Data science for social work practice

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Abstract
Data science is merging of several techniques that include statistics, computer programming, hacking skills, and a solid expertise in specific fields, among others. This approach represents opportunities for social work research and intervention. Thus, practitioners can take advantage of data science methods and reach new standards for quality performances at different practice levels. This article addresses key terms of data science as a new set of methodologies, tools, and technologies, and discusses machine learning techniques in order to identify new skills and methodologies to support social work interventions and evidence-based practice. The challenge related to data sciences application on social work practice is the shift on the focus of interventions. Data science supports data-driven decisions to predict social issues, rather than providing an understanding of reasons for social problems. This can be both a limitation and an opportunity depending on context and needs of users and professionals.

Keywords
Big data, data science, machine learning, management, research, social work

Introduction
Data Science is a research tool that allows the exploration and quantitative analysis of a wide range of available data, both structured and unstructured, in order to develop understanding, extract knowledge, and formulate actionable results. Commonly, data science refers to the connection among different fields, including statistics, engineering, and mathematics, solid knowledge about a specific field, scientific method applications, data exploration, and data analysis. For social work intervention at different practice levels, all of these fields can be an asset and a powerful tool to improve professional performance.

Data science seeks work with different kinds of data, in order to make better decisions that drive actions. This approach takes advantage of analytic thinking by transforming raw data into valuable asset. Thus, data science can be a part of an innovative set of tools and strategies to improve social work practice to achieve intervention goals applying a time sensitive and scientific approach in order to increase the pace of action to reinforce evaluation.

Data science can enhance organization mission and social work practice by integrating thinking on data, decisions, and actions. This approach can provide innovative methods to enhance complex intervention tasks. Therefore, data science can make the institutional mission stronger by encouraging managers and professionals to effectively learn from history, that means, work with data in a retrospective approach. Moreover, social workers at managerial levels frequently need to give a specific answer to the question about what will happen, in other words, it is necessary to think in terms of predictive analysis. Social workers can take advantage from prescriptive analysis results from data science techniques, such as machine learning methods.

Data science can improve management tasks by retrospective data analysis, predictive analysis, real-time information, and prescriptive interventions. According to Rudin and Wagstaff (2014), data science implies finding, acquiring, cleaning, transforming, and understanding data, in order to identify relationships and delivering value from data. These skills can be combined with multidisciplinary approaches. Social workers at any level of management can lead a data science team. In that sense, managers should know well what should be done professionally as a data scientist. First, a data scientist should know basics of computing and hacking skills, in addition, should have a strong background in statistics, but...
most importantly, a data scientist needs to develop a deep understanding of specific fields. This means professionals in data science teams should demonstrate substantive expertise on issues and needs that require data analysis, and, moreover, quick and innovative responses in a wide range of social services fields, such as public health, education, child welfare, homeless, domestic violence, and substance abuse, among others.

Since fields and issues where social work professionals acting are complex, one of the most important skills that social workers can deploy at different levels is the scientific method to conduct valuable research. However, it is possible to identify social work as an art as well, due to the dynamic reality that practitioners face every day. Thus, data science can be a complementary set of tools to merge the art of social work with the ability to accomplish scientific evidence to enhance people’s well-being.

Therefore, this article includes an exploration on data science key concepts, describes machine learning techniques applied to social work research, and introduces the importance of managing data to support evidence-based practice, discusses examples of data science projects and products, and finally, suggests ethical dilemmas about biases on machine learning applications.

**Data science concept and keys elements for social work practice**

Data science has a core component related to computer programming, which can be analogous to social work practice. According to Donald Knuth (1974), the main difference between science (e.g. computer programming) and art is the degree of knowledge about specific issues, and, ultimately, the simplest way to communicate this knowledge, for example, is to teach how to proceed a machine in certain circumstances, based on previous knowledge. In other words, science is knowledge so understandable that it is easy to teach to a computer. Anything else could be understood as “art.” In order to take advantage of data science for social work practice, it is necessary to question how much knowledge practitioners have, and how easy is it to communicate it to a wide range of clients and organizations, and it depends on contexts, expectations, and social constructions. Thus, social work practice can be understood as an informed art that creates an equilibrium between the general and structured knowledge and intuition to decide about critical social conditions (Graybeal, 2007). In addition, intuition seems to be a contradictory skill for social science. However, it could be part of wide range of abilities:

Competence in social work therefore will be found not by seeking to avoid intuition, but by its recognition and development, by the creation of uncommon common sense. Social work is a matter of intuitive understanding, but it must be intuition which is unusually sound, unusually fluent and accessible, and subject to unusually careful evaluation. The absence of a framework for such evaluation in social work is the biggest single expression of the confusion about social work’s character, and also one of the biggest obstacles to social work’s wider plausibility. Social work can achieve no effective evaluation if it denies its essentially intuitive character. (England, 1986: 39)

Data science can improve social work scientific knowledge by creating innovative approaches to quantitative data, beyond the traditional statistical analysis. Data science focuses on real scenario analysis, incorporating flexible frameworks and theoretical approaches.

Therefore, several standard schemas can help to visualize how data science tools and technologies apply to social work practice, and ultimately, communicate interventions results, and make predictions.

Moreover, every data science process should start identifying the goals of a specific project. That means, understand the “business.” Then, it is necessary to collect, review, and understand data in order to prepare them to reach useful conclusions. These conclusions allow better decisions, valuable actions, and accurate information and communication. In other words, data science projects can lead faster and innovative data manipulation and allow drawing strong conclusions in a simple and understandable way. The data science process involves hacking skills, statistical thinking, computer programming, and scientific knowledge in a specific area. For social work practice, this approach has several advantages, such as reproducible results, and improving achievement communication. The challenge for social work, for example, in human service agencies, nonprofit organizations, and direct practice duties is how to build data projects, in order to combine scientific knowledge and practice intuition to tackle and resolve significant social issues and conflicts.

In addition, data science and its tools to enhance data analysis, such as machine learning, algorithms, and visualizations, are the most important elements to consolidate intervention process, by refining raw data for decision-making actions. Moreover, to start a data science project in the context of social work practice it is not absolutely necessary to know how to program complex statistical models or sophisticated machine learning algorithms, but it is mandatory to know how to apply these tools. That is one of the critical advantages of data science when applied to social work as the intuition and expertise can lead to innovative research projects and help reach conclusions and obtain responses to social problems, quickly and effective, deploying and optimizing data, as resources are already available at any level of organizations and agencies.

Peng and Matsui (2016) propose a synthesis to explain the data science process by several steps. According to these authors, data science and data analysis seems to be a linear process, however, rather than a step-to-step
procedure, data science is “highly iterative and non-linear process, better reflected by a series of epicycles” (Peng and Matsui, 2016: 4). The key element of the idea of epicycles is that information is learned in each step. Then, it is possible to refine, refresh the action that was just performed or proceed to the next step. Epicycles of analysis can be defined as follows:

An epicycle is a small circle whose center moves around the circumference of a larger circle. In data analysis, the iterative process that is applied to all steps of the data analysis can be conceived of as an epicycle that is repeated for each step along the circumference of the entire data analysis process. Some data analyses appear to be fixed and linear, such as algorithms embedded into various software platforms, including apps. However, these algorithms are final data analysis products that have emerged from the very non-linear work of developing and refining a data analysis so that it can be “algorithmized.” (Peng and Matsui, 2016)

Since social work practice is based on understanding complex issues, epicycles of analysis represent an innovative resource to improve social work research. In concrete, epicycles of analysis involve three preliminary processes: first, it is necessary to match expectations related to data available and second, develop these expectations, in order to reach the third and last process, which is collect data.

Once these three processes finish, epicycles of analysis can be performed. By integrating five main actions, it is possible to organize a data science project, which is similar to a traditional research project. Therefore, a data science project can start by stating and refining a question that needs to be answered to resolve a problem or conflict. Then, by exploring data it is possible to build formal statistical models, which allows interpreting the results. Finally, epicycles allow an effective communication of the results, using modeling and visualization tools.

Nonetheless, it is important to notice that the main difference is, in a data science project, researchers assume that data have already collected. This situation can have important implications on evidence-based practice, in terms of starting from the reality that is reflected by data. Again, for social work, flexibility and contingency are core components of practice. Thus, to conduct a data science project that can impact positively on a specific social issue is crucial to collecting information in the form of structured or unstructured data, comparing them to the expectations, and if the expectations do not match, it is mandatory revising them or fixing the data, so that expectations and the data match, in order to resolve the question. The data analysis portion of data analysis is what can make the difference for social work. Indeed, when social workers coping complex questions to solve, a good start is to think about whether these questions can be answered by a data-driven solution. If the question is a data-driven question, the goal should find patterns, learn from data, discover issues, and, ultimately, lead long-term solutions to reach significant and positive social changes, based on predictions to improve evidence-based practice, rather than merely understand problems and conflicts.

**Machine learning techniques for social research and predictions**

Currently, the interest in data science has led to the popularity of data-driven research. Thus, it is possible to argue that data science now is a core component of every professional field, since their expertise and interventions are in the context of a data-driven society. Practically, every organization is managing its information, through data science methods, in order to improve understanding of how to create, share and deploy new services and products, and ultimately help customers and clients to generate new opportunities.

According to professor Christopher Brooks (2016), a good data scientist should be able to bring skepticism, experimentation, simulation, and replication to accept different explanations to a particular issue. In terms of social work practice, data science can help practitioners to innovate on communication skills, for example, in the form of charts, graphs, and significant visualizations. It is important to notice that data science can help in communicating findings clearly. These skills are common to data science and social work.

In other words, a data scientist is “a professional who uses scientific methods to create new create meaning from raw data” (Donoho, 2015). Therefore, in addition to the epicycles of analysis explained before, the data science approach deploying six key activities that include data exploration and preparation, involving cleaning data and manipulating it for further analysis, data representation and transformation, computing data, predictive data modeling, data visualization and presentation, and finally, “the science about data science,” which implies a reflection about what would not work in data science.

As David Donoho (2015) states,

Data scientists are doing science about data when they identify commonly-occurring analysis/processing workflows, for example using data about their frequency of occurrence in some scholarly or business domain; when they measure the effectiveness of standard workflows in terms of the human time, the computing resource, the analysis validity, or other performance metric, and when they uncover emergent phenomena in data analysis, for example, new patterns arising in data analysis workflows, or disturbing artifacts in published analysis results. The scope here also includes foundational work to make future such science possible, such as encoding documentation of individual analysis and conclusions in a standard digital format for future harvesting and meta-analysis.

As data analysis and predictive modeling becomes an ever more widely distributed global enterprise, “Science about Data Science” will grow dramatically in significance. (p. 25)

In terms of social science fields, it is possible to think about the epistemology around data science. Specifically for
social work practice, data science can support a new way of thinking and know, and, moreover, innovative social interventions. Data science thinking is useful for social work manager because this unique approach to problems proposes critical thinking skills bases on data and evidence. Nonetheless, data science as a new approach to professional practice involves several challenges. According to Thomas and McSharry (2015), it is possible to identify at least five key challenges related to data and social work intervention.

Collecting data implies a computation of all the information available. For example, if a social worker, working for an agency that needs to request for funding and resources, it is necessary to inspect the data from a vulnerable population. Thus, the challenge is how data is collected and processed. Computers and new technologies can enhance these activities by providing a wide range of software application and data storing. Interpretation involves quantifying uncertainty within data. At this level, it is possible to use sentiment analysis to discover trends in unstructured data. For social workers, this part of data science projects, crucial skills are the collaboration with third parties, cultural competence, and leadership in order to reach a complete interpretation from data.

Transparency is fundamental to improve policy decisions and social interventions. Social workers at management level should be aware of the gap between quantitative analysis and data models and how they deploy their outcome by managers and professionals. Therefore, prediction seeks to enhance evidence-based policies by establishing standards and protocols. For social work managers, communication is a critical domain; therefore, data treatment must be in line with effective communication process in order to guarantee high levels of confidence in predictions.

Finally, scenarios refer to a future situation based on probabilities and support decisions in terms of reducing risks. Scenarios can lead social work managers to properly assess client needs, organization weakness, and evaluate program outcomes. This is important when agencies and organizations work with a vulnerable population at complex socio-cultural contexts, and can help to perform accurate predictions.

One of the most used tools of data science is machine learning. As a data-driven method, machine analysis and can support the epicycles of analysis. Machine learning is a class of generalizable algorithms that are data-driven, which means that rules and solutions are derived by examining data, based on the patterns that exit within any data set. Machine learning’s origins are related to artificial intelligence and statistics. Its goal is to “teach” computers through “examples.” This technique is similar to inferential statistics since it uses data collected in the past to predict the future. Thus, it is possible to “train” a data set in order to test specific hypothesis and predict what would be a certain outcome, based on a current scenario. Machine learning involves a process where a computer program learns from experience based on specific tasks, in order to measure different performances to improve that experience. Machine learning can be classified into two general categories depending on the nature of the problem that this technique needs to tackle.

Supervised learning involves a data set which is already known in terms of their output. Supervising learning problems are categorized into regression problems, which involve a prediction from quantitative variables, using a continuous function, and classification problems, which seek predict results from discrete qualitative variables. For instance, given data about the number of users of a certain therapeutic program try to predict the number of people who dropout from the process. The number of clients leaving the program is a continuous output, thus this is a regression problem. On the other hand, if it is necessary to know whether clients will reenter in a specific program, the supervised learning is working on a classification problem.

However, it is important to notice that social science and machine learning have different philosophic approaches. According to Rudin et al. (2014), social science interventions, for instance, social work research, are hypothesis driven. For example, to reach a causal inference about how education impacts salaries it is necessary to find a model that supports this idea, which is often a linear model. Since the machine is focused on data-driven analysis, it tests several different methods, rather than justify one exclusive model as the correct one previously. Social sciences work mainly with a causal hypothesis, which is investigated based on assumptions before the data were generated. Machine learning aims to predict an outcome based only on the data that were produced independently from any singularities (Rudin et al., 2014).

For social work practice, it is important to know that machine learning generates predictions, not explanations, thus it does not aim to establish causal effects. Therefore, a key question is how machine learning techniques can improve social interventions on complex social issues.

Grimmer (2015) states that machine learning can improve causal inferences. This opportunity comes from big data analytics. The analysis of large datasets produced by people through their own activities on the Internet, allows designing experiments from observational data. Predictions, as the main outcome of machine learning techniques, can improve the precision of estimated effects (Grimmer, 2015). That means to say machine learning may not need of theory to establish conclusions and decisions.

**Machine learning and evidence-based practice**

Machine learning techniques imply handling data and transforming them to enhance decision-making process. Thomas and McSharry (2015) explain that any analysis based on data must consider computation, interpretation, and transparency of the information. In addition, social workers should be aware that data-driven and machine learning projects, implies prediction, thus evidence-based policies should integrate
specific standards and protocols to design scenarios, which are the key elements to improve decisions and reduce risk (Thomas and McSharry, 2015). This requirement can be achieved by machine learning.

For instance, Government agencies produce data that can help to understand society, and, as a consequence, improving policy design. Based on this information, interventions could have a greater likelihood of being effective. Thomas and McSharry (2015) propose a goal for machine learning as a core component of data science:

The emphasis now should also be placed on improving socio-economic wellbeing of all member of society. By focusing on the measurement of both rewards and risks for individuals and society at large, it will be possible to create a knowledge-based society where the policymaking process is transparent and supported by empirical evidence. (p. 90)

This definition has significant implications for social work. Data can change the relationship between agencies, programs, and clients. Large datasets produced by clients and organization can also deeply modify culture within agencies, in terms of public relations, human resources, supervision, mission, and culture. Since data are already produced by clients, organizations no longer require conducting expensive and time-consuming surveys to access opinions and needs. Rather ask clients what they feel, think, and expect, data offers enough information in real time. Moreover, machine learning is grounded on this data and information.

Data and machine learning models can offer an option to enhance evidence-based macro practice. As a source of information, large datasets help to share knowledge and communicate information. For social work interventions, data can be merged with some elements from models of evidence-based practice.

Since evidence-based practice refers to the randomized controlled studies results and meta-analysis of existing studies (Nair and Guerrero, 2014), machine learning techniques can support research in terms of improving the quality of studies on social work interventions, policy and management. In other words, as Nair and Guerrero (2014) state, the interpretations of evidence-based practice outcomes allow understanding of leadership, community development, and social planning. Machine learning could be a specific kind of evidence-based practice, and not only as a source of information, but an innovative approach to communicating outcomes, and, therefore, enhance the decision-making process.

In order to communicate outcomes and results, data can improve evidence-based practice. In terms of social work interventions, machine learning can enhance macro practice by predicting behaviors and social conflicts. By creating machine learning models, practitioners can connect expectations of clients, consumers, and stakeholders; with goals and objectives of donors, agencies, and organizations (Thomas and McSharry, 2015).

Evidence-based practice seeks to improve collaboration, thus a crucial element is sharing resources and data. Gathani et al. (2014) and Benerjee and Dulfo (2014) propose that monitoring the progress of specific can increase the option of success and measuring the impact of interventions and improve evaluation by providing valuable data. According to Thomas and McSharry (2015), some data are time-sensitive for organizations. Thus, traditional data collection methods could be efficient in terms of quality, but discovering patterns and facts sometimes could be too late to make good decisions. Machine learning provides tools to manage data in a continuous manner and analyzing data-stream almost immediately. In terms of evidence-based practice and social work practice, data and machine learning techniques become networks of individual, clients, and communities powerful. Without a network data, information available is limited. Limited data reach to the decision based more on opinions, which can produce less efficient interventions.

Research shows the potential uses of communication technologies to improve evidence-based practice within social service agencies and organizations. Schoech et al. (2006) conclude that rural areas frequently experience a scarcity of specialized professionals, resources, and clinical services, researchers have acknowledged that e-mail, instant messaging, and video conferencing can create opportunities for people in remote areas. In the same sense, populations, for instance, people with limited mobility or disabilities will be able to receive assessment and counseling services using remote devices and software (Csiernik et al., 2006; Kowalenko et al., 2003).

Social work interventions seek to improve wellbeing and overcome vulnerabilities. Therefore, one of the most important elements in the social work field is human behavior. At organizations and social service agencies, human behavior is a key variable to develop management strategies. Data science is also related to human behavior since data are produced by the same clients or consumers. However, despite this key issue in common, one of the main concerns about data science methods applications to social work research and social work management is the primary goal of each field. Social work attempts to improve life conditions and well-being; on the other hand, data science aims to improve business.

A critical question is if it is possible to reach valuable knowledge from data produced by individuals, in order to establish long-term and significant interventions, considering ethical and privacy issues related to gathering and manipulating client’s information. An answer to this problem is managing data as a product.

Organizations produce their own data related to their mission, programs, budget, and outcomes. Moreover, these data can be merged with socio-demographic information from clients and consumers. Thus, for social service agencies, data are both an asset and a product. In order to collect the proper amount of data, managers should follow at least five steps, as Dreyer-Lassen and Barfort (2016) propose. First, generate new data; second, manipulate data; third, visualize the
information; and fourth, reproduce findings; and finally, predict new events. According to Thomas and McSharry (2015), market segmentation as a business strategy is practically overcome. The idea of building products and services for costumer and user instead of creating markets is part of the competitive advantage of data as a product. Then, “marketing and selling will become a much more personalized initiative, with the winner being the fastest to achieve personalization” (Thomas and McSharry, 2015: 162).

By translating this idea to social work management, it is possible to think about whether it is possible to build services for clients instead of policy. Moreover, new approaches to managing data within organizations and agencies can personalize service, which can be a new way to provide empowerment to communities. Technically, a data product is the output from a statistical analysis. In other words, data products perform complex analysis tasks or use technology to expand the utility of a model to reach inferences (Caffo, 2015). For social work management, data products can help practitioners to tell a story about a specific social issue to a mass audience, based on data available.

Using technology can lead social work managers to achieve more efficiency in their interventions. Therefore, organization and social service agency should use technology, as a key element of the data product. Moreover, they must include people in the data driven and technologies approach.

Data products evidence the power of data-driven decisions at organization settings. For instances, as Reardon argues, “funders, regulators, and members of the public are increasingly demanding evidence that organizations are accountable and that their services are producing the desired results. Data also help organizations evaluate employees, manage risk, and defend themselves against lawsuits” (Reardon, 2015).

Examples of data products that can help social work include mobile apps development, interactive visualization, and machine learning algorithms, text mining, cooperative dashboards, cloud technologies, and user research (UX), among others. However, including technology and data products process to organizations could be a challenge, especially to social workers.

UX research integrates communication strategies that can change work practice dramatically (Csiernik et al., 2006; Hill and Ferguson, 2014; Mishna et al., 2012), since technology and practice create new options for social workers to become more efficient through reduction of paperwork and expansion of time with clients (Reardon, 2010).

There exist several examples of data science project in the field of social science and social services. Several articles discuss computerized data management systems affect social work organizations, practitioners, and clients. Burton and Van den Broek (2009) analyzed the influence of new technology on the bureaucratization of social work. In this study, the Australian social workers reported that data collection technology made them feel less connected with clients and shifted their priorities from quality of output to quantity of output. Workers also felt that organizations did not appreciate the amount of time it took to produce reports for funders demanding an ever-increasing amount of data about programs.

In the same sense, Carrilio (2007) worked with 245 community social workers to learn about which variables affected their willingness to use client information systems. Carrillo found that workers’ skill and experience with computers and workers’ perceptions about the user-friendliness of the systems and usefulness of data affected utilization. Nonetheless, attitudes about data use did not have a strong effect on system utilization.

This evidence confirms the need to improving training and innovation on social work management field. Data science can help to enhance the relationship between practice and methods to achieve better results in social service management.

Data Kind is a nonprofit focused on data science projects, whose aim is, for instance, supporting financial inclusion in Senegal by the application of predictive modeling. The Data Science for Social Good program at the University of Chicago seeks similar goals. This initiative has been working on proactive outreach to reduce harassment of New York rental housing tenants, and it has deployed a program to identify factors that drive school dropout in El Salvador.

**Ethical dilemmas and social work challenges on machine learning algorithms**

Data can be a valued asset for organizations. Thus, for social work management, data should be seen as a product. Indeed, the increase in the adoption of communication technologies impacts individuals. Social connections are one of the most significant uses of Internet technologies and tools (Mishna et al., 2012). These tools support knowledge and skills; therefore, it is possible to reach significant implications for social work practice (Cwikel and Cnaan, 1991; Kreuger and Stretch, 2000). As Csiernik et al. (2006) point out, Facebook, Instagram, Pinterest, Twitter, and LinkedIn are common networking platforms used by approximately 73% of online adults. In addition, 91% of American adults own a cell phone and use it for services other than phone calls, such as text messaging, accessing the Internet, downloading online applications, and participating in video chats. The key element of technology is how people collect and share information and change the way that people interact with one another, including the manifestation of social problems.

Machine learning projects use the same algorithms and techniques that business and companies use to increase profits. Thus, it is possible to improve nonprofits and social
service agencies’ missions by data-driven planning. However, algorithms can lead to biases and segregation. As Megan Garcia (2016) states, “distorted data can skew results in web searches, home loan decisions, or photo recognition software.” The merging of greater than before consideration to the inputs could contribute to a more equal access to digital resources by vulnerable populations. Nonetheless, it is absolutely necessary to pay attention to biases in data, since technology could be just as racist, sexist, and xenophobic as people actually are (Garcia, 2016).

These biases can put in risk one grand challenge for social work which is the harness technology for social good. According to the American Academy of Social Work and Social Welfare “information and communication technologies can be deployed to improve the efficacy of social programs” (American Academy of Social Work and Social Welfare (AASWSW), 2018). Thus, “transform the social work profession to respond in ways that ensure technology is ethically used to reduce the inequalities that exist today” (Berzin et al., 2015) are critical tasks. In this context, it is important to eradicate biases in new technology applications such as data science.

**Conclusion**

Data science approach involves three different domains, including programming, statistics, and a deep understanding of a specific topic. This last element involves professional expertise, which can range from business to physics, including health care, and social services. Therefore, social work management can take advantage of data possibilities and improve interventions.

By definition, data science is an innovative approach to gather information and produce knowledge. As a fast growing methodology, social work managers should focus on providing critical knowledge of complex social problems, combining it with big data, machine learning, visualizations, and data mining, among other techniques in order to learn about this new approach.

Learning from data is also an asset for human service agencies. Real-time data collection and proper analysis can save time and resources. Thus, social workers at management level must treat data as a product. This situation implies a more deep collaboration among organizations, consumers, and clients. In other words, data-driven analysis and best-informed decision-making processes are significant assets of data science and for management as well.

Since data can be provided by people, social service agencies, organizations, and practitioners should be aware of collaboration in terms of data production. Therefore, crowdsourcing is a key element to improve data management to reach sustainable change at organizational settings.

Indeed, ethical dilemmas arise from data science approach. Biases in machine learning applications seem to be in conflict with the open data movement. New standards for data and information are needed within organizations. Ultimately, the challenge for social work management is acquiring new skills based on new technologies. Research on social work and new technologies is increasing; however, knowledge of data science approach in specific is limited.

Therefore, full understanding of data science as a part of new communication technologies and as a tool in social work practice is required (Hill and Ferguson, 2014). In addition, it is important to identify social workers who are more able in getting into technology-based practice (Gillingham, 2014). Data can help to build social work practice based on cost-effective models in order to enhance service delivery (Smith, 2009).

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