus, we anticipate that the cycle of stimuli and action will be relatively simple. The ability of the machine learning system to analyze differentiations will be used to generate additional learned sets of behaviors (Sui 2015). These will be adopted by the system after diagnosis by human experts, performed in collaboration with Poriya’s ER experts.

## 3.3 Research Timetable

In accordance with the program outlined above, the research timetable allows for the deployment of RoboTreat technology in the Poriya ER so that real-time data, as well as hospital data and ER load, can be used 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 of the year, we will set up the sensors and required equipment, the data interface, and the conceptual data mining models, before running a short pilot. In the second half of the year, we will start the data collection and validate our real-time and static data, as well as generating insights into violence identification and crowdedness measures.
* In the second year, we will examine the results of our first-year pilot and expand it onto a much wider platform conceptually and technically. The dynamic and static data will be integrated into a merged model, enhancing our ability to identify verbal violence and other violent behaviors with the use of real-time cameras and sensors.
* The focus in the third year will be on additional data mining and the artificial intelligence algorithm, which will be activated in the same format as in the second year. The main objective is to enable comparative analysis of the different models in order to increase the accuracy and precision of the entire software-based system, which is key to leveraging the machine learning performance. The last stage of the third year will be dedicated to reflection on the social and technical implications of our results.

## 3.4 Preliminary Results

For almost three years, the first PI has investigated different aspects of verbal violence in the Poriya Medical Center and its costly consequences, using a mixed-method research design in which 487 medical staff members (half of the medical staff) filled in validated questionnaires, and 45 interviews were conducted with medical staff from a range of disciplines (nurses, doctors, logistics, etc.). The results indicate that 40% of the respondents do not feel protected from violence at work and that 25% of instances of verbal violence are perpetrated by patients and their family members. It was agreed with the hospital management that violence should be dealt with as part of the organizational strategy, as it impacts the quality of work life of employees, the ethical climate of the hospital, and ultimately its performance.

## 3.5 Research Infrastructure

The current project will be conducted under the auspices of Kinneret Academic College, which has a well-established engineering school equipped with suitable technology and infrastructure to support the project. Additionally, the college has established an innovation center that is a potential source of a range of technical experts if required.

The PI’s expertise in the abovementioned methodologies, demonstrated in various previous projects, will be complemented by that of Dror Ben Ami, a key expert with more than 20 years of experience as a senior programmer and CTO in hi-tech companies, in the development of expert systems (ES), and in decision support systems (DSS) based primarily on data mining and artificial intelligence models. In the last five years, Dror has also been involved as a private advisor and entrepreneur in machine learning R&D and practical projects, most recently in analysis of web users’ behavior for an OECD country and in detection of mines by means of machine learning techniques. These projects required wide knowledge and implementation competencies in big data systems, as well as a strong mathematical background in image processing and optimization models.

In addition, the third PI is the manager of the ER at Poriya Medical Center, who can contribute his expertise in data science and his vast experience and familiarity with the challenges of the ER. MA and PhD students will also be employed as research assistants, with BA students employed on an hourly basis to carry out specific tasks related to the project.

## Expected Significance, Pitfalls, and Alternative Routes to Desired Results

Given the well-established relations with the study site, and specifically the partnership with the ER manager and the Poriya Health Center management, the first PI’s expertise in the study of verbal violence, and the second PI’s extensive knowledge of data science project management, we are highly confident that the project will achieve its objectives. Our decision to focus on the nurse station will reduce the number of intervening factors, affording us greater control over the different aspects of the project. The results are expected to add significantly to our knowledge regarding the identification, mitigation, and prediction of violence in healthcare. Although we can expect challenges in establishing the data infrastructure and the model for the innovative intervening analysis, we are positive that this well-planned project can reach its goals.

# References

Andersson, L. M., & Pearson, C. M. (1999). Tit for tat? The spiraling effect of incivility in the workplace. *Academy of management review, 24*(3), 452-471.‏

Anglin, D., Kyriacou, D. N., & Hutson, H. R. (1994). Residents' perspectives on violence and personal safety in the emergency department. Annals of emergency medicine, 23(5), 1082-1084.‏

Arnetz, J. E., Fitzpatrick, L., Cotten, S. R., & Jodoin, C. (2019). Workplace bullying among nurses: developing a model for intervention. *Violence and victims, 34*(2), 346-362.‏

Aquino, K., & Thau, S. (2009). Workplace victimization: Aggression from the target's perspective. *Annual review of psychology, 60*, 717-741.‏

Awad, M. and Thuraisingham, B. and Wang, L., 2009. *Design and Implementation of Data Mining Tools*, CRC Press.

Ben Ami, D., 2019*,* Preprocessing strategy in web-mining: recommended or inevitable? *IADIS conference, Utrecht University, Netherlands*.

Brandl, E. J., Lett, T. A., Bakanidze, G., Heinz, A., Bermpohl, F., & Schouler-Ocak, M. (2018). Weather conditions influence the number of psychiatric emergency room patients. *International journal of biometeorology, 62*(5), 843-850.‏

Caponecchia, C., Branch, S., & Murray, J. P. (2020). Development of a taxonomy of workplace bullying intervention types: Informing research directions and supporting organizational decision making. *Group & Organization Management, 45*(1), 103-133.‏

Dachyar, M., & Pertiwi, C. H. (2020, June). Improvement in Emergency Medical Services using Internet of Things (IoT). Hospital Emergency Department Case: a BPR Approach. In *23rd Asian Forum of Business Education (AFBE 2019)* (pp. 79-87). Atlantis Press.

Du, Y., Wang, W., Washburn, D. J., Lee, S., Towne, S. D., Zhang, H., & Maddock, J. E. (2020). Violence against healthcare workers and other serious responses to medical disputes in China: surveys of patients at 12 public hospitals. *BMC health services research, 20*(1), 1-10.‏

Dunham, M.H., 2003. *Data Mining: Introductory and Advanced Topics*, Prentice Hall, Pearson Education Inc.

Edwards, M., & Blackwood, K. M. (2017). Artful interventions for workplace bullying: exploring forum theatre. *Journal of Workplace Learning*.‏

Einarsen, S., & Raknes, B. I. (1997). Harassment in the workplace and the victimization of men. *Violence and victims, 12*(3), 247-263.‏

Foust, D., & Rhee, K. J. (1993). The incidence of battery in an urban emergency department. Annals of emergency medicine, 22(3), 583-585.‏

Gates, D. M. (2004). The epidemic of violence against healthcare workers.‏ Journal of Occupational and Environmental Medicine, 61, 649-650

Gates, D. M., Ross, C. S., & McQueen, L. (2006). Violence against emergency department workers. The Journal of emergency medicine, 31(3), 331-337.‏

Gerberich, S. G., Church, T. R., McGovern, P. M., Hansen, H. E., Nachreiner, N. M., Geisser, M. S., ... & Watt, G. D. (2004). An epidemiological study of the magnitude and consequences of work related violence: the Minnesota Nurses’ Study. Occupational and environmental medicine, 61(6), 495-503.‏

Han, J., and Kamber, M., 2011. *[Data Mining: Concepts and Techniques](http://www-faculty.cs.uiuc.edu/~hanj/bk2/)*[,](http://www-faculty.cs.uiuc.edu/~hanj/bk2/) 3rd Edition, Morgan Kaufmann.

Hatzi, O., and Zorbas, N. and Nikolaidou, M. and Anagnostopoulos, D., 2014. Panhellenic Conference on Informatics, *An intelligent tool for expediting and automating data mining steps*, ACM International Conference Proceeding

Hodgins, M., MacCurtain, S., & Mannix-McNamara, P. (2014). Workplace bullying and incivility: a systematic review of interventions. *International Journal of Workplace Health Management.‏*

Howard, M. S., & Embree, J. L. (2020). Educational Intervention Improves Communication Abilities of Nurses Encountering Workplace Incivility. Th*e Journal of Continuing Education in Nursing, 51*(3), 138-144.‏

Hutton, S., & Gates, D. (2008). Workplace incivility and productivity losses among direct care staff. *AAOHN journal, 56*(4), 168-175.‏

Itzkovich, Y. (2015). *Uneconomic relationships: The dark side of interpersonal interactions in organizations.* Tel Aviv, Israel: Resling.

Itzkovich, Y., & Heilbrunn, S. (2016). The role of coworkers' solidarity as an antecedent of incivility and deviant behavior in organizations. *Deviant Behavior, 37*(8), 861-876.‏

Itzkovich, Y., Alt, D., & Dolev, N. (2020). Th*e Challenges of Academic Incivility: Social-Emotional Competencies and Redesign of Learning Environments as Remedies*. Springer Nature.‏

Jakobsen, S. (2020). Managing tension in coopetition through mutual dependence and asymmetries: A longitudinal study of a Norwegian R&D alliance. *Industrial Marketing Management, 84*, 251-260.‏

Kaur, J. and Garg, K., 2019. Advances in Intelligent Systems and Computing, *Efficient management of web data by applying web mining pre-processing methodologies*, Vol. 731, pp. 115-122.

Keashly, L. (2001). Interpersonal and systemic aspects of emotional abuse at work: The target's perspective. *Violence and victims, 16*(3), 233-268.‏

Kowalenko, T., Walters, B. L., Khare, R. K., Compton, S., & Michigan College of Emergency Physicians Workplace Violence Task Force. (2005). Workplace violence: a survey of emergency physicians in the state of Michigan. Annals of emergency medicine, 46(2), 142-147.‏

Krell, M. and Wilshusen, N, and Seeland, A., and Kim, S.K., 2017. Classifier transfer with data selection strategies for online support vector machine classification with class imbalance*,* *Journal of Neural Engineering, Vol.14, Issue 2*.

McCord, M. A., Joseph, D. L., Dhanani, L. Y., & Beus, J. M. (2018). A meta-analysis of sex and race differences in perceived workplace mistreatment. *Journal of Applied Psychology, 103*(2), 137.‏

Mento, C., Silvestri, M. C., Bruno, A., Muscatello, M. R. A., Cedro, C., Pandolfo, G., & Zoccali, R. A. (2020). Workplace violence against healthcare professionals: A systematic review. *Aggression and violent behavior, 51*, 101381.‏‏

Meyers, E. (2019). Charge Nurse Expertise: Implications for Decision Support of the Nurse-Patient Assignment Process.

Murray, J. P., Branch, S., & Caponecchia, C. (2019). Success factors in workplace bullying interventions. *International Journal of Workplace Health Management*.‏

Nevo, T., Peleg, R., Kaplan, D. M., & Freud, T. (2019). Manifestations of verbal and physical violence towards doctors: a comparison between hospital and community doctors. BMC health services research, 19(1), 1-7.‏

Nowrouzi-Kia, B., Isidro, R., Chai, E., Usuba, K., & Chen, A. (2019). Antecedent factors in different types of workplace violence against nurses: a systematic review. *Aggression and violent behavior, 44*, 1-7.‏

Olsen, J. M., Aschenbrenner, A., Merkel, R., Pehler, S. R., Sargent, L., & Sperstad, R. (2020). A Mixed-Methods Systematic Review of Interventions to Address Incivility in Nursing. *Journal of Nursing Education, 59*(6), 319-326.‏

Pan, B., and Shi, Z., and Xu, X., 2018, *MugNet: deep learning for hyperspectral image classification using limited samples*, ISPRS J. Photogramm. Remote Sens. 145, 108–119.

Park, J., & Kim, H. J. (2020). Customer mistreatment and service performance: A self-consistency perspective*. International Journal of Hospitality Management, 86*, 102367.‏

Penttinen, E., Jyrkinen, M., & Wide, E. (2019). Methods to Prevent and Tackle Emotional Workplace Abuse. In *Emotional Workplace Abuse* (pp. 63-74). Palgrave Pivot, Cham.‏

Sabbath, E. L., Williams, J. A., Boden, L. I., Tempesti, T., Wagner, G. R., Hopcia, K., ... & Sorensen, G. (2018). Mental health expenditures: Association with workplace incivility and bullying among hospital patient care workers. *Journal of occupational and environmental medicine, 60*(8), 737.‏

Salin, D., Cowan, R. L., Adewumi, O., Apospori, E., Bochantin, J., D'Cruz, P., ... & Işik, I. (2018). Prevention of and interventions in workplace bullying: A global study of human resource professionals' reflections on preferred action. *The International Journal of Human Resource Management*, 1-23.‏

Schilpzand, P., De Pater, I. E., & Erez, A. (2016). Workplace incivility: A review of the literature and agenda for future research. *Journal of Organizational behavior,* 37, S57-S88.‏

Shafran-Tikva, S., Chinitz, D., Stern, Z., & Feder-Bubis, P. (2017). Violence against physicians and nurses in a hospital: How does it happen? A mixed-methods study. Israel journal of health policy research, 6(1), 59.‏

Simpson, A. V., Farr-Wharton, B., & Reddy, P. (2020). Cultivating organizational compassion in healthcare. *Journal of Management & Organization, 26*(3), 340-354.‏

Sivakumar, P., and Prakash, M., and Singaravel, G., 2015., *Efficient methods for distinction preclusion in data mining,* [International Journal of Applied Engineering Research](https://www.scopus.com/sourceid/21100217234?origin=recordpage" \o "Go to the information page for this source), Vol. 10, Issue 55, pp. 2212-2215.

Sommovigo, V., Setti, I., O'Shea, D., & Argentero, P. (2020). Investigating employees' emotional and cognitive reactions to customer mistreatment: an experimental study. European *Journal of Work and Organizational Psychology*, 1-21.‏

Spelten, E., Thomas, B., O’Meara, P., van Vuuren, J., & McGillion, A. (2020). Violence against Emergency Department nurses; Can we identify the perpetrators?. PLoS one, 15(4), e0230793.‏

Speroni, K. G., Fitch, T., Dawson, E., Dugan, L., & Atherton, M. (2014). Incidence and cost of nurse workplace violence perpetrated by hospital patients or patient visitors. *Journal of emergency nursing, 40*(3), 218-228.‏

Sui, J. (2015). *Understanding and fighting bullying with machine learning* (Doctoral dissertation, The University of Wisconsin-Madison).

Walsh, B. M., & Magley, V. J. (2014). An empirical investigation of the relationship among forms of workplace mistreatment. *Violence and Victims, 29*(2), 363-380.‏

Wang, Y. C., & Lin, Y. K. (2014). Association between temperature and emergency room visits for cardiorespiratory diseases, metabolic syndrome-related diseases, and accidents in metropolitan Taipei. *PloS one, 9*(6), e99599.‏

Yang, L. Q., Caughlin, D. E., Gazica, M. W., Truxillo, D. M., & Spector, P. E. (2014). Workplace mistreatment climate and potential employee and organizational outcomes: A meta-analytic review from the target's perspective. *Journal of occupational health psychology, 19*(3), 315.‏

Zhao, H., & Guo, L. (2019). Abusive supervision and hospitality employees' helping behaviors. *International Journal of Contemporary Hospitality Management*.‏

Zhang, L., and Du, B., 2016, *Deep learning for remote sensing data: A technical tutorial on the state of the art*, IEEE Geosci, Remote Sens. Mag. 4(2), 22–40.

Zhou, Z. E., Che, X. X., & Rodriguez, W. A. (2020). Nurses experiences of workplace mistreatment. In *Handbook of Research on Stress and Wellbeing in the Public Sector*. Edward Elgar Publishing.‏

1. RoboTreat is the name we choose to reflect the integrated nature of the project, which uses technology to mitigate a social challenge. [↑](#footnote-ref-1)