Evaluation of a Training Program to Improve Organizational Capacity for Health Systems Analytics

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Abstract

Objective   The Leadership in Analytics and Data Science (LEADS) course was evaluated for effectiveness. LEADS was a 6-month program for working biomedical and health informatics (BMHI) professionals designed to improve analytics skills, knowledge of enterprise applications, data stewardship, and to foster an analytics community of practice through lectures, hands-on skill building workshops, networking events, and small group projects.

Methods   The effectiveness of the LEADS course was evaluated using the Kirkpatrick Model by assessing pre- and postcourse knowledge, analytics capabilities, goals, practice, class lecture reaction, and change in the size of participant professional networks. Differences in pre- and postcourse responses were analyzed with a Wilcoxon signed rank test to determine significance, and effect sizes were computed using a z-statistic.

Results   Twenty-nine students completed the course with 96% of respondents reporting that they were "very" or "extremely" likely to recommend the course. Participants reported improvement in several analytics capabilities including Epic data warehousing ($p = 0.017$), institutional review board policy ($p = 0.005$), and data stewardship ($p = 0.007$). Changes in practice patterns mirrored those in self-reported capability. On average, the participant professional network doubled.

Conclusion   LEADS was the first course targeted to working BMHI professional at a large academic medical center to have a formal effectiveness evaluation be published in the literature. The course achieved the goals of expansion of BMHI knowledge, skills, and professional networks. The LEADS course provides a template for continuing education of working BMHI professionals.

Keywords
► clinical informatics
► education
► analytics
► professional training
► workforce

Background and Significance

Data analytics is continuing to transform many industries, including health care.[1,2] In the business world, companies with sophisticated integration of analytics into their business models and decision-making tend to outcompete their competitors over time.[1] With increasing pressure to decrease costs and increase efficiency while improving quality of care, health care enterprises need analytics to thrive.[3] Effective analytics requires a critical mass of biomedical and health informatics (BMHI) professionals trained to access, analyze, and interpret data to glean insights that can be used to transform care and operational processes.[1,3,4]

Many educational programs have been developed to fill the workforce need in this burgeoning field through formal degree and certificate programs.[5] These programs focus on BMHI core knowledge, knowledge of medicine and health, and informatics such as programming languages and database management.[5,6] Extensive research has been devoted to the development of curricula that communicate core BMHI knowledge and skills,[7–13] but data on continuing education and development of the existing workforce is lacking. Given the rapidly evolving nature of the field, BMHI analysts need to engage in continuous life-long learning,[5,14,15] with adult learning theory dictating that working professionals prefer that content be directly relevant to work and connected to prior knowledge.[16] Quality information technology professionals continue to be in high demand and short supply,[15,17–20] so enterprises need to retain and enhance the skills of existing staff even as they seek to hire additional staff.[4]

The Leadership in Analytics and Data Science (LEADS) program was developed at Johns Hopkins Medicine (JHM) in 2017 to improve organizational capacity and effectiveness in analytics through didactics, analytics skills practice, and mentoring (►Table 1). The course meets once a week over lunch for a 6-month duration, teaching analytics and data stewardship skills to participants as well as fostering interpersonal networks within the enterprise. Interpersonal networks are a source of important knowledge in the BMHI workplace[21] and can impact job productivity[22,23] and creativity.[24] A functioning BMHI social network can evolve into a community of practice[25–27] where group members have a shared interest and commitment, engage in joint activities, help one another, and work together to develop a shared repertoire of resources and tools for problem solving.[26,28] Thus, a central goal of the LEADS course was to foster a community of practice.

Table 1 Goals for leadership in analytics and data science course

1. Improve knowledge and practice of technical analytical skills
2. Improve knowledge of specific enterprise applications and shared data sources
3. Improve data stewardship practices and knowledge of institutional policies
4. Enhance active networking and mentorship to foster an analytics community of practice

Fig. 1 The Kirkpatrick Model for evaluation of course effectiveness. The model is illustrated as a pyramid to demonstrate that participant reaction to an educational intervention influences learning, which influences behavior change that determines results.

To understand whether the LEADS course was successful at achieving these stated goals, course effectiveness was evaluated using the Kirkpatrick Model[29–31] (see ►Fig. 1), which assesses four levels of course effectiveness including participant reaction, learning, behavior, and institutional impact. Precourse, intracourse, and postcourse surveys were administered to participants.

Objective

In this research, a study was conducted to investigate the effectiveness of the LEADS course with the goal of improving analyst technical skills, increasing knowledge of applications, data stewardship and policies, and creation of an analytics community of practice. The course effectiveness was evaluated using scheduled course assessments that examined participant reaction, learning, and behaviors.

Methods

Setting

JHM is an integrated global health enterprise with over 40,000 full-time employees, 2.8 million outpatient visits, and 110,000 inpatient admissions per year.[32] The JHM Data Trust (DT) was established with the mission "to provide JHM with the technical infrastructure, standards, policies and procedures, and organization needed to bring together patient and member-related data from across the health system."[33] The DT cataloged data sources within JHM as comprising more than 500 databases, 70,000 tables, and 35 terabytes of data (personal communication from Paul Nagy, 2019). The DT created a hybrid reporting structure where employees work in business units within the organization as well as serve on functional analytic teams to coordinate activities and provide data stewardship. The teams are built around functional analysis of data including (1) ambulatory operations, (2) hospital operations, (3) care coordination and utilization management, (4) finance-integrated analytics, (5) population health, (6) quality, safety, and

service, (7) research/center for clinical data analysis, (8) technology innovation center, and (9) planning and market analysis. There are currently over 300 individuals serving as members on the DT analytics teams.

The LEADS course was offered to BMHI professionals with roles as data analysts working within JHM. The target participants for the LEADS course were current or future members of DT analytic teams. The program was created as part of a strategic goal by the DT to advance the training of analytic teams across the enterprise and foster employee collaboration, development, and engagement in a difficult-to-recruit workforce. The Technology Innovation Center (TIC) (https://tic.jh.edu/) developed and implemented the program.

Program leadership was created with a program director, two program managers, an advisor, and a coordinator. Thirty-three key influencers of the JHM analytics community were identified by the course organizers and DT team leaders and invited to act as faculty in the program. The faculty was asked to provide lectures, mentorship, and was invited to participate in class discussions. Faculty was encouraged to attend the weekly lectures to interact with colleagues and to hear what other analytics activities were taking place.

Interested analysts employed at JHM applied to the program through an open enrollment period. The application required a letter of recommendation from their supervisor, tuition cost center information, and a letter of commitment of the time required to complete the course. The program was capped at 30 students each year to provide close mentoring and maintain class engagement. The $4,000 tuition was covered by the participant's departments. The classes were organized over lunch and catering was provided. Participants' departments were charged for the course tuition.

Curriculum Development

The LEADS course was developed with the help of a multidisciplinary team featuring TIC administrators, physician informaticians, DT team leaders, and experts in assessment. This group developed the course curriculum and goals based on literature survey of core BMHI skills,[5,8,12,13] prior experience, and an informal survey of DT team leaders to determine key employee development needs. Institutional BMHI leadership was also involved in the process to ensure that course content aligned with institutional goals, existing data sources, and upcoming software implementations. ►Table 2 contains an outline of the curriculum.

In addition to lectures and workshops, students were divided into small groups with mentored faculty supervision to complete a practical data analytics project. A skill assessment performed prior to the course was utilized to gauge the analytics skills of each student. Students were then split into teams of 5 members with a mix of technical expertise, and were supported by 2 faculty mentors. Team members shadowed their peers and documented their work processes to share skills. Each team developed a data product that was composed of a social network analysis of LEADS faculty members and their professional networks. Teams performed team building activities, created a normalized data model, cleaned and transformed data in a SQL server environment, used Tableau to create innovative data visualizations, and generated a final data product. An award was given at the end of the course to the team with the best project based on faculty vote. See ►Supplementary Appendix A (available in the online version) for small group instructions.

Assessment

The effectiveness of the course was evaluated using a framework based on the Kirkpatrick Model[29–31] (see ►Fig. 1). The Kirkpatrick Model seeks to assess four levels of course effectiveness: (1) reaction, (2) learning, (3) behavior, and (4) results. The first level seeks to assess participant reaction to a session's instructor, setting, materials, and content, which are important prerequisites for learning.[29] The second level assesses the

Table 2 Overview of the leadership in analytics and data science curriculum

Data Trust and Analytic Teams	Data structures and warehousing concepts	Data analysis	Project planning	Practicum
1. Data sources used by each analytics team	1. Database relationships	1. Developing key performance indicators	1. Requirements gathering	1. Team-based project analyzing deidentified EMR data
2. Types of requests (clinical, operational, and research)	2. Structured Querying Language	2. Scorecards and dashboards	2. Project management	2. Assignments for data cleaning, joining, and analysis
3. Types of analysis for customers	3. ETL processes and provenance	3. Information visualization	3. Design thinking	3. Hands-on environments (Jupyter, Tableau, and SQL Server)
4. Data trust policies	4. Data quality assessment	4. Inferencing and spurious correlations	4. Business intelligence	4. Engage with faculty and members of varying functional units
5. Data governance	5. Working with EMR transactional data	5. Machine learning with Python		
6. Data security	6. Hadoop and precision medicine			

Abbreviations: EMR, electronic medical record; ETL, Extract, Transform, Load.

extent of learning or expansion of knowledge.[34] The third level of evaluation determines the extent of application of new skills in the workplace.[29,34] The fourth level measures the organizational impact of the course.[34] Our evaluation of the LEADS course focused on levels 1 to 3.

Assessment tools were developed with the help of the office of assessment and evaluation at JHM. Participant reaction was assessed through weekly and whole-course class satisfaction surveys. Participant learning was assessed through a pre- and postcourse multiple-choice knowledge assessment and self-reported capability assessment. Participant behavior was assessed through a pre- and postcourse self-reported practice assessment. The professional network was assessed through a pre- and postcourse self-reported social network analysis (see ►Supplementary Appendix B [available in the online version] for assessment instruments). All surveys were administered electronically on an internally hosted MachForm (https://www.machform.com/) survey engine. ►Table 3 contains the schedule of assessment tools. ►Supplementary Appendix B (available in the online version) contains copies of the assessment tools.

Data Analysis

The LEADS program manager and coordinator organized the surveys and replaced student identifiers with research identity numbers. Data were submitted as comma-separated values (CSV) files and analysis was conducted in Python 3.5.2 using Jupyter Python notebooks. Graphs were generated with the plotting libraries matplotlib version 2.1.0 and seaborn version 0.8.1. Data manipulation was done using pandas version 0.21.0 and mathematical analysis was done with the numpy library version 1.13.3. Wilcoxon signed rank test was used to calculate the significance of the difference in pre- and postcourse capability, practice, and social network size. Effect sizes were computed using the z-statistic from scipy version 1.0.0, using the simple difference formula.[35]
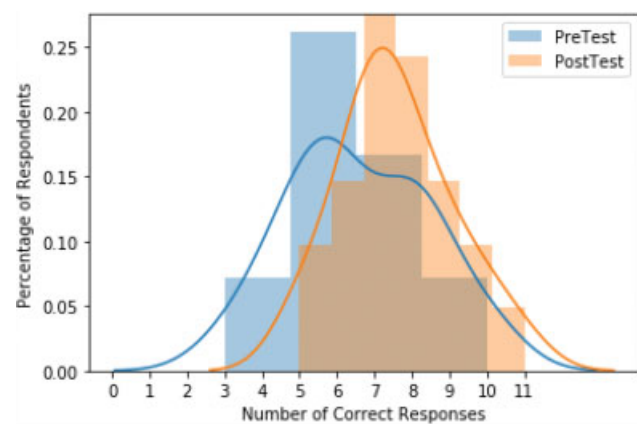
Results

Reaction

In the first year of the program, LEADS had 42 applicants, with 30 analysts accepted into the program, and 29 completing the course. One participant left the organization during the program. Attendance was tracked through a sign-in sheet and with a mean attendance of 84% and no class with < 70% attendance. Class and instructor evaluation were assessed

with a 4-point Likert score (not at all, somewhat, very, and extremely). Each class was assessed for whether it was interesting, engaging, applicable, and important. Students were emailed weekly surveys that they could optionally fill over the 21-class sessions. There was a 23% response rate to these surveys. The sessions with the highest scores were finance and analytics, emergency medicine and readmissions, data mart, business intelligence and intro to Tableau, Epic reporting and analysis tools, the nature of data in Epic, project management, and data structure fundamentals.

After completion of the course, a final course evaluation was administered, during which participants reported on their evaluation of the course as well as barriers on applying the knowledge they gained in the course as part of their job. All course participants completed this survey. Evaluation of the course was positive, with 100% of responses in the positive range for interest, engagement, applicability, driving career growth, course organization, and logistics. Thirty percent of responses were in the highest quartile of extremely positive. Ninety-six percent of respondents reported that they were "very" or "extremely" likely to recommend the course. In identifying organizational barriers in applying the skills learned, the most common barriers to application were lack of applicability to job tasks and lack of depth in learning of skills with 58% of respondents reporting these as barriers. See Supplementary Appendix C (available in the online version) for final course evaluation results.

Learning

Learning was assessed with a multiple choice, 10-question knowledge assessment delivered at the beginning and end of the course. Eighty-six percent (24/28) of participants in the course completed both the pre- and postcourse knowledge test. Scores moved in a positive direction with a precourse mean score of 61% (standard deviation [SD] 17%) and a postcourse mean score of 69% (SD 14%). This difference was significant with paired *t*-test *p*-value of 0.003. Of the 24 participants who completed the precourse knowledge survey, 63% had a score increase, 17% had an equal score, and 20% had a score decrement (see ►Fig. 2). The questions with the largest improvement in correct answers were on data visualization

Table 3 Schedule of assessment tools

Assessment	Precourse	Weekly	Postcourse
Class satisfaction		x	
Knowledge	x		x
Capability	x		x
Practice	x		x
Professional network	x		x
Course assessment			x

Fig. 2 Knowledge assessment. Histogram of knowledge assessment scores on the pretest versus posttest.

(21% improvement), enterprise analytics tools (23%), and Python (37%). The questions with mild score decrement include SQL (5% decrement) and R (2% decrement).

Behavior

Before and after the LEADS course, participants were asked to self-report their current capabilities, goal capabilities, and current practice patterns with a variety of key BMHI skills. The self-assessment for capabilities asked participants to rank themselves as a beginner, novice, intermediate, or expert for particular skills. Goals used the same scale. For the purposes of calculation of change, beginners through experts were assigned numerical values between 1 and 4. Participants' self-report of capabilities significantly improved through the course with regard to data stewardship, data policies, use of the Epic data warehouse, data governance, knowledge of institutional review board (IRB) policy, and predictive analytics. There was no change in self-report of skill with Excel, databases, project management, or use of Tableau. Changes in capabilities and goals are reported in ►Table 4.

A decrease was observed in the goals individuals set between the pre- and postcourse evaluations while also seeing a reported increase in self-reported capability. For example, an individual starting the course may have a goal of becoming an expert at databases and once the course completed choose to downgrade their postcourse goal to be intermediate. To understand this shift, a goal-gap was com-puted, which examined the difference between capabilities in a skill with their goal changes from pre- to postcourse. The mean goal-gap across all 10 tools was 1.34 before the course, and 0.92 postcourse, meaning that the student goals and capabilities were more closely aligned in the end of course survey than at the beginning.

A pre- and postpractice assessment was administered to see if their overall application of skills acquired increased. The survey used a 4-point scale to determine the frequency of skill use in terms of rarely, sometimes, often, and always. For the purposes of calculation of change, rarely through always were assigned numerical values between 1 and 4. In terms of practice, there was a significant increase in self-report of the frequency of use of skills with Excel, data stewardship, data policies, Epic data warehouse, data governance, and employ-ment of IRB policy. While other skills suggested an improve-ment, they were not statistically significant (see ►Table 5).

Professional Network

A professional network questionnaire was performed pre- and postcourse. The survey listed the members of the DT by the analytic team and requested to know which of the members the participant knew and identified as part of their professional network. The professional network size partic-ipants identified ranged between 0 and 32 with an average of 11 before the course and between 6 and 44 with an average of 22 after the course. Social network analysis revealed an

**Table 4** Pre- and postcourse student self-evaluation of current capabilities and goal capabilities

BMHI skill	Capability versus goal	Precourse	Postcourse	p-Value (significant < 0.05)	Effect size (small = 0.1, medium = 0.3, large = 0.5)
Excel	Capability	3.1	3.1	0.009	0.526
	Goal	3.7	3.8	0.034	0.425
Databases	Capability	2.6	2.8	0.419	0.162
	Goal	3.4	3.1	0.008	0.532
Tableau	Capability	2.2	2.4	0.092	0.336
	Goal	3.5	3.3	0.014	0.489
Project management	Capability	2.2	2.4	0.19	0.262
	Goal	3.4	3.3	0.019	0.468
Data stewardship	Capability	1.6	2.2	0.007	0.537
	Goal	3.1	3.2	0.199	0.257
Data Trust policy	Capability	1.6	2.3	< 0.001	0.799
	Goal	3.4	3.3	0.064	0.371
Epic data warehouse	Capability	1.5	2	0.017	0.476
	Goal	3	3.1	0.522	0.128
Data governance	Capability	1.8	2.4	0.003	0.597
	Goal	3.3	3.2	0.163	0.279
Predictive analytics	Capability	1.4	1.8	0.007	0.539
	Goal	3	3.1	0.391	0.171
IRB rules	Capability	1.4	1.8	0.005	0.557
	Goal	2.9	2.7	0.118	0.313

Abbreviations: BMHI, biomedical and health informatics; IRB, institutional review board.

Table 5 Pre- and postcourse evaluation of student practice patterns

BMHI skill	Precourse	Postcourse	*p*-Value (significant < 0.05)	Effect size (small = 0.1, medium = 0.3, large = 0.5)
Excel	3.3	3.6	0.048	0.395
Databases	2.5	2.9	0.277	0.217
Tableau	2.5	2.8	0.118	0.313
Project management	2.1	2.6	0.109	0.321
Data stewardship	1.6	2.2	0.001	0.649
Data Trust policy	2.5	3.7	< 0.001	0.814
Epic data warehouse	1.7	1.7	0.016	0.279
Data governance	2.3	3.6	< 0.001	0.732
Predictive analytics	1.5	1.7	0.687	0.081
IRB rules	1.7	2.3	0.044	0.403

Abbreviations: BMHI, biomedical and health informatics; IRB, institutional review board.
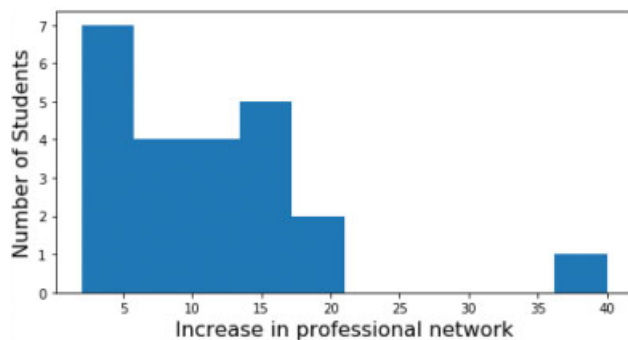

Fig. 3 Histogram of professional network growth. Change in size of professional network on the precourse evaluation versus postcourse evaluation.

average doubling of individual's professional network from an average of 11 to 23. All participants reported an increase in the size of their social networks. See ►**Fig. 3** for a histogram of individual increase in network size.

Small Group Projects

For the class project, each team of students was provided a CSV file that detailed the professional network of each course faculty member. Teams were asked to build an interactive map of the data analytics community at JHM, with the dual goal of teaching team members how to create an innovative data visualization and providing them a useful living document to use to find answers to analytics questions in the future using contacts in their professional network. See ►**Fig. 4** for an example of a student-generated data visualization.
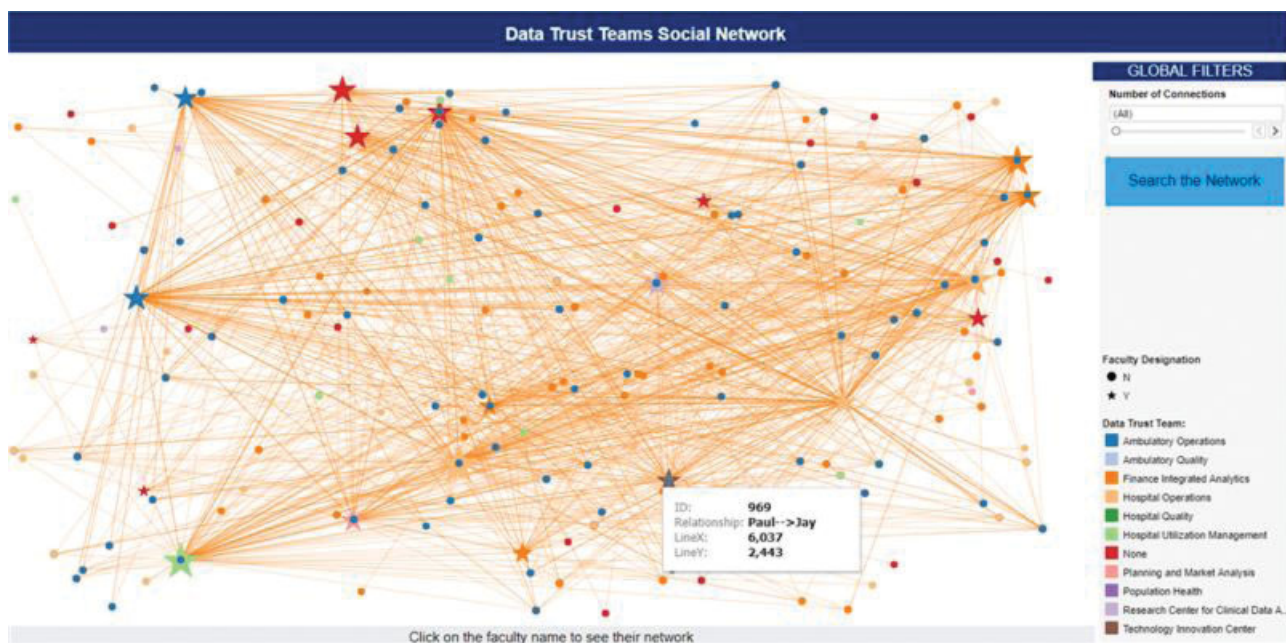
Fig. 4 Example of student small group professional network visualization using Tableau. Red stars indicate course faculty. Colored dots indicate individuals on data trust analytic teams. Gold lines indicate social network connections among individuals and course faculty.

Discussion

LEADS was the first course targeted toward continuing education of working BMHI professionals at a large academic center to undergo formal evaluation for effectiveness. The course goals were split between didactic, practical, and social components, with many course activities focused on fostering a community of practice where participants developed shared rules, norms, and artifacts such as specific work products. The evaluation of course effectiveness using the Kirkpatrick Model sought to address each of these course components in context.

Course participants rated the most popular lectures as those that could help data analysts be maximally effective in their jobs, such as lectures on key data sources, financial analytics, and data visualization. This matches with theories of adult learning, which suggest that content should be relevant, useful to the learner's life, and connected to prior knowledge.[16] In LEADS, the content was tailored specifically to the needs of the DT teams by the leaders of these teams, and the most popular lectures were the most applicable to the participant's daily work. All this being said, response rates to the weekly class reaction surveys were low at 23%, making generalization of respondent feedback difficulty. Future iterations of the course will incorporate weekly feedback into class participation and will focus most heavily on lectures that impart practical skills.

The knowledge assessments showed limited change in knowledge from precourse to postcourse. The test assessed basic aptitude only and was not built based upon psychometric analysis, which leaves the opportunity for rewriting of test items in future iterations of LEADS. The slight decrement in scores on test questions involving SQL and R points toward the opportunity to offer in-depth seminars on technical topics in future iterations of the class. The knowledge test was useful in that it helped the course faculty to conduct an initial needs assessment and organize participants into balanced groups based on technical skills and knowledge.

The capability and practice assessments mirrored one another in showing ability and use of data policies, data stewardship, data governance, use of IRB policy, and utilization of a key enterprise data source, the Epic data warehouse. This may represent the successful fostering of a community of practice with shared rules and norms of behaviors through shared social time, lectures, and team-based data analytics experience. It points to the effectiveness of the LEADS course at transmitting standards of data governance and stewardship and therefore in supporting the transformation of the organization by providing institution context and imparting institutional values.

Technical skills, including use of Tableau and database management, did not change significantly during the course. This may be due to the exposure nature of the course with relatively short lectures given on technical topics. This points to an opportunity to offer in-depth seminars with intensive skills training in future iterations of the class. Additionally, some of the skills and methodologies taught in LEADS may not yet have diffused fully across the institution, so the actual job tasks of analysts may not have allowed for increased use or practice of acquired skills over the relatively short 6-month timeframe. The narrowing of the gap in self-reported technical capabilities and goals may show that participants realized that these technical skills take a long time to acquire as participants began to move from a lack of awareness of what they did not know toward knowledge of just how much they had to learn.

The size of social networks of the participants expanded from precourse to postcourse. Course comments showed that the pre- and postclass networking time was helpful for participants, and this may partly explain this expansion. The networking changes indicated that analysts participating in the course may have expanded in their ability to work across teams to accomplish high-quality work. In future iterations of the course, effort will be invested in determining whether specific social network connections enhance work productivity and whether participant demographics, such as time employed at JHM, influence change in social network size. The team will also investigate whether the enhancement of social network during the LEADS course portends greater employee satisfaction and retention. In the future, it is possible that an abbreviated symposium version of this course could be offered to BMHI professionals outside of JHM, though the social network benefits would not accrue to these students.

The course had several limitations in addition to those mentioned above. Participant job productivity after the LEADS course was not assessed. Future iterations of the course will address this important metric through follow-up evaluation on work productivity and retention. Future assessments will also incorporate psychometric testing and improved Likert scales. Another significant limitation was the multiple confounding factors influencing the work environment of students, thus altering their familiarity with software and technical processes regardless of what was going on in the course. Despite these limitations, the course was effective in achieving the goals of fostering the development of technical skills and helping to create a community of practice among BMHI professionals.

Conclusion

The LEADS course was effective at achieving the four goals of improving participant data analytical skills, knowledge of enterprise applications and data sources, skill in data stewardship, and in fostering a community of practice as evidenced by changes in pre- and postcourse assessments of knowledge, capabilities, practice, and social networks. The LEADS course provides a template for continuing education of BMHI professionals to enhance workplace effectiveness and aid in the diffusion of standardized practices across a medical enterprise.

Clinical Relevance Statement

Health systems can deliberately manage and build analytics capacity through building communities of practice and the creation of focused learning and growth opportunities. This study shows that working BMHI professionals can improve technical analytics skills, knowledge of enterprise applications,

institutional policies, and active networking to foster creation of an informatics community of practice through a targeted continuing education program. Consistent with adult learning theory, participants are most interested in learning skills that are pertinent to their everyday work.

Multiple Choice Questions

1. Which of the following practices increased significantly for participants in the LEADS course?
   a. Predictive analytics.
   b. Use of database technology.
   c. Project management.
   d. Data governance.

   Correct Answer: The correct answer is option d, data governance. The LEADS course impacted several practical skills including data stewardship, IRB rules and institutional policy, and shared data resources such as the data warehouse. The course did not impact the use of specific technologies by BMHI professional participants, which points toward the need for more in-depth instruction for those interested in these complex tools.

2. Each of the following is a metric of educational course effectiveness in the Kirkpatrick Model except:
   a. Reaction.
   b. Reflection.
   c. Learning.
   d. Behavior.

   Correct Answer: The correct answer is option b, reflection. The four levels of the Kirkpatrick Model of course assessment are reaction, learning, behavior, and results. The immediate reaction of participants to course content is related to the amount that participants learn, which impacts changes in behavior and ultimately alters results or outcomes. This model was used to evaluate the LEADS course and is helpful because it assesses each level in turn, allowing for modifications of specific course components in future course iterations.

3. What is an analytics community of practice?
   a. A social group of analysts designed to foster workplace friendships and facilitate job retention.
   b. An online forum for sharing useful code and ideas that is specific to a given workplace.
   c. A group whose members develop shared rules and interests through engagement in joint activities with similar resources.
   d. A community developed by enterprise leadership to facilitate promotion of talented individuals.

   Correct Answer: The correct answer is option c. The definition of an analytics community of practice is a group where members have a shared interest and commitment, engage in joint activities, help one another, and work together to develop a shared repertoire of resources and tools for problem solving. The LEADS course was designed to foster this through shared social time, lectures, and team-based data analytics experience.

Protection of Human and Animal Subjects
This study was performed in compliance with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects, and was reviewed by the JHM Institutional Review Board.

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