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Implementation of Behavioural and Medical Health Management Applications: Reducing High Intensity Medicaid Services Utilization for Individuals with Serious Mental Illness

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Abstract

Health challenges for persons with serious mental illness and comorbid medical conditions were related to application design and usability. An application suite to improve community care was deployed in the community services division of South Beach Psychiatric Center, a large state-run facility in New York, USA. The association between the use of the Medicaid utilization application and changes in the use of Medicaid publicly paid medical inpatient and emergency services was evaluated. A Generalized Linear Mixed Model (GLMM) was developed and applied to assess for longitudinal (5-year) reductions in utilization, the impact of colocation of behavioural and medical health services, and the effects of intra subject correlation, zero inflation, and over-dispersion of the data. Significant reductions in the use of Medicaid-paid inpatient and emergency services were observed. Colocation of services was not significant. Significant effects for intra subject correlation, zero inflation, and overdispersion were obtained and accounted for in the model.

Keywords: Medical informatics; Clinical applications; Community care; Comorbidity; Mortality; Serious mental illness; Generalized linear mixed model; Medical outcomes ; Medicaid utilization

Introduction

Provider supporting, dynamic, self-service applications may deliver actionable information to support care management, quality of care, best practices, value based purchasing, and cost control for persons with Serious Mental Illness (SMI) [1]. Health analytics as a self-service (AaaS) can be provisioned in a streamlined way in LAN/WAN and cloud environments. These platforms can support Health Level 7, Version 3 (HL7 V3) CDA (Clinical Document Architecture) implementation guides [2] and FHIR (Fast Health Interoperability Resources) [3] for clinical documentation, messaging, and interoperability. Specifically, these can be implemented with Apache Spark® and Hadoop®, Google BigQuery®, Amazon Cloud MapReduce®, Microsoft SQL Server® with Azure®, IBM DB2® with Websphere®, Oracle RMDBS® with Cloud Applications/Platform Services, and many other platforms [4-6]. Availability, functionality, and usability of such systems are critical for chronic care management for clients with SMI and chronic comorbid medical conditions [7,8]. An application suite to improve behavioural and medical services was deployed in the community services division of South Beach Psychiatric Center (SBPC), a large state-run facility in New York, USA. As an exemplar of application effectiveness analysis, the association between the use of a Medicaid utilization application and changes in the use of two high intensity Medicaid-paid medical services, inpatient hospitalization and emergency room services, by a balanced panel of 416 patients, over a five-year period, was evaluated.

Clinical risk, comorbidity, and mortality

Elevated mortality rates, medical comorbidity, and excessive use of high intensity medical and behavioural health services is common among persons with SMI and the integration of behavioural and medical health services has been lacking [9,10]. The overall odds of metabolic, pulmonary, cardiovascular, and liver diseases are elevated compared to the general population, even controlling for risk factors such as smoking and weight [11,12]. In an important study in Ohio, USA, Years of Potential Life Lost (YPLL), calculated for this population, had a mean=32.0 ± 12.6 years with the aggregated Standardized Mortality Ratio (SMR)=3.2 [13]. Charleson et al. [14] demonstrated a strong relationship between a composite comorbidity index, based on the number and severity of various medical and behavioural health diagnoses, and high costs incurred by the Medicaid program in New York State. Health outcome disparities have also been noted between adults with SMI and those without these disorders, internationally including in Australia and South Korea [15,16], and among older adults [17]. This population has a high rate of preventable inpatient medical hospitalizations for both acute and chronic disease Ambulatory Care Sensitive (ACS) conditions, with significantly higher odds of any ACS hospitalization at various follow up points [18,19]. In a prospective study, it was noted that patients with SMI and diabetes had a significantly higher odds ratio of re-hospitalization (OR=1.24, 95% CI: 1.07, 1.44) within 30 days of the index hospitalization, than those without SMI [20]. Emergency services utilization is also elevated due to poor care coordination and lack of integration with medical services [21]. In a retrospective study of emergency services related Medicaid claims it was noted that persons with SMI and diabetes were much more likely to overuse emergency services than patients with either diagnosis alone [22]. Risk factors such as age and substance use disorder (SUD), in addition to SMI and medical comorbidity, were also related to elevated emergency services utilization [23,24].

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Design and usability requirements

Design and usability have significant impacts on the effective use of medical informatics, electronic health record, practice management, financial and claims, and quality of care related systems [25]. It is important to achieve ease of cognitive effort through reasonably low page complexity, simple and redundant hyperlinks, and high comprehensibility. Considerable research related to human factors, quality, and safety has been done in other high stakes industries such as aviation, and similar preferred design and usability characteristics have been noted [26,27]. Recent American Medical Informatics Association (AMIA) design and usability recommendations include: 1) common terminology and language 2) standardization of interoperability 3) common user interface style and design patterns 4) the streamlined and standardized visual display of prioritized cases 5) on-going testing of patient safety related to the quality of care software 6) prioritizing clinician usability recommendations and 7) on-going monitoring of use patterns of HIT systems to improve design and usability [28]. These features are incorporated into the design of NYS-OMH (New York State Office of Mental Health) applications which also have Clinical Decision Support (CDS) and Visual Analytics (VA) characteristics. CDS interface designs emphasize longitudinal continuity, acceptable density, flexibility, integration with workflow, high clinical validity, normalization, fast search, and clinician satisfaction [29]. VA simplifies complex health information so as not to surpass the limits of human cognition and streamlines critical and actionable information in visual displays [30]. VA is useful for combining longitudinal, clinical, population health and statistical information in efficient ways [31].

Community services applications

The suite of SBPC clinical and care management applications is intended to support identified agency and facility goals of clinical accountability, best practices, and care coordination for inpatient and outpatient services. The applications were developed over the first decade of the 21st century and were deployed and implemented by late 2009 by a project team which included executive, administrative, clinical, and programming staff. These applications were created empirically with extensive discussion and modelling of workflows, continuously validating the representation of real world health events occurring for clients. An important principle guiding these efforts was that the systematic recognition and consistent anticipation of individual clinical and case management needs has direct positive health outcomes. Access is provided on a need to know basis related to administrative roles, clinician scope of practice, and treatment team membership. Security features are implemented through Microsoft Active Directory® and application level coding in ASP.net and C#. Entry to the portal for the SBPC self-service applications described in this section, with links, is displayed in Figure 1.

The general development strategy has been to develop secure dynamic webpages consistent with HL7 implementation guides for clinical document architecture with embedded SQL code using ASP.net, VB.net, and Cold Fusion as server-side web application frameworks with HTML, CSS, and JavaScript. Normalized ORACLE 11g® tables and views are accessed and joined, and various outcomes of interest and lists are coded. Quest Toad for ORACLE® and Adobe Dreamweaver® have been implemented for rapid development and deployment. HL7 clinical documents such as the Continuity of Care Document (CCD) have been extracted and created for enhanced clinical care and eventual interoperability with external systems such as Regional Health Information Organizations (RHIO) which have been established in New York State.

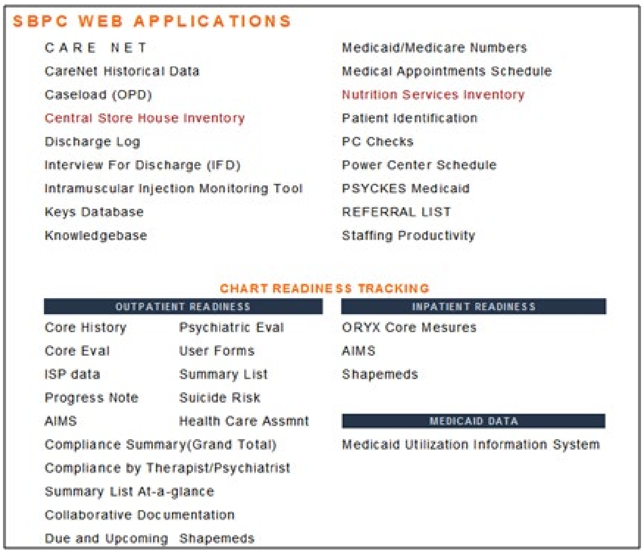

Figure 1: Entry portal into South Beach Psychiatric Center Self Service Applications.

Strategies include: 1) supporting the integration of detailed health information at the individual level and, 2) providing flexible forms of summary information, such as stratifying on utilization, risk, or prescribing practices for clinics and the entire community services division. The suite of applications provides information on: 1) assessment, prescribing, risk 2) the use of these high intensity/high cost services and 3) Electronic Health Record (EHR) sourced health information with flexibly targeted, self-service, live, and on-demand characteristics.

Before describing and reporting on the evaluation of our exemplar, the Medicaid Utilization application, several applications deployed in the suite are reviewed next. Each application has specifically targeted functionalities and they are interoperable and synergistic with the Medicaid Utilization application and with each other. This is provided to review the overall capabilities of the system for possible replication elsewhere; further details are available from the corresponding author.

The Caseload Management application provides a capability for clinicians and administrators to review information for individual and clinic wide caseloads driven directly from databases supporting the electronic health record, and the Admission, Discharge, and Transfer (ADT) database elements. This facilitates understanding of specific caseload assignments, overall risk, and incident management. The clinical documentation applications provide information on timeliness and completeness of the EHR by clinician and clinic. Our working assumption is that consistent and collaborative documentation in the EHR is a critical indicator of reliable on-going clinical processes. Clinicians self-monitoring of their adherence to quality and timeliness documentation policies and administrators' overall view of these metrics supports improved care. The application helps assure that clients participate in their care consistently and are re-engaged when necessary. All data elements within EHR forms are available for programming into efficient dynamic webpages bound to database tables and views.

Prescribing and medication monitoring applications have been deployed by SBPC and NYS-OMH. At the agency level, the Psychiatric Services and Clinical Knowledge Enhancement System for Medicaid (PSYCKES-Medicaid) is web-based portfolio of tools designed to support prescribing, quality improvement, and clinical decision-making for the outpatient Medicaid population [32]. PSYCKES also has been implemented as an inpatient application for state run facilities with favorable results as reported by Uttaro et al. [33] and Finnerty et al. [34]. SHAPEMEDs is another NYS-OMH developed application deployed in 2010, which asks physicians eight questions about clients medication regimens. Responses are stored in an interactive database accessible through the EHR and the SBPC applications portal. These include questions about diagnoses, polypharmacy, targeted symptoms, side effects, adherence, preference, and cost [35].

Suicide Screening and Assessment web applications have been in use at SBPC since 2007 and interoperate with the other applications in the suite [36]. It is well known that people with SMI and medical comorbidities have elevated rates of suicidal behavior and suicide attempts [37], which results in the use of high intensity services. Unmanaged comorbid medical and psychiatric disorders are experienced as highly distressing and sometimes painful, requiring intensive treatment and care management [38]. Suicide screening and assessment are critical dimensions of care and research indicates that significant reductions in suicidal behavior are associated with the use of suicide prevention applications at SBPC and elsewhere [39,40]. Comprehensive individual reviews and treatment interventions related to suicidality are performed using the abundance of clinical and utilization information linked to the SBPC application. Overall reports for clinics and the community services division can be created.

The CareNet inpatient application is frequently used to enhance treatment planning and care management for outpatients who were previously served on SBPC inpatient units. ORACLE® tables are joined and views are created from the EHR, nurse manager reports, pharmacy, medical, and quality management applications, with individual and summary reporting made available in real time. This provides enhanced information related to treatments and care processes that were effective (or not) during inpatient hospitalizations. CareNet also provides for enhanced information on transitions of care, prevalence of comorbid conditions for outpatients treated on the inpatient service, and health information exchange between inpatient and outpatient care teams. Clinicians and administrators can interoperate the applications, which are redundantly and closely linked, for greater detail on outliers and to examine aggregated clinical and utilization patterns.

The Medicaid utilization application

The use of claims related information is ubiquitous in healthcare management and can provide valuable insights to improve care and reduce costs. Research has shown that claims information is valuable: 1) to improve the quality of diabetes care [41], 2) for performance improvement of Medicare Accountable Care Organizations (ACO) [42], 3) for the identification of dialysis and end-stage renal disease patients [43], 4) for the prediction of hospital lengths of stay [44], 5) for the identification of heart failure events and arteriosclerosis risk [45], 6) for the validation of predictive models to identify patients with undiagnosed COPD [46], and 7) in several other areas of clinical and health systems management [47].

New York State has embarked on a health system transformation to integrate and improve care and to reduce the costly burden of its Medicaid program [48]. Preventing multiple chronic inpatient admissions, and overuse of emergency services, is critical to success and the Medicaid utilization application and information system was designed to address these priorities. The application provides information on the use of four high intensity/high cost services: inpatient behavioural, inpatient medical, emergency behavioural, and emergency medical services. The goals of the application are to facilitate best practice interventions, improve care coordination, integrate behavioural health and medical care at the individual and system levels, and to reduce costs to Medicaid. The application was deployed at all eight of the SBPC outpatient clinics and in central administrative areas for clinical and administrative leaders. The ORACLE® database tables described above, as well as those from the New York State Medicaid DataMart, are joined and views are created in real time as these tables are continuously updated.

A heuristic workflow and a selection window arranged by frequency of inpatient services with selection links (unit/clinic, clinician, first and last names, DOB, frequency) for generating self-service reports has been implemented in a drop down and smart select format. Self-service generated individual detail and clinic summary reports are created using joined clinical and claims related data elements. These include psychotropic and non-psychotropic medications, mental health, non-mental health, inpatient, emergency, dental, vision, laboratory, and radiology services, dates of service, along with diagnoses and procedures, all of which are available from successfully adjudicated Medicaid claims. Selection parameters facilitate rapid drill down for aggregate pattern identification and individual patient outliers. The Medicaid utilization application also facilitates discovery of details on outliers through interoperation with the other applications in the suite as described above.

At the individual level examples of use cases might include: 1) a client with diagnoses of schizophrenia and anxiety disorder along with COPD, who is a high utilizer of emergency medical services, presents with panic, anxiety, and respiratory symptoms. A targeted intervention will directly address these symptoms but also help the client develop coping and communication strategies to access behavioural and medical care when symptoms first emerge instead of using emergency services, 2) a client with cognitive disorganization due to schizophrenia along with diabetes and repeated inpatient medical hospitalizations might need assistance with smoking cessation, nutrition, glucose testing, medication adherence, symptom management, exercise, and intensive collaboration with a psychiatric nurse practitioner, 3) a client who is a high utilizer of emergency services due to an inability to navigate healthcare networks and transportation systems might require health systems orientation, frequent call backs, and travel training.

Colocation of medical and behavioural health services

Distinct from innovations in HIT [49], innovative care delivery program models have been introduced to integrate care. These include the colocation of behavioural and medical health services [50-52] and the establishment of health homes [53-55], patient centred medical homes (PCMH) [56,57], and specialty care medical homes [58]. Various forms of case management [59] and assertive community treatment [60] program models have been adopted. Colocation is considered a stronger form of integration than the other models mentioned above, but the evidence is mixed regarding its efficacy and effectiveness in terms of improved health outcomes over and above other models.

The setting for this research provided a unique opportunity to evaluate the association between colocation and the reduction in use of intensive medical services. Three of the SBPC clinics have embedded, licensed medical clinics operated by Maimonides Medical Center of Brooklyn. Maimonides physicians, nurses, and other clinicians, along with their electronic health record and other resources are integrated into the operations of the SBPC clinics. This creates high availability of primary and specialty medical care and opportunities for integrating care at the level of treatment teams and individual clinicians. Since colocation was available as a binary identifier we included it in our statistical models to evaluate whether colocation was associated with reduced utilization over and above the suite of applications and usual care.

Method

Progress in the reduction of two of the four targeted services, inpatient and emergency medical services, over the five-year period was measured. Subjects comprised a balanced panel of 416 clients, each having utilization measures on each of the five years. Many of these clients represented complex cases with comorbid medical and behavioural health conditions. The clinicians and administrators responsible for their care were actively using the suite of web applications based on clinical and meeting reports and browsing history. The subjects had no breaks in Medicaid fee for service eligibility and were receiving mental health care at SBPC clinics continuously from January 1, 2010 to December 31, 2014. SBPC does not remove patients from the census or discharge them for behavioural health or medical inpatient hospitalizations unless the patient expresses a desire not to return to their clinic after hospitalization. Subject information was strictly deidentified and their Medicaid claims data was available for analysis as abstracted totals for each of the five years for emergency and inpatient medical related services. Random patient identifiers and a binary colocated medical clinic indicator were created. Two institutional review board leaders reviewed the study and it was approved as a technical and program evaluation.

Descriptive statistics were calculated to understand the distributions of inpatient medical and emergency medical services for the five-year period. These also facilitated the development of appropriate model for testing longitudinal change, accounting for real world subject characteristics and data assumptions. Zero inflation was quantified in terms of the percent of observations with entries that were equal to zero and over-dispersion was assessed by examining means, variances, ranges, and the Fano factor index of dispersion. Two Generalized Linear Mixed Models (GLMM), which evaluate for both fixed and random effects, and account for violations of distributional assumptions, zero inflation, and over-dispersion of the observations, were used [61]. The GLMM is often appropriate for longitudinal designs in which intra subject correlation, which represents the influence of a subject on their repeated observations (longitudinal observations nested within subjects), must be measured and tested for significance [62,63]. Mixed models such as GLMM are more frequently used in longitudinal health science research in recent years because strengths in modelling actual patients as subjects.

As will be shown in the results section, the distributions of observations show evidence of zero inflation and over-dispersion. The GLMM longitudinal five-year analyses were performed using SAS PROC NLMIXED which models likelihoods based on a set of built in distributions, or when distributional assumptions are violated, a general likelihood can be specified [64,65]. Zero Inflated Poisson (ZIP) GLMM models, based on this general likelihood, were appropriate for the data and were specified in the form:

$$\text{for } y = 0 \qquad f(y) = \omega + (1-\omega)e^{-\lambda} \tag{1}$$

$$\text{for } y \neq 0 \qquad f(y) = (1-\omega)\lambda^{y}\, e^{-\lambda/y!} \tag{2}$$

$$\text{where} \qquad \lambda = e^{\beta_0+\beta_1 t_{j=1}+\beta_2 t_{j=2}+\beta_3 t_{j=3}+\beta_4 t_{j=4}+\beta_5 C_{ik}+U_{ijk}} \tag{3}$$

Each of the five years (tj) was represented through a coded fixed effects term (β0 through β4) with β0 representing the year 2014 and β1 through β4 representing the comparison of years 2010 to 2013 to year 2014. C was a dichotomously coded fixed effect for colocated medical clinic, U was the intra subject random effect, and ω is the zero-inflation effect. All analyses were implemented using SAS 9.4.

Results

Descriptive statistics and graphed distributions for observations collapsed over the five-year period for emergency and inpatient services utilization data are displayed in Figure 2.

Distribution tests of the null hypothesis that the observed inpatient and emergency services distributions followed a standard Poisson distribution were rejected at the $p<0.001$ level, and the graphs above suggest a high degree of zero inflation with 81.8% (1701/2080) of emergency services and 88.2% (1835/2080) of inpatient services observations equal to zero. Higher levels of variances compared to means for both distributions suggested that standard Poisson distributions, which are constrained to have equal means and variances, did not represent the observations, and that the data was over-dispersed. The Fano factor indices of dispersion which is $F = \alpha^2/\mu = 5.95$ for emergency services and $F = \alpha^2/\mu = 2.78$ for inpatient services, were both much higher than 1.0, the expected F for the standard Poisson distribution. Descriptive statistics for colocation are as follows; three of eight SBPC CMHC based clinics have colocated licensed Maimonedes medical clinics, 30.5% of clients (127/416) and observations (635/2080), were from clinics having collocated services.

The ZIP distribution with over-dispersion represented the longitudinal inpatient and emergency services data well and was specified. The results for the two non-linear mixed models, with inpatient and emergency services as outcome variables, including fixed effects for year (comparison), colocation, and zero inflation, and a random effect for subject intercorrelations are displayed in Table 1 (inpatient services) and Table 2 (emergency services). The fixed longitudinal effect of year is aided in interpretation through examination of Figure 3, which displays the inpatient and emergency services utilization rate per patient per year for each of the 5 calendar years 2010-2014, rates are compared visually to year 2014.

For inpatient medical services the longitudinal effect was significant for b1, which compares 2010 to 2014, at $p<0.001$. The change in rate of hospitalization was from 0.3894 to 0.1370 hospitalizations per patient per year from 2010 to 2014. The other longitudinal effects were not significant although b4 which compares 2013 to 2014 comes close to significance at $p<0.0512$. The fixed effect of colocation of the medical clinics, C, was not significant for inpatient hospitalizations. Significance was found for the random effect of U, intra subject correlation, and ω, the fixed effect of zero inflation of the inpatient hospitalizations distribution, both at $p<0.001$. These results indicate a significant decrease in the rate of inpatient hospitalization over the five-year period with most of the longitudinal effect occurring during the first year of implementation, as evident in Figure 3.

For emergency medical services, the longitudinal effect was significant for b1, which compares 2010 to 2014, and b2 which compares 2011 to 2014 at the $p<0.001$ level, and was also significant for b3, which compares 2012 to 2014, at the $p<0.05$ level. The change in rate was from 0.7933 to 0.2813 emergency services per patient per year from 2010 to 2014. The fixed effect of colocation of the medical clinics, C, was not significant for emergency services. Significance was found for the

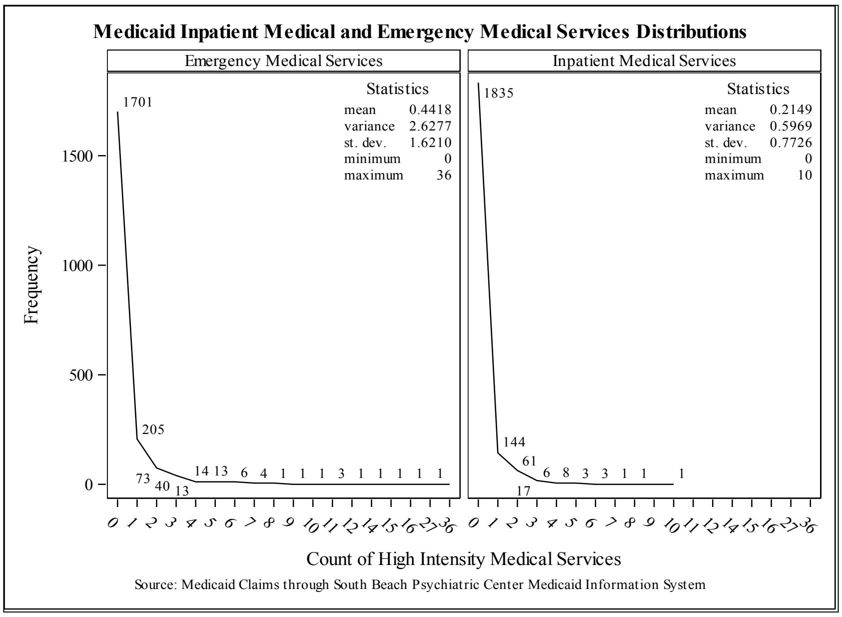

Figure 2: Medicaid Inpatient and Emergency Services Medical Services Distributions.

Parameter Estimates							
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**	**Lower**	**Upper**
$b_{0(2014)}$	-0.7437	0.2149	415	-3.46	0.0006	-1.1661	-0.3214
$b_{1(2010-2014)}$	1.0499	0.2069	415	5.07	<0.0001	0.6432	1.4565
$b_{2(2011-2014)}$	0.2942	0.2405	415	1.22	0.2218	-0.1785	0.7669
$b_{3(2012-2014)}$	0.4078	0.2315	415	1.76	0.0789	-0.04728	0.8628
$b_{4(2013-2014)}$	0.4499	0.2300	415	1.96	0.0512	-0.00229	0.9020
C	-0.06465	0.1656	415	-0.39	0.6965	-0.3902	0.2609
U	0.4938	0.1323	415	3.73	0.0002	0.2338	0.7538
ω	0.7784	0.02016	415	38.61	<0.0001	0.7388	0.8180
Pr>t is the significance level of each parameter with upper and lower confidence levels.							

Table 1: Non-Linear Mixed Model Results for Inpatient Medical Services.

Parameter Estimates							
Parameter	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr>|t|**	**Lower**	**Upper**
$b_{0(2014)}$	-0.5031	0.1508	415	-3.34	0.0009	-0.7995	-0.2067
$b_{1(2010-2014)}$	1.0097	0.1456	415	6.93	<0.0001	0.7235	1.2959
$b_{2(2011-2014)}$	0.7753	0.1695	415	4.57	<0.0001	0.4420	1.1085
$b_{3(2012-2014)}$	0.4367	0.1705	415	2.56	0.0108	0.1014	0.7719
$b_{4(2013-2014)}$	0.03737	0.1894	415	0.20	0.8437	-0.3350	0.4097
C	-0.07745	0.1516	415	-0.51	0.6096	-0.3754	0.2205
U	0.8033	0.1198	415	6.70	<0.0001	0.5677	1.0388
ω	0.6978	0.01796	415	38.85	<0.0001	0.6625	0.7331
Pr>t is the significance level of each parameter with upper and lower confidence levels.							

Table 2: Non-Linear Mixed Model Results for Emergency Medical Services.

random effect of U, the intra subject correlation, and ω, the fixed effect of zero inflation of the emergency services distribution, at the $p<0.001$ level. A steady, continuous reduction in the rate of emergency services utilization from 2010 to 2013 is evident in Figure 3.

The significance of U is important to account for, as we have done in both models, to disentangle the fixed longitudinal effect from intra subject correlation. The significance of the zero-inflation fixed effect parameter confirms that zero inflation was important to account for in both models, and that our distributional assumptions were likely to have been appropriate. Confidence intervals for all parameter estimates have also been reported. Additional details related to these analyses are available from the corresponding author.

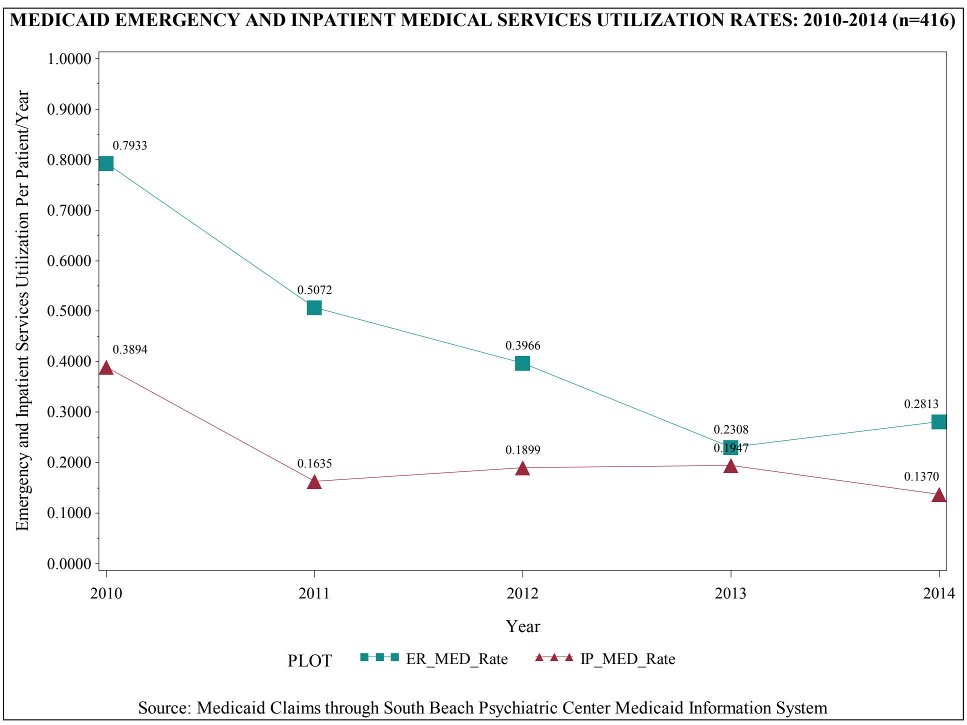

Figure 3: Medicaid Emergency and Inpatient Medical Services Utilization Rates 2010-2014.

Discussion and Conclusions

The suite of self-service intranet based applications described in this report was designed to address multiple aspects of community care for clients with SMI. These applications are redundantly linked and interoperate in powerful and efficient ways to support accountability, best practices, and care coordination. The participation of clinicians and administrators was essential to the development of these applications to assure high validity and usability. As an integrated information system designed specifically to support community care, the suite represents a major advance in behavioural health information technology and management. It is transferable and scalable to other facilities and organizations, and to support New York State health system transformation. An international priority exists to address health outcomes associated with medical comorbidity and early death for clients with SMI and potentially life-threatening comorbid medical conditions. The results indicate that the use of the Medicaid utilization application, interoperating with other medical informatics applications is associated with significant and important reductions in the use of inpatient and emergency medical services. Such reductions suggest improved care coordination, disease management, clinical interventions, and health status, and reduced costs. Joining detailed claims and EHR data, and data from other applications appears to facilitate self-service reporting with high usability, informing successful interventions.

The results are temporally coincident with application implementation and use, and are suggestive of a relationship between such use and the reductions in Medicaid utilization. Clinicians were supported through classroom and personalized, individual training on an on-going basis. This was supplemented through train the trainer sessions during which administrators and information technology staff learned to train groups of clinicians. These approaches resulted in considerable use of the applications as measured by browser behavior. The Medicaid Utilization application was also reviewed at each Community Services meeting to assess for progress for targeted cases. It is also important to note that there are program features unique to each clinic in the community services division, and that clinicians serve in overarching roles as both treatment providers and care managers throughout the system of care. These program and staffing model features may have been important factors driving reductions of high intensity services and improved overall care through use of the Medicaid utilization application. Finally, these applications provide both actionable information for intervention but also information on the results of such interventions as outcome measures. Comprehensive workflow analyses will be needed to disentangle these issues in future research.

Statistical models for longitudinal patient health data must model health outcomes and events for real patients in a veridical manner. Assumptions for model development are sometimes inappropriate for this type of data and spurious results may be obtained. The GLMM statistical procedures used in this research account for intrasubject correlation of repeated measures, zero-inflation and over dispersion of health event data. Is critical to develop and use statistically appropriate models for longitudinal health data such as the subject observations in this research.

Operationally, application functionality that allows for multiple views and layers of the same data, with high usability, is essential for achieving these desirable results. The ongoing review of individual and aggregate health information, in a collaborative way among clinicians, facilitates the assessment of clinical challenges and risks. Such review also indicates the health status of high utilizers, and supports new interventions. It is essential to maintain consultation with clinicians and administrators around the development of data infrastructure and applications, such as by including them on HIT project implementation teams. Ongoing positive feedback and increased transparency about individual and system level health outcomes supports the perception that quality can consistently improve. The successful implementation of the application suite strengthened an already existing culture of consistent monitoring and quality of care. This study also suggests that colocation of behavioural and medical services, such as in health care networks, may not be critical if the integration of interoperable electronic health information is strengthened.

Recent advances in big data analytics in healthcare can optimize the vast information available for clinical interventions and care management and makes related data elements available for coding system level applications. Segmentation approaches, such as for comorbid conditions and predictive modelling, depend on our ability to work with information which has high velocity, high-volume, and high-variety characteristics. The issues of veracity, accuracy, reliability, and overall quality of big data in health care, including behavioural health, is gaining appropriate and increasing attention [66].

Ultimately, the integration of electronic health records for physical and mental health holds the greatest promise to reduce comorbidity and mortality for the seriously mentally ill. EHR vendors have created the functionality to integrate documentation across providers who use their platforms. Cross-vendor platforms are in development through HL7 emergent technologies such as CDA and FHIR, as described above. There are differences in emphasis in the documentation of medical and mental health providers, each of which are critical to improve health outcomes for this population. The databases which undergird these within vendor and across vendor platforms are the foundations for application development, such as described here, to improve the health outcomes of the seriously mentally ill.

Author Contributions

TU researched literature, gained ethical approval, prepared the document, designed the study, and performed statistical analyses. TU and KW aligned application workflows operationally with care services. BR was responsible for programming the applications, data preparation, networking, and security. TU, KW, and BR approved final implemented applications, trained staff, and reviewed, edited, and approved the final version of the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

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