I. Introduction

The decision-making process is fundamental for healthcare facilities struggling to improve healthcare quality. Monitoring activities is the first step in this process, yet it remains a challenge for healthcare facilities, requiring maturity of their decision information system where information is collected correctly, shared in a timely manner in a representative form, and personally adapted to health professionals’ needs.

As an emerging data science field to leverage data and to translate it into actionable insights, business analytics (BA) empowers decision makers with data and supports them...
to make decisions. BA may be defined as “a broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions” [1].

Three types of BA are employed by organizations: descriptive, predictive, and prescriptive [2,3]. Most healthcare facilities start with descriptive analytics, using data to understand past and current healthcare decisions and to make informed decisions [4]. Studies of applied descriptive analytics for chronic diseases [5], cardiovascular diseases [6], diabetes, oncology, elderly care, gynecology, mental health [7], supply chain management, and clinical research have shown that it can enable the delivery of timely care and cost-saving by eliminating inefficiencies.

The majority of BA users are in developed countries; therefore, there is a need for promotion of research on BA in developing countries [8].

This study aimed to describe the experience of a low-income healthcare facility in adopting BA where business processes were adjusted according to BA insights and to discuss implementation challenges in such an environment.

II. Case Description

1. Project Settings
The University Psychiatric Centre Ibn Rochd (CPU) is the reference public teaching hospital for mental health in the Greater Casablanca region of Morocco with an estimated population of 6.812 million citizens in 2014 and a litter capacity of 104 beds.

CPU has utilizes an Electronic Medical Record (EMR) system in outpatient consultation, which it adopted in 2015. Each time a patient has a consultation, the doctor adds clinical notes to the patient record in the EMR system and a single computerized physician order entry (CPOE) of psychiatric drug prescription. However, not all patient visits are recorded in the EMR system. The ratio of patients seen with and without CPOE was 0.48 (2,200/4,560) in 2016, 2.33 (5,496/2,358) in 2017, and 1.27 (4,540/3,568) in 2018.

To monitor this activity, we applied BA techniques to EMR data over a 3-year period from Jan 19, 2016 to Dec 31, 2018. The monitored key metrics were the following: (1) monthly number of consultation represented by the monthly number of CPOEs; (2) number and proportion of mental diseases represented by the 10th revision of the International Classification of Diseases (ICD10); (3) number of prescribed psychiatric drugs aggregated by family and specialty names; (4) monthly number of CPOEs performed by a particular physician; (5) number of CPOEs for a particular geolocation using patient district geolocation; and (6) monthly averaged outpatient care wait time computed by calculating for each patient the delay between patient arrival time and CPOE time.

2. Business Analytics Techniques
Descriptive business analytics was conducted including three steps.
1) Data extraction
It includes three processes namely extraction, transformation, and load (ETL) to extract EMR data fields using structured query language queries, to compute new fields, and to store fields in a data warehousing server. We used Pentaho Data Integration as an ETL graphical tool [9]. Figure 1 shows

![Figure 1. Pentaho ETL Editor showing a drug dimension transformation. ETL: extraction, transformation, and load.](image-url)
a drug dimension transformation.

2) Data modeling
A data star schema model [10] transforms data fields to a dimension data model where the dimension hierarchy and measures are defined. Using Pentaho Model Editor, we created the data model represented in Figure 2.

3) Data visualization
For representing outcomes, we used Pentaho Report Editor included in Pentaho BA Solution [11]. Figure 3 shows the graphical interactive reporting editor for creating graphs.

3. Statistical Analysis
Using R statistics version 3.5.3, we describe continuous variables by mean ± standard deviation, and categorical variables by number (%). We applied the Student t-test to compare CPOE means of 2 years and ANOVA one-way test to compare multiple outpatient wait care time annual means. A p-value less than 0.05 was considered statistically significant.

4. Results
1) Acts quantitative assessment
CPU outpatient acts are estimated by the monthly number of CPOEs (Figure 4). This number increased significantly \((p < 0.0001)\) in 2017 (mean ± SD, 433 ± 66) compared to 2016 (183 ± 88). However, a significant decrease was noted \((p = 0.028)\) in 2018 (378 ± 47) compared to 2017.

2) Medico-economic key metrics
Care insights were obtained according to several medico-economic dimensions, such as socio-demographic factors...
(sex, marital status), economic factors (patient health insurance), medical factors (diagnosis, clinical scales, hospitalization decision). Figure 5 shows the top five diagnoses according to time dimension, and Figure 6 shows the top five diagnoses according to gender dimension in 2018.

3) Psychiatric drug needs according to prescription
Monitoring drug prescriptions allows CPU to have a real estimation of drug needs. BA Roll UP and Drill Down techniques allow reporting of (1) aggregated measures of drug families, drug specialties or (2) detailed information about a particular prescribed drug (Figure 7).

4) Health professional performance monitoring
Physician performance was evaluated by monitoring each physician’s monthly number of CPOEs over time. Figure 8 shows a personal follow-up of one physician whose activity drastically improved after the first-year feedback meeting.

5) Outpatient care wait time monitoring
The monthly averaged outpatient care wait time in minutes is presented in Figure 9. A significant progressive decrease was noted ($p < 0.0001$) between 2018 (68 ± 49), 2017 (81 ± 56) and 2016 (93 ± 56).

6) Psychiatric drugs distribution mapping
Using a country-based geographical location database [12], a district-based map of prescribed psychiatric drugs weighted by patient count was created (Figure 10). Prescribed psychiatric drugs and patient count are graphically correlated (green color goes with bigger dots).

Figure 4. Monthly CPOE number at the University Psychiatric Centre outpatient consultation by year. CPOE: computerized physician order entry.

Figure 5. Top five diagnoses by year at the University Psychiatric Centre outpatient consultation.

Figure 6. Top five diagnoses by gender at the University Psychiatric Centre outpatient consultation in 2018.
## Drug family

| Drug family    | Drug name       | Patient | Doctor |
|----------------|-----------------|---------|--------|
| Antipsychotics | OLANZAPINE      | 1,286   | 622    | 26     |
|                | RISPERIDONE     | 1,166   | 561    | 26     |
|                | CHLORPROMAZINE  | 1,133   | 614    | 26     |
|                | LEVOMEPRAMINE   | 967     | 540    | 26     |
|                | HALOPERIDOL     | 533     | 280    | 26     |
| Antidepressants|                 |         |        |        |
| Anxiolytics    |                 |         |        |        |
| Thymoregulators|                 |         |        |        |
| Hypnotics      |                 |         |        |        |

### Drug dosage

| Drug family  | Drug name       | 10 mg | 20 mg | 5 mg | 15 mg | 2.5 mg |
|--------------|-----------------|-------|-------|------|-------|--------|
| Antipsychotics | OLANZAPINE | 485   | 283   | 275  | 87    | 53     |

---

Figure 7. Prescribed psychiatric drug at the University Psychiatric Centre outpatient consultation in 2018.

Figure 8. Monthly number of CPOEs performed by one physician at the University Psychiatric Centre outpatient consultation by year. CPOE: computerized physician order entry.

Figure 9. Monthly averaged the University Psychiatric Centre outpatient care wait time in minutes over year.
In addition to obtaining data-driven quantitative assessment of activity, we also adjusted many CPU business processes according to BA insights:

- EMR adoption was enhanced based on CPOE monitoring. The number of CPOEs significantly increased in 2017 compared to 2016 (Figure 4) due to BA report feedback.
- The significant decrease in the number of CPOEs in 2018 compared to 2017 (Figure 4) coincided with CPU manager (project leader) departure, which spurred the new manager to resume efforts to ensure project sustainability.
- Intern training was adapted to the distribution of mental disorders (Figure 5).
- Drug-need estimation was for the first time data driven (Figure 7).
- Private manager–physician meetings to discuss poor CPOE activity in 2016 (Figure 8) drastically impacted physician performance in subsequent years.
- Outpatient care wait time excessive average in May 2016 (Figure 9) led to better physician leave planning in subsequent years.
- The Mental Health League (non-governmental association dispensing free psychiatric drugs to patients) used a drug-distribution map (Figure 10) to rationalize psychiatric drug dispensing.

Several challenges in BA adoption were encountered in our experience:

- Maturity of strategic needs and business organization: Higher investment in technology may not bring more returns, rather organizational capability acts as a key mediator in value creation [13]. CPU managers are more aware of BA strategy plan need to become a data-driven facility.
- Data quality and governance: Underlying data quality and semantic interoperability systems adoption are data success factors to address in decision-making process [14,15]. To tackle data issues, CPU adopts structured clinical templates and data repositories along with BA fuzzy matching techniques.
- Quality key metrics issues: It is important to identify appropriate metrics to know whether an implemented change represents an improvement over existing processes [16]. Bringing relevant metrics out of the existing EMR system designed only for continuity of care was quite challenging in this project.
- Audit and feedback: Continued auditing and feedback of performance has been recognized as critically important [4,16]. Annual feedback meetings based on BA reports have been a key success factor for project sustainability.
- Reporting and interpreting results: Reporting should be collaborative between health professionals and data sci-
entists who know data limits and weaknesses [17]. Collaboration between CPU medical staff and medical informatics staff was important for interpreting outcomes.

- Evaluation of BA adoption impact on healthcare facility: BA impact on business performance and business value creation implies a multidimensional relationship evaluation model [18]. The relationship between BA and firm performance is to a large degree mediated by process change capabilities [19]. Project stakeholders positively perceive BA impact on business processes and on information processing.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

ORCID

Samy Housbane (http://orcid.org/0000-0002-3973-9123)
Adil Khoubila (http://orcid.org/0000-0003-3771-0201)
Khaoula Ajbal (http://orcid.org/0000-0001-8748-296X)
Zineb Serhier (http://orcid.org/0000-0002-0856-6960)
Mohamed Bennani Othmani (http://orcid.org/0000-0001-7828-8831)

References

1. Bayrak T. A review of business analytics: a business enabler or another passing fad. Procedia Soc Behav Sci 2015;195:230-9.
2. Khalifa M. Health analytics types, functions and levels: a review of literature. Stud Health Technol Inform 2018;251:137-40.
3. Sivarajah U, Kamal MM, Irani Z, Weerakkody V. Critical analysis of Big Data challenges and analytical methods. J Bus Res 2017;70:263-86.
4. Galetsi P, Katsaliaki K. Big data analytics in health: an overview and bibliometric study of research activity. Health Info Libr J 2020;37(1):5-25.
5. Raghupathi W, Raghupathi V. An empirical study of chronic diseases in the United States: a visual analytics approach. Int J Environ Res Public Health 2018;15(3):431.
6. El Morr C, Ginsburg L, Nam S, Cheung W, Brien H, Maloul A, et al. Insight into health care outcomes for persons living with heart failure using health data analytics. Stud Health Technol Inform 2019;257:98-102.
7. Riahi S, Fischler I, Stuckey MI, Klassen PE, Chen J. The value of electronic medical record implementation in mental health care: a case study. JMIR Med Inform 2017;5(1):e1.
8. Mehta N, Pandit A. Concurrence of big data analytics and healthcare: a systematic review. Int J Med Inform 2018;114:57-65.
9. Pentaho from Hitachi Vantara - data integration [Internet]. [place unknown]; Sourceforge.net; 2019 [cited at 2019 Feb 21]. Available from: https://sourceforge.net/projects/pentaho/files/Data%20Integration/6.1/.
10. Wu C. Development of a medical informatics data warehouse. AMIA Annu Symp Proc 2006;2006:1148.
11. Hitachi Vantara. Pentaho Business Analytics [Internet]. Santa Clara (CA): Hitachi Vantara; c2020 [cited at 2019 Feb 21]. Available from: https://www.hitachivantara.com/en-us/products/big-data-integration-analytics/pentaho-business-analytics.html.
12. GeoNames [Internet]. [place unknown]: GeoNames; c2019 [cited at 2019 Feb 21]. Available from: http://www.geonames.org/.
13. Vidgen R, Shaw S, Grant DB. Management challenges in creating value from business analytics. European Journal of Operational Research 2017;261(2):626-39.
14. Loewen L, Roudsari A. Evidence for business intelligence in health care: a literature review. Stud Health Technol Inform 2017;235:579-83.
15. Bouayad L, Ialynytchev A, Padmanabhan B. Patient health record systems scope and functionalities: literature review and future directions. J Med Internet Res 2017;19(11):e388.
16. Valentine EA, Falk SA. Quality improvement in anesthesiology – leveraging data and analytics to optimize outcomes. Anesthesiol Clin 2018;36(1):31-44.
17. Friedman LM, Furberg CD, DeMets DL, Reboussin DM, Granger CB. Reporting and interpreting of results. In: Fundamentals of clinical trials. Cham: Springer; 2015. p. 479-99.
18. Krishnamoorthi S, Mathew SK. Business analytics and business value: a comparative case study. Inf Manag 2018;55(5):643-66.
19. Torres R, Sidorova A, Jones MC. Enabling firm performance through business intelligence and analytics: a dynamic capabilities perspective. Inf Manag 2018;55(7):822-39.