
Digital Health for the Opioid Crisis: A Historical Analysis of NIH Funding from 2013 to 2017

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Cite this chapter as: Lin EJD, Schroeder M, Huang Y, Linwood SL. Digital Health for the Opioid Crisis: A Historical Analysis of NIH Funding from 2013 to 2017. In: Linwood SL, editor. *Digital Health*. Brisbane (AU): Exon Publications. Online first 2022 Jan 30.

Doi: <https://doi.org/10.36255/exon-publications-digital-health-opioid-crisis>

Abstract: Prior to the COVID-19 crisis, the opioid crisis was the major public health challenge ravaging economies and communities across the United States. Digital health offered new ways to reach, diagnose, and treat individuals with opioid use disorders. Federal research funding usually reflects the nation's research priorities and shapes the direction of innovation. We reviewed funded projects by the National Institute on Drug Abuse (NIDA) from 2013 to 2017, a period leading to the substantial increase in federal funding and the launch of the \$500M HEAL (Helping End Addiction Long-TermSM) initiative in 2018. We presented our viewpoint of the research landscape of the digital health development for the opioid crisis. Overall, there was a gradual increase in NIDA grant funding for technology

In: Linwood SL, editor. *Digital Health*. Exon Publications, Brisbane, Australia.

ISBN: 978-0-6453320-1-8. Doi: <https://doi.org/10.36255/exon-publications-digital-health>

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in the opioid crisis and the percentage of NIDA technology awards funding new projects had nearly doubled in that period. We categorize the types of applications and potential challenges in five emerging technology categories: electronic health, mobile health, virtual reality, artificial intelligence, and biosensor. Diversification of funding in these categories offers the promise of more innovation in new technologies to combat the opioid epidemic.

Keywords: biosensors; digital health for opioid crisis; NIH funding for opioid crisis; technology innovations to address opioid crisis; virtual reality applications

INTRODUCTION

Prior to COVID-19, the United States was in the midst of a devastating opioid crisis. In 2016, 2.1 million people began misusing prescription opioids, and 170,000 injected heroin for the first time (1). In the same year, 42,249 people died of opioid-related drug overdoses, a 27.9% increase from 2015 (2). Opioid abuse had contributed to the decline in the size of the workforce, and the Council of Economic Advisors estimated that the effects of opioid abuse costed over 500 billion US dollars in 2015 alone (3, 4). Despite increased awareness and strong efforts to curb opioid abuse, the crisis had continued to worsen. From July 2016 to September 2017 opioid overdose-related emergency department visits rose 30% (5). Total overdoses in 52 areas in 45 states also rose by 30% over the same period (6). While the damaging effects of opioid abuse were highly visible in communities and economies across the country, it was estimated that only 10% of people with substance use disorders receive treatment (7, 8). With such large increases in opioid abuse and so few people receiving treatment, it was imperative that the healthcare system finds new ways to effectively treat and prevent opioid abuse.

TECHNOLOGY INNOVATIONS TO ADDRESS OPIOID CRISIS

Technology has the potential to become the underpinnings of innovative solutions to revolutionize how opioid abuse is diagnosed, treated, and prevented as demonstrated by many research studies (9–13). Technology is ubiquitous in this constantly connected world. In the United States, 9 in 10 individuals owned a mobile phone and 76% were using the Internet in 2016 (14, 15). Technology applications in the opioid crisis include social media support groups, wearable biosensors that collect real-time patient data to monitor opioid agonist treatment adherence, machine learning applications that synthesize vast amounts of data to predict problematic opioid usage, and many others (9, 10, 16). From 2007 to 2017, the number of opioids-focused technology publications in PubMed almost tripled (Figure 1). We broadly divide the technology used in the opioid crisis into five interrelated categories: electronic health (e-health), mobile health (m-health), virtual reality (VR), artificial intelligence (AI), and biosensor technology (Table 1) (17, 18).

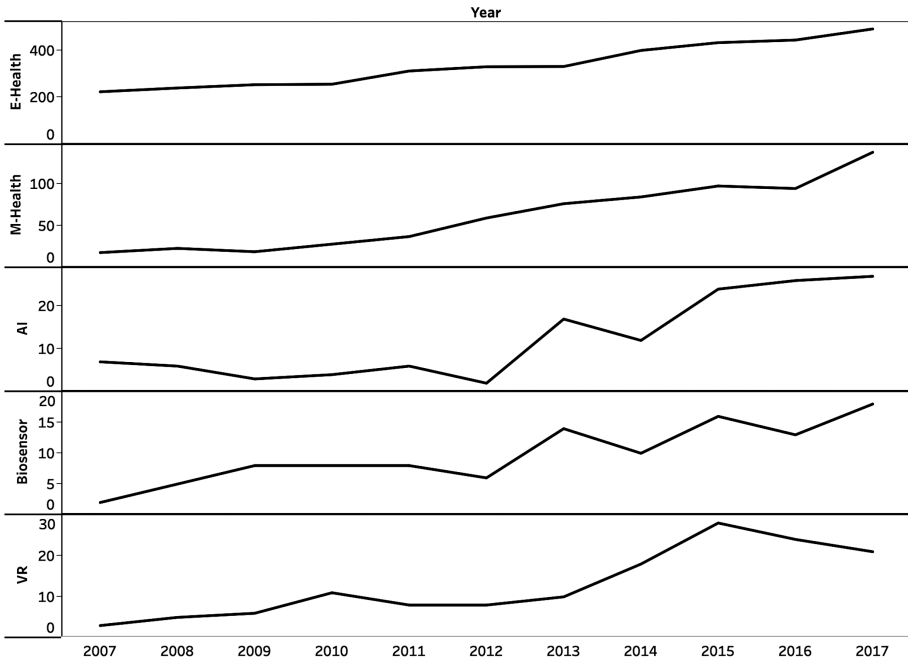


Figure 1. Number of opioid focused technology research papers in the PubMed database from 2007 to 2017 by technology category and plotted against year of publication. Search terms used for each of the five categories are listed in Table 2.

Research in the field represents a multidisciplinary effort from experts in public health, healthcare services, biomedicine, digital technology, and data analytics. While research publications often act as early indicators of innovation trends, research funding that provide continued investment into the development of these technology is a critical driver for innovation.

Technology Funding Trends

We examined research funding trend by the U.S. National Institute of Health (NIH) between 2013 and 2017, using the NIH Research Portfolio Online Reporting Tools (RePORTER). We chose this period as there was a substantial increase (124%) in total federal funding dedicated to address the opioid epidemic in 2018, including the launch of the HEAL (Helping End Addiction Long-TermSM) initiative by NIH with over \$500 million in research funding. The change in funding mechanisms could limit the comparability for the years 2018 and 2019, so these were excluded from the analysis. Our preliminary assessment showed that most of the opioid addiction research was funded by the National Institute of Drug Abuse (NIDA), with 3091 funded projects out of a total of 4,348 projects (see Table 2 for search terms used). Consequently, for each technology category listed

TABLE 1**Technology Category Descriptions and Applications in the Opioid Crisis**

Technology Category	Description	Examples
Virtual Reality (VR)	Engaging digital rendering of real-world or experience.	Reducing opioid prescription and abuse through pain management and behavioral therapy (12, 21).
Biosensor Technology	Mobile sensors used to measure biometric data.	Monitoring opioid agonist treatment adherence and detecting opioid tolerance prior to the prescription of opioids (16).
Artificial Intelligence (AI)	Data-driven machine learning and computerized adaptive testing.	Predicting risk factors for opioid agonist treatment and identifying individuals at risk for relapse from social network language (9, 13, 24).
Mobile Health (m-health)	A branch of e-health technologies that requires the use of a wireless device or wireless device associated capabilities such as SMS texting or GPS.	Performing real-time health assessments and intervening in risky situations (23, 27, 28).
Electronic Health (e-health)	Electronic or Internet-based methods of integrating information and associated web services.	Educating adolescents and healthcare providers on opioids and supporting internet-based recovery social networks (31–34).

TABLE 2**Search Method using the NIH Research Portfolio Online Reporting Tools (RePORTER) and PubMed**

Substance abuse search terms	(“opioid addiction” OR “opiate addiction” OR “opiate abuse” OR “opioid abuse” OR “substance abuse” OR “drug abuse” OR “injection drug use” OR “Injected drug abuse” OR (addiction AND(opioid OR opiate)) OR “substance use disorder” OR “prescription drug use” OR “prescription drug abuse”)
	AND (search terms for individual category)
Technology Category	Search Terms
Virtual Reality	(“virtual reality” OR “video game”)
Artificial Intelligence	(“artificial intelligence” OR “machine learning” OR “machine learning algorithms” OR “computerized adaptive testing”)
Mobile	(“cellular phone” OR “cell phone” OR “mobile health” OR m-health OR “mobile phone” OR smartphone OR iPhone OR “short message service” OR “text messages” OR “mobile application”)
Web-based	(“electronic health” OR e-health OR computer OR internet OR “web-based” OR web-based)
Biofeedback	(biofeedback OR neurofeedback OR “wearable technology” OR biosensor)

above, we searched projects funded by NIDA whose titles, terms, or abstracts contained at least one term from both a list of category-specific terms and a list of substance abuse-related words (Table 2).

Abstracts from the resulting searches were reviewed by two authors and compiled into a list divided by technology category and fiscal year. Results were restricted to technology-based solutions directly used by people with substance use disorders (SUDs), caregivers, community resources, or clinicians with the goal of treating or preventing SUDs. Projects were included if directed towards substance abuse in general but projects specific to non-opioid substances were not included. As shown in Figure 2, results were split into two groups: projects in the first year of funding, and projects in subsequent years of funding. The Biomedical Research and Development Price Index (BRDPI), a weighted average of yearly changes in purchasing power with respect to biomedical resources used in NIH funded research, was used to calculate all monetary values in 2017 dollars.

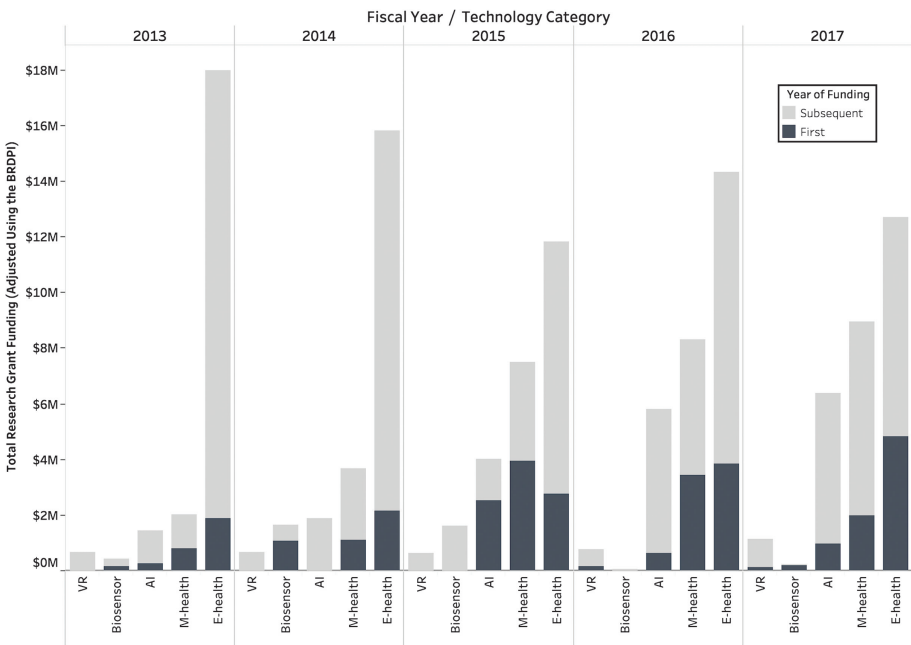


Figure 2. Total research grant awards for projects funded by the National Institute on Drug Abuse (NIDA) from fiscal year (FY) 2013 to 2017. These data were obtained from RePORTER, a database of all NIH funded projects, and categorized by fiscal year and type of technology. Award totals are further divided into funding for projects in their first year of funding and funding for projects in subsequent years of funding. All values were adjusted to 2017 dollars using the Biomedical Research and Development Price Index.

TECHNOLOGY FUNDING TRENDS

Federal funding for the NIDA, remained stagnant between FY 2013 and 2017, in spite of relevant inflation in the cost of biomedical research (19,20). Despite this stasis in funding, research grant awards for technology used in the opioid crisis have increased 63% over the 5-year period. In addition, the percentage of funding to new technology projects has nearly doubled from 13.95% to 27.88%, indicating continued effort in innovation.

Virtual reality applications

Up until 2017, virtual reality was not heavily funded by NIDA. VR has been used in the opioid crisis to train healthcare providers on the proper prescription and administration of opioids and to augment therapy sessions, providing low-risk environments for patients and healthcare providers to practice responsible behaviors (21). VR is also being used in pain management to distract patients from potentially painful or stressful experiences, thus reducing opioid prescriptions for pain (12). Notably, the application of VR in pain management has been studied since 2000 and is well-supported, although the application in the context of reducing opioid prescriptions is more recent. Nonetheless, it is interesting that federal funding for VR applications was not more, given the maturity of the technology and research evidence.

One may contemplate whether the limited federal support for VR research is in part due to the availability of other sources of funding. Major contributors to advances in VR research are video game companies such as Oculus VR, a division of Facebook Inc. and maker of Oculus VR headsets. Private corporations like Facebook Inc. can make large investments for research and development provided consumers are interested in the product, whereas federal awards are limited by taxpayer funds appropriated by Congress. Commercial investment allows for rapid innovation and development of technology tools that can then be adapted for healthcare purposes.

While commercialization of healthcare technology may reduce costs and increase the availability of products, commercial development does not necessarily include clinical testing. This highlights the need for research funding to support rigorous clinical trials for evaluating healthcare applications and the dissemination of these research. In addition, care must be taken to ensure that commercially developed technology applications are using safe and effective evidence-based practices (22, 23).

Biosensor

While areas of technology like m-health have seen drastic increases in both funding and research, areas such as biosensor technology have not (Figure 2). Biosensor technology has immense potential in monitoring and treating opioid addiction as it allows for real-time tracking of biometric data such as blood opioid levels, heart rate, and temperature. Combining a pill-based sensor that measures blood substance levels with a doctor and patient-facing m-health application may enable doctors to monitor patients in real-time and provide immediate feedback when a

patient deviates from an opioid agonist treatment. Despite the prospective uses of biosensor technology, funding has remained low. From 2013 to 2017, biosensor innovations have accounted for less than 5% of the yearly funding for technology in the opioid crisis, and unlike other areas, there was no steady trend in research dissemination.

Barriers in developing biosensors for opioid-related applications include regulatory and privacy considerations. Unlike most m-health applications, biosensors are often considered medical devices that need to comply with FDA regulations, a non-trivial undertaking. Additionally, biosensor applications rely on collecting patient data in real-time or storing patient data for later retrieval. Many people are hesitant with the constant collection of personal health information. Moreover, information such as blood opioid levels may implicate individuals in legal cases thereby further reducing the acceptability of biosensor applications (16). While the ethics surrounding biosensor technology must be clarified before it can become widely accepted, recent breakthroughs show promise. For example, a research team from the University of Massachusetts Medical School rigorously tested a previously developed biosensor that uses temperature and movement to detect opioid use and showed the biosensor could accurately differentiate between individuals with a tolerance to opioids and individuals without such a tolerance, providing a novel way to diagnose opioid addiction (11).

Artificial intelligence

With the huge strides in machine learning approaches such as deep learning, AI-driven analytics has become the new pursuit for healthcare in the past few years. This is reflected in the impressive 376% increase in AI funding from FY 2013 to FY 2017. Correspondingly, the percentage of NIDA funding for technology in the opioid crisis distributed to AI research projects tripled in the same period. AI is being used in addiction healthcare to predict the risk of prescription opioid misuse, detect red flags for relapse in language on social media, and provide adaptive computerized interventions to prevent relapse in recovery (9, 13, 24).

Although AI is receiving much attention in the media and has seen increases in funding and research output, more work is needed to effectively integrate the areas of AI and opioid addiction healthcare. Development of AI applications requires a strong grasp of computer science and statistics, a deep understanding of the nature of the problem to be modeled, and sufficient data. A major stumbling block for the use of AI in healthcare is the lack of usable data. Privacy considerations and the long-standing challenges surrounding data collection and standards have resulted in a lack of quality data to train AI applications. This is even more so for data related to opioid addiction. Specific challenges include: (i) people with opioid addiction often have inconsistent treatment through different providers hence difficult to have the complete medical record; (ii) many individuals with opioid addiction are in and out of the criminal justice system; (iii) environmental and social determinants play a critical role in the opioid crisis, yet there are limited data collection and data access on these critical factors; and (iv) potential legal implications reduce willingness to contribute data by individuals and likely limit the ability to collect and share data by care providers. The most likely approach to overcome some of these challenges is to develop state or federal level initiatives, such as policies on data reporting and standardization with support funding. Quality data collected through these initiatives

can be made available to approved AI experts through a data use agreement. In parallel, strong guidelines need to be established for data protection and usage to protect privacy.

Mobile health

Funding for opioid-related m-health innovation has shown the most consistent increase from FY2013 to FY2017. Similar to other industries, the ubiquitous access of mobile devices has fueled intense efforts to develop smartphone applications. For the opioid crisis, mobile devices offer specific features to address the gaps in services. With the shortage of addiction treatment professionals, and the need for continuous support in the recovery process, m-health applications provide extension of addiction services to underserved populations and can enhance treatment compliance through greater social engagement. M-health applications also offer novel functions such as geo-tracking and voice interactive applications. These capabilities facilitate ecological momentary assessment and intervention, real-time methods of recognizing and intervening in dangerous situations, aiding in the reduction of relapse in opioid addiction recovery (25–28).

E-health

Projects involving e-health have received the largest proportion of technology funding due to the wide range of electronic or internet-based applications that can be developed. With the mandate for all healthcare providers to adopt and demonstrate meaningful use of electronic health records (EHR) by the US federal government, by 2017, 96% of hospitals and 86% of physicians' offices in the US started using EHR (29, 30). This created opportunities to develop clinical decision support systems to guide opioid prescribing (31, 32) and to identify individuals at risk for opioid overdose (33). Computer-based or online e-learning modules have also been developed for substance abuse prevention programs or treatment/recovery programs (34).

CONCLUSION

Over 400,000 people have died from opioid overdoses since 1999 (35). More than 115 people die from opioid overdoses every day (2). Technology opens up innovative ways to combat the opioid crisis. Moreover, technology can fill in the 'gap' when healthcare resources are scarce or inaccessible, as observed during the COVID pandemic. Going forward, it is imperative that funding and support for technology in the opioid crisis be improved. It is only when public policymakers, healthcare professionals, and technology experts work together that technology can transform the way opioid abuse is diagnosed, treated, and prevented. It is only with public awareness, federal and local support, that we can put an end to this opioid crisis.

Acknowledgment: This work was supported by the Nationwide Children's Hospital Research Institute internal fund to S.L.L.

Conflict of Interest: The authors declare no potential conflicts of interest with respect to research, authorship and/or publication of this manuscript.

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