Published in final edited form as:
J Elder Abuse Negl. 2020 ; 32(1): 97–103. doi:10.1080/08946566.2019.1682099.

Can Artificial Intelligence Help Identify Elder Abuse and Neglect?

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Abstract

A health care encounter is a potentially critical opportunity to detect elder abuse and initiate intervention. Unfortunately, health care providers currently very seldom identify elder abuse. Through development of advanced data analytics techniques such as machine learning, artificial intelligence has the potential to dramatically improve elder abuse identification in health care settings.

Keywords

elder abuse; machine learning; electronic health records; insurance claims

Elder abuse encompasses behaviors or negligence against an older adult that results in harm or the risk of harm committed by someone in a relationship with an expectation of trust, or when the victim is targeted because of age or disability (Lachs & Pillemer, 2015; National Center for Elder Abuse). This abuse includes: physical abuse, sexual abuse, neglect, psychological abuse, and financial exploitation (Lachs & Pillemer, 2015; National Center for Elder Abuse). Elder abuse is common, affecting 5–10% of community dwelling older adults each year, with institutionalized older adults at even higher risk (Lachs & Pillemer, 2015; National Center for Elder Abuse). Elder abuse can have profound medical consequences for victims, significantly increasing their risk for mortality, exacerbations of chronic illness, and depression (Lachs & Pillemer, 2015; National Center for Elder Abuse). Previous research has suggested that elder abuse victims have higher rates of Emergency Department use, hospitalization, and nursing home placement (Lachs & Pillemer, 2015; National Center for Elder Abuse). The societal cost, though not well-examined, is likely many billions of dollars annually in direct medical costs, services provided for victims, and financial loss through exploitation (National Center for Elder Abuse).

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Though common, serious, and costly, elder abuse is dramatically under-recognized, with research suggesting that only 1 in 24 cases of abuse is identified and reported to the authorities (Lachs & Pillemer, 2015). Under-identification and reporting have likely contributed to much of the associated morbidity and mortality. Also, abuse typically occurs over years and may increase in severity over time. As a result, improving early identification of elder abuse has become an important public health priority.

Health care encounters, which may be the only time a victimized older adult ever leaves their home or institutional environment, have been recognized as potentially critical opportunities to detect cases so that interventions may be initiated (Rosen, Stern, Elman, & Mulcare, 2018). Unfortunately, health care providers currently very seldom identify or report elder abuse, suggesting this opportunity is usually missed (Rosen et al., 2018). As a result, several screening tools with multiple questions that providers may ask older adults have been developed (Fulmer, Guadagno, Bitondo Dyer, & Connolly, 2004; Platts-Mills et al., 2018; Yaffe, Wolfson, Lithwick, & Weiss, 2008). These screening tools are challenging to incorporate into brief clinical encounters, though. Additionally, many victims do not disclose abuse when asked, and screening tools based on self-report are not useful for older adults with cognitive impairment, who may be at an even higher risk for victimization. Other tools incorporating providers' observations and physical findings (Fulmer, 2003; Platts-Mills et al., 2018) have also been developed, but these may be time-consuming and have other limitations.

Through development of machine learning algorithms, artificial intelligence within health care has the potential to dramatically improve identification of elder abuse.

Machine Learning: Increasingly Recognized as a Valuable Tool

Innovations in artificial intelligence have made it possible and financially feasible to analyze (or "mine") vast amounts of data. Within artificial intelligence, machine learning refers to algorithms that use this data to "learn" how to make better predictions and to identify often hidden patterns. Without additional programming, as they analyze more data, these algorithms improve their ability to make predictions. Many private industries have used machine learning algorithms successfully for years. For example, these algorithms have been used by hedge funds to guide stock purchasing and selling, and by professional sports franchises to make decisions on drafting, acquiring, and trading players (LeCun, Bengio, & Hinton, 2015).

More recently, the potential utility for machine learning algorithms and artificial intelligence in general in health care has been recognized, given the enormous amount of available data and the importance of using patterns for prediction (Kvancz, Sredzinski, & Tadlock, 2016; Topol, 2019). Their use is becoming more prominent, particularly to improve early and accurate diagnosis and to provide more cost-effective care (Bates, Saria, Ohno-Machado, Shah, & Escobar, 2014; Naidus & Celi, 2016). Insurance claims data have been used for early detection of common diseases including diabetes (Krishnan et al., 2013) and identification of rare diseases such as hereditary angioedema (Kvancz et al., 2016). Electronic health record data has been used for early identification of diagnoses including heart failure (Blecker et al., 2018), to assess risk for developing delirium in hospitalized patients (Wong et al., 2018), and to predict discharge diagnoses after hospitalization (Rajkomar et al., 2018). Machine learning algorithms have been used in radiographic, photographic, and ophthalmologic imaging to improve accurate diagnosis of diseases including ischemic stroke (Beecy et al., 2018), skin cancer (Esteva et al., 2017), and diabetic retinopathy (Gulshan et al., 2016).

A machine learning approach has also recently been applied to improve the delivery of social services. Notably, machine learning has been used to impact family violence. Allegheny County, Pennsylvania has designed an algorithm to predict the risk of future severe harm to a child among reports received by Child Protective Services, which helps guide response (Hurley, 2018). This algorithm analyzes patterns, incorporating previous Child Protective Services data as well as data about the child and family from jails, psychiatric services, public/welfare benefits, and drug and alcohol treatment centers (Hurley, 2018). The deployment of this algorithm has already substantially improved the accuracy of predicting bad outcomes for at-risk children (Hurley, 2018).

Potential for Machine Learning Algorithms Using Health Care Data to Improve Elder Abuse Identification

Applying machine learning algorithms to health care data has enormous potential to improve elder abuse identification. Insurance claims, electronic health records, and medical images contain vast information about older adults including: health care utilization (including ED, hospital, and outpatient), diagnoses, clinical documentation from providers from many disciplines, laboratory tests conducted and test results, radiographs, photographs, and medications prescribed.

Using machine learning, algorithms may identify patterns that distinguish victims of elder abuse or those at high risk from other older adults. These subtle differences may represent “red flags” suggestive of potential victimization and assist in finding these “needles in the haystack.” Additionally, there may be specific laboratory and imaging tests ordered and diagnoses made commonly among abuse victims. For example, it is possible that a significant percentage of elder abuse victims: (1) have two or more visits to different EDs with a hospitalization within a 3-month period, (2) receive forearm x-rays, (3) are diagnosed with an ulnar fracture, (4) do not follow up after discharge with a primary care provider or refill chronic medications. If this pattern is very seldom seen in other older adults, it may suggest potential victimization. Subtle differences in brain CT scan or MRI results may distinguish abuse or neglect from unintentional injury and normal aging.

Machine learning forms the back end of a potential clinical decision support tool which may be developed in the future to assist in early identification. This tool may notify health care providers that a patient should receive screening / evaluation for elder abuse as part of the health care encounter. This targeting would represent an improvement over universal screening, which has been proposed but is often impractical in a brief clinical encounter. Also, a tool developed from this approach may be used to notify aging services, Medicare, or other insurers that an older adult is at risk, triggering an assessment by a social worker or care manager. Integrated health systems are particularly well-positioned to respond to notification that a patient is a potential abuse victim with further multi-disciplinary assessment and intervention.

Potential Data Sources: Advantages and Challenges

EHRs offer the most attractive potential health care data source to mine given the depth and variety of information they contain on older adult patients. Because of the fragmentation within the US health care system, though, a single EHR often does not contain all health-related information about an older adult. Many older adults receive care from hospitals and providers affiliated with different health systems and, therefore, only a fraction of their health information is available in each EHR.

Until recently, data sharing between health systems for quality improvement or research has been uncommon. Interoperability issues across different health systems and EHR vendors create another barrier for consistent information storage and retrieval. Challenges presented by this fragmentation may be particularly relevant for elder abuse victims, as experts have suggested that abuse victims may be more likely than other older adults to present for care at multiple different EDs / hospitals and outpatient providers (Rosen et al., 2018). The increasing adoption of common data model (CDM) by organizations nationwide such as the Observational Medical Outcomes Partnership (OMOP) is promising in mitigating this challenge (Hripcsak et al., 2015). Also, large clinical research networks such as the PCORI-funded New York City Clinical Research Work (NYC-CDRN) can significantly reduce data missingness and scarcity (Kaushal et al., 2014).

Large insurance claims databases are another type of useful data source. Claims data includes information on all health care utilization from different institutions, providers, and health care systems, from ED visits and hospitalizations to pharmacy refills and outpatient appointments. These utilization events, when examined together, form unique patterns of care. By comparing these patterns of care among abuse victims to other older adults who are not victims, it may be possible to identify important differences. Using insurance claims may be particularly appropriate for US older adults, given that Medicare is the primary insurance provider for the nearly all U.S adults aged ≥65. Claims data, however, has been designed for use to facilitate payments rather than for comparative utilization research, and transforming it to allow for this analysis is labor-intensive and requires expertise.

Ideally, EHR and claims data would be linked and analyzed to allow for better pattern recognition. This may be most likely for patients cared for in integrated health systems.

The Importance of Identifying Cases Accurately

A critical challenge in all elder abuse and neglect research that this new machine learning approach also faces is identifying appropriate older adult case subjects for study. A uniform “gold standard” does not exist to determine that an older adult is a victim of abuse or neglect. Also, it is difficult to ensure that a comparison group of non-victimized older adults does not include unidentified victims. Even the most sophisticated machine learning algorithm using a large amount of data, if applied to a sample of inaccurately categorized victims and non-victims, will not be able to accurately identify cases of elder mistreatment. Therefore, any successful machine learning approach would need to be accompanied by a rigorous methodology to identify cases and a comparison group. Some studies have convened an "expert panel" to assess cases to determine that abuse occurred (Fulmer et al., 2005; Wiglesworth et al., 2009). Additionally, recent strategies have included examining cases already investigated by Adult Protective Service or legally adjudicated cases where the presence of abuse has been established by the criminal justice system.

Furthermore, characteristics of elder abuse and neglect cases that are identified and reported likely differ in important ways from those that are not. If a machine learning algorithm is designed using only cases that have been already identified, it will likely not be able to effectively detect many occult cases, its primary goal. Therefore, creative approaches are needed to find occult cases and include them in this machine learning approach to further optimize the resulting algorithm.

Next Steps

Projects to explore a machine learning approach for elder abuse using Medicare claims data and legally adjudicated cases are already underway (National Institutes of Health). They should be supported and expanded to include electronic health record data and medical imaging. Strategies should be developed to overcome challenges in analyzing health care data for this purpose. In the future, health care data may be combined with other administrative databases, such as area agencies on aging, law enforcement, Veteran's Administration, and Adult Protective Services to improve pattern identification and early case finding. Early identification has the potential to significantly increase quality of life and improve health for these vulnerable older adults, most of whom are suffering in silence. Identification may also lead to reduced health care and other related costs.

Ultimately, artificial intelligence has the potential to transform approaches to elder abuse, improving our ability to identify these vulnerable older adults and impact their health and safety.

Funding sources:

Our work has been supported by a grant from the National Institute on Aging (R01 AG060086). Tony Rosen's participation has also been supported by a Paul B. Beeson Emerging Leaders Career Development Award in Aging (K76 AG054866) from the National Institute on Aging.

References

Bates DW, Saria S, Ohno-Machado L, Shah A, & Escobar G (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. Health Affairs (Millwood), 33(7), 1123–1131. doi:10.1377/hlthaff.2014.0041

Beecy AN, Chang Q, Anchouche K, Baskaran L, Elmore K, Kolli K, … Min JK (2018). A Novel Deep Learning Approach for Automated Diagnosis of Acute Ischemic Infarction on Computed Tomography. JACC Cardiovascular Imaging, 11(11), 1723–1725. doi:10.1016/j.jcmg.2018.03.012 [PubMed: 29778866]

Blecker S, Sontag D, Horwitz LI, Kuperman G, Park H, Reyentovich A, & Katz SD (2018). Early Identification of Patients With Acute Decompensated Heart Failure. Journal of Cardiac Failure, 24(6), 357–362. doi:10.1016/j.cardfail.2017.08.458 [PubMed: 28887109]

Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, & Thrun S (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115–118. doi:10.1038/nature21056 [PubMed: 28117445]

Fulmer T (2003). Elder abuse and neglect assessment. Journal of Gerontological Nursing, 29(6), 4–5.

Fulmer T, Guadagno L, Bitondo Dyer C, & Connolly MT (2004). Progress in elder abuse screening and assessment instruments. Journal of the American Geriatrics Society, 52(2), 297–304. [PubMed: 14728644]

Fulmer T, Paveza G, Vandeweerd C, Guadagno L, Fairchild S, Norman R, … Bolton-Blatt M (2005). Neglect assessment in urban emergency departments and confirmation by an expert clinical team. The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences, 60(8), 1002–1006. doi:10.1093/gerona/60.8.1002

Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, … Webster DR (2016). Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA, 316(22), 2402–2410. doi:10.1001/jama.2016.17216 [PubMed: 27898976]

Hripcsak G, Duke JD, Shah NH, Reich CG, Huser V, Schuemie MJ, … Ryan PB (2015). Observational Health Data Sciences and Informatics (OHDSI): Opportunities for Observational Researchers. Studies in Health Technology and Informatics, 216, 574–578. [PubMed: 26262116]

Hurley D (2018, 1 2, 2018). Can an Algorithm Tell When Kids Are in Danger? New York Times Magazine.

Kaushal R, Hripcsak G, Ascheim DD, Bloom T, Campion TR Jr., Caplan AL, … Tobin JN (2014). Changing the research landscape: the New York City Clinical Data Research Network. Journal of the American Medical Informatics Association (JAMIA), 21(4), 587–590. doi:10.1136/amiajnl-2014-002764 [PubMed: 24821739]

Krishnan R, Razavian N, Choi Y, Nigam S, Blecker S, Schmidt A, & Sontag D (2013). Early detection of diabetes from health claims. Paper presented at the Machine Learning in Healthcare Workshop, NIPS.

Kvancz DA, Sredzinski MN, & Tadlock CG (2016). Predictive analytics: a case study in machine-learning and claims databases. 8(6), 214–219.

Lachs MS, & Pillemer KA (2015). Elder Abuse. New England Journal of Medicine, 373(20), 1947–1956. doi:10.1056/NEJMra1404688 [PubMed: 26559573]

LeCun Y, Bengio Y, & Hinton G (2015). Deep learning. Nature, 521(7553), 436–444. doi:10.1038/nature14539 [PubMed: 26017442]

Naidus E, & Celi LA (2016). Big data in healthcare: are we close to it? Revista Brasileira de terapia intensiva, 28(1), 8–10. doi:10.5935/0103-507X.20160008 [PubMed: 27096670]

National Center for Elder Abuse. The Elder Justice Roadmap: A Stakeholder Initiative to Respond to an Emerging Health, Justice, Financial, and Social Crisis. Retrieved from https://www.justice.gov/file/852856/download

National Institutes of Health. NIH RePORTer: Identifying Patterns of Health Care Utilization among Physical Elder Abuse Victims Using Medicare Data and Legally Adjudicated Cases. Retrieved from https://projectreporter.nih.gov/project_info_description.cfm?aid=9589637&icde=42536001&ddparam=&ddvalue=&ddsub=&cr=4&csb=default&cs=ASC&pball=

Platts-Mills TF, Dayaa JA, Reeve BB, Krajick K, Mosqueda L, Haukoos JS, … Zimmerman S (2018). Development of the Emergency Department Senior Abuse Identification (ED Senior AID) tool. Journal of Elder Abuse & Neglect, 30(4), 247–270. doi:10.1080/08946566.2018.1460285 [PubMed: 29652592]

Rajkomar A, Oren E, Chen K, Dai AM, Hajaj N, Hardt M, … Sun M. J. n. D. M. (2018). Scalable and accurate deep learning with electronic health records. 1(1), 18.

Rosen T, Stern ME, Elman A, & Mulcare MR (2018). Identifying and Initiating Intervention for Elder Abuse and Neglect in the Emergency Department. Clinics in Geriatric Medicine, 34(3), 435–451. doi:10.1016/j.cger.2018.04.007 [PubMed: 30031426]

Topol EJ (2019). High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56. doi:10.1038/s41591-018-0300-7.

Wiglesworth A, Austin R, Corona M, Schneider D, Liao S, Gibbs L, & Mosqueda L (2009). Bruising as a marker of physical elder abuse. Journal of the American Geriatrics Society, 57(7), 1191–1196. doi:10.1111/j.1532-5415.2009.02330.x [PubMed: 19558476]

Wong A, Young AT, Liang AS, Gonzales R, Douglas VC, & Hadley D (2018). Development and validation of an electronic health record–based machine learning model to estimate delirium risk in newly hospitalized patients without known cognitive impairment. 1(4), e181018–e181018.

Yaffe MJ, Wolfson C, Lithwick M, & Weiss D (2008). Development and validation of a tool to improve physician identification of elder abuse: the Elder Abuse Suspicion Index (EASI). Journal of Elder Abuse & Neglect, 20(3), 276–300. doi:10.1080/08946560801973168. [PubMed: 18928055]