Analytics and Lean Health Care to Address Nurse Care Management Challenges for Inpatients in Emerging Economies

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Key words

analytics, Artificial Intelligence, lean healthcare, nurse-to-patient ratio, Nursing management, optimization

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Abstract

Purpose: Prescriptive and predictive analytics and artificial intelligence (AI) provide tools to analyze data with objectivity. In this paper, we provide an overview of how these techniques can improve nursing care, and we detail a quantitative model to afford managerial insights about care management in a Hospital in Colombia. Our main purpose is to provide tools to improve key performance indicators for the care management of inpatients which includes the nurse workload.

Methods: The optimal nurse-to-patient assignment problem is addressed using analytics, lean health care, and AI. Also, we propose a new mathematical model to optimize the nurse-to-patient assignment decisions considering several variables about the patient state such as the Barthel index, their risks, the complexity of the care, and the mental state.

Findings: Our results show that there are several processes inherent to compassionate nursing care that can be improved using technology. By using data analytics, we can also provide insights about the high variability of the care requirements and, by using models, find nurse-to-patient assignments that are nearly perfectly balanced.

Conclusions: We illustrated this improvement with a pilot test that makes the equitable distribution of nursing workload the functionality of this strategy. The findings can be useful in highly complex hospitals in Latin America.

Clinical Relevance: The proposed model presents an opportunity to make near perfectly balanced nurse-to-patient assignments according to the number of patients and their health conditions using technology.

Introduction

The work done by nurses reflects a high level of commitment toward the care of their patients, but the complexity of the condition of a clinic, the number of patients per nurse, and the lack of technological tools to facilitate the care process can generate, most of the time, excessive workload amongst professionals (Sato et al., 2016; Següel Palma et al., 2015). Experts in the field say that both revising and organizing the process are adequate ways to alleviate the burden (Andreasson et al., 2016) and that the use of technology and quantifiable data are important to identify managerial elements that can be improved (Sato et al., 2016).

In fact, new technologies must build upon the fundamental principles of nursing. This is achieved when

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the professionals and the patients perceive that the new devices and software facilitate human contact between them, instead of building barriers that generate frustration, additional administrative tasks, and increased workload for nurses (Harris et al., 2018). Therefore, technology must promote compassionate care, since it is fundamental for the nursing profession. By critically examining the influence of technology in the practice of nursing and, specifically, artificial intelligence (AI) for compassionate nursing care, the profession can plan a future route in the technological world (Buchanan et al., 2020).

AI, conceived particularly to be applied in the compassionate care of patients, can be defined as the development and use of complex algorithms that are integrated into logical sequences of software that make use of various types of medical data to predict possible future scenarios and then facilitate decision-making and actions for medical and nursing staff. Consequently, AI tools will free nursing staff of nonvalue-added activities, allowing them to focus on professional activities that require the maximum out of their education, training, and experience (Robert, 2019). Thus, increasing the time spend with patients, instead of performing administrative tasks. As a result, while the current use of technologies for nursing care has proved to lead to better results in patients (Elgin & Bergero, 2015; Rouleau et al., 2017), there is still room for improvement in the use of technology to optimize the nursing workload.

As an example, electronic medical records (EMRs) contain a great amount of information and their analysis constitutes a fundamental input for followups, analyzing patterns, and making decisions that could have a positive effect on the management of nursing staff (Carroll, 2019). Based on these systems and AI prescriptive models, better management decisions can be made, as well as those related to the health care given to patients. These models can be used to analyze data and make clinical decisions and diagnoses, among others (Sousa et al., 2019), including logistics of the nursing practice (Brennan & Bakken, 2015). From this point of view, the analysis of information has a great impact on practice because it modifies how nurses plan, provide, document, and evaluate nursing care (Rouleau et al., 2017), which allows better administration of resources. Also, data analysis allows nursing managers to obtain information to make predictive analyses and to predict and minimize risks, identify the needs of patients, and make decisions to personalize the nursing care plans (Fulton et al., 2019).

Previously, using big data and AI in health institutions has been associated with more stable conditions in patients and a reduction of the required time for nursing care (Rowney & Lipscomb, 2019) as well as balanced workload distribution (Tassopoulos et al., 2015). Though using algorithms to balance the nurse workload has been reported, there is a need to generate studies to confirm and evaluate the impact of these in practice (Zhao et al., 2016). Also, there is a lack consensus on how to calculate the allocation of patients to nurses, wanting to privilege care, quality of life of workers, and reduction nurse turnover rate (Gaviria, 2013).

Therefore, to adequately use technology in a hospital, we first analyze the process of care (Fulton et al., 2019), by building a multidisciplinary team including clinical nurses (Elgin & Bergero, 2015) and engineers for a better understanding of management and automatization opportunities in hospital processes (Mazur & Chen, 2010). The goal is to develop the required methods to optimize the operation, guarantee humane and safe care, responding to efficiency criteria with the reduction of waste and unnecessary activities (Borrero, 2018; Salgin et al., 2016). Later, we analyze, build, and implement models of AI, to discuss how these new technologies make a trade-off between risks and benefits. Further, we analyze how it allows the development of nursing practice, with a special focus on "humane" assistance (Carvajal Hermida & Sánchez-Herrera, 2018) or compassionate care of patients based on ethical principles, to help patients to adapt better to their health conditions (Arroyo-Marlés et al., 2018).

The proposed methodology to generate change and innovation at a university hospital is validated in a hospital in Colombia working under a continuous improvement philosophy, including a model to predict and optimize the workload associated with nursing care.

Methods

This methodological research aims to develop a concept test of a prescriptive mathematical model that is incorporated through an IT system. The process is done in two phases as follows: 1) the data collection to analyze the nursing processes. In this stage, we use Lean Health care techniques to identify opportunities for improvement that impact performance indicators and 2) development of an optimization model. For this stage, we applied descriptive and predictive analytics to analyze the workload for nurses using historical data. We propose a mathematical model to optimize nurse-to-patient allocation. The following sections describe these methods.

Lean Health Care

Lean health care is a continuous improvement methodology done by working with people to identify and eliminate eight wastes (mudas) (Manos et al., 2006). These wastes are associated with defects, overproduction, waiting, nonvalue-added processing, transportation, inventory, motion, and employees underutilized. A recent literature review on Lean Health care is presented by Antony et al. (2019). In our case, a field observational study is performed for the inpatient hospital floor, observing for several days the frequency in which wastes occur using the guide for field notes proposed by Phillippi et al. (2018) to collect the time, frequency, cause, and impact of every event or activity that is classified as a waste in the Lean Health care methodology. To do so, a randomized selection of days and times is performed using a computer program. The observations are made by trained engineering students under the supervision of the authors. The principal investigator validated the observations. The wastes are categorized to document the process and to estimate the time that was spent to perform the activity. Table 1 presents examples of each type of activity that represents some kind of waste.

Analytics

Using historical information from nursing records of 17,618 inpatients hospitalized between 2017 and 2018 in a hospital in Colombia with risk factors, a descriptive analysis is performed to characterize the variability of the patients' care requirements over a period of 386 days. Further, the main objective is to characterize, and predict, the workload for the nursing staff. A clustering approach based on *K-means* allowed us to classify the different types of nursing requirements between days. This method is an exploratory data analysis technique that aims to make a partition of a set of observations that are associated with multiple dimensions. As a result, we obtain subgroups of

observations. The idea is that the observations composing each particular subgroup are very similar, whereas observations in different subgroups are very different. This approach is useful to predict the workload for nursing staff per shift and support staffing decisions in each subgroup of observations.

Mathematical Programming Model

The proposed mathematical model is explained here. The purpose of the model is to compute and automate the process to allocate nurses to patients with a compassionate care approach, for each shift on the inpatient floor. Thus, this involves understanding the patients' needs and capabilities in the event of hospitalization, which also affects the workload of nursing care. To do this, it is necessary to determine the physical functionality per patient with the Barthel index. This index determines the ability of the patient to perform activities of daily living with a score from 0 to 100. This index scores 0 for a totally dependent patient and 100 for a fully independent patient. Also, the cognitive ability of the patient is considering with the Short Portable mental state questionnaire of Pfeiffer (SPMSQ) that scores from 0 to 10. A score on 10 indicates a severe cognitive impaired patient, whereas a score of 0 represents a normal mental functioning patient. The association of these factors reflects the patient's condition and directly affects the type of care a patient demands from the nursing staff and, therefore, should be considered as a determinant of workload. These scales are chosen since they are easily administered by any clinician, and they have been tested and validated in the scientific literature.

Next we define the mathematical notation for the model. Each shift we have a set of hospitalized patients $I = \{1, ..., n\}$ with information about their dependence level (Barthel score) denoted as B_{i} ; their complication risks (risk of falling, nutritional risks, agitation risks,

Table 1. Types and examples of wastes in lean health care

WASTE	TYPE	Types of activities
1	Defects	Medication errors, missing items, missing/wrong info., retesting
2	Overproduction	Unnecessary tests/procedures, extra copies of charts/reports
3	Waiting	Waiting for people, bed, equipment, signatures, supplies, info., etc.
4	Nonvalue-added processing	Never used data put onto forms, entering repetitive info.
5	Transportation	Moving patients, specimens, supplies, equipment, charts
6	Inventory	Excess supplies, outdated meds, obsolete charts/files/manuals
7	Motion	Searching for patients, charts, orders, meds, supplies, info.
8	Employees Underutilized	Not engaged in continuous process improvement

Source: (Graban, 2016)

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among others), denoted as R_i ; the complexity of their diagnosis C_i ; and the Short Portable Mental Status Questionnaire, denoted as S_i . These parameters allow us to estimate the workload required by a patient as a linear function. This workload is denoted as W_i , which is computed using eq. (1)

$$W_{i} = f(B_{i}, R_{i}, C_{i}, S_{i}) = \beta_{0} + \beta_{1}B_{i} + \beta_{2}R_{i} + \beta_{3}C_{i} + \beta_{4}S_{i}$$
(1)

The coefficient β_0 represents the average workload required for a hospitalized patient, and the coefficients $\beta_1 - \beta_4$ are associated with the marginal workload for patients presenting dependency levels, complication risks, complex diagnosis, and neurological risks respectively. Also, a set of nurses $J = \{1, ..., m\}$ is available to take care of the patients.

The main criteria to decide the assignment of patients to nurses corresponds to the balance of the workload. That is, the assignment of patients to nurses should be balanced, to avoid unfair work policies and excessive workload. Thus, the decision variables of this problem are

- 1. $X_{ij} = 1$ if patient $i \in I$ is allocated to nurse $j \in J.0$ otherwise
- $2.W_{\text{max}}$ = maximum workload allocated to a nurse

 $3.W_{\min}$ = minimum workload allocated to a nurse

The objective function that represents the criteria to be optimized is presented in eq. (2) to minimize the imbalance in the workload allocation. The imbalance is computed as the difference between the maximum workload W_{max} and the minimum workload W_{min} .

$$MinW_{max} - W_{min}$$
 (2)

A feasible assignment is guaranteed by the following equations:

$$\sum_{i} W_{i} \cdot X_{ij} \ge W_{min}, \forall j \in J$$
(3)

$$\sum_{i} W_{i} \cdot X_{ij} \le W_{max}, \forall j \in J$$
(4)

$$\sum_{j} X_{ij} = 1, \forall i \in I$$
(5)

$$\sum_{i} X_{ij} \ge 1, \forall j \in j \tag{6}$$

$$X_{ij} \in \{0, 1\}, \forall i \in I, \forall j \in J$$
(7)

$$W_{min}, W_{max} \ge 0$$
 (8)

Eq. (3) and (4) compute the maximum and minimum workload assigned to the nursing staff. Eq. (5) states that each patient must be allocated to a single nurse, whereas eq. (6) forces each nurse to be allocated to at least one patient. The variables' nature is stated by eq. (7)-(8).

Results

First, the lean healthcare philosophy allowed us to characterize the operation, estimate the time spent in non-value added activities by the nursing staff, and provide insights about the processes where technology can make significant improvements. Figure 1 presents the average impact in time produced by the 7 wastes in the two different floors that are analyzed. The 8th waste, associated with underutilized employees, was not detected in our observations. Future research includes making further efforts to detect this waste. During this study, it was determined that the nursing staff at the institution spends more than 50% of their time on activities that are not typical of the nursing practice. This seems to be a very common fact in Colombia.

It can be concluded that little differences are perceived between both floors. Also, the most wasted time comes from defects. This waste is originated from wrong information problems, such as wrong information in prescriptions, which can produce delays up to 1 hour in the processes (several times per day), missing information problems, and missing items. One example of the former issue is when the medication cart does not have the proper supplies.

Also, wastes associated with waiting appear frequently in the nursing process. On average, 85 min were spent waiting in our observations. Most of the time spent waiting by the nurse is because the nurse requires a doctor's approval for an activity. Also, nurses spent some time waiting for supplies (such as medicines and equipment).

The third most relevant issue is the nonvalue-added processes. Typical examples of these issues are the processes associated with collecting data that are never used. Some processes require nursing staff to register patients' information in systems that are not integrated and do not provide business intelligence tools for decision-making. These processes could account for up to 10% of the nursing working time.

Overproduction wastes also appear. A typical example of these activities is the extra copies of reports. Often, nurses are required to generate several copies of reports, especially about the risks and



Figure 1. Time spent in activities unrelated to nursing care. Results of the field observational study *Source:* Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]



Figure 2. Technology integration proposal for care processes of nursing Source: Own elaboration.

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complications of patients that need to be registered in a logbook on a daily basis. Also, a complete report about the shift must be presented every time the shift ends. The lack of integration in information systems produces waste.

The other types of wastes have a smaller impact on the nursing workload. These are transportation, inventory, and motion wastes. Examples of these wastes include the time spent doing inventory counting, filling the medication cards for patients, and the time required to search for supplies and medicines. Therefore, a technology mapping process, and based on the collected information, allow us to identify the following improvement opportunities with results in the short term:

- 1. Management of medication inventories: depending on the situation, a nurse may take between 30 min and 210 min to manage medication inventories per shift. This includes logistic activities such as ordering to the pharmacy, checking prescriptions and medication expiration dates, checking the supplies in the crash cart, among others. We propose the elimination of the manual Kardex of patient medication, to provide information to the doctor so they formulate medication that is available at the pharmacy and to have the technology to automate the medication inventory such as RFID technology.
- 2. Input information into systems: this task takes about 65 min of their time per shift. We propose the use of technological aids to allow more friendly and efficient interaction between systems. This is achieved by allowing the use of tools that ease the acquiring of information (Mobile apps, natural language processing [NLP], etc.), technologies made to consolidate and summarize activities from different sources of information and analyze the activities to prevent adverse events in patients.
- 3. Using workflows that automate the tasks and the follow-up of activities (Business process management Systems or BPM): We propose a mapping of processes that are susceptible to automate, integrating BPM systems with different systems of information, and developing models of machine learning (ML) that suggests improvements on processes based on information that is collected daily.
- 4. Automation of processes for patients: We propose the implementation of voice commands to activate simple processes (on/off of lights, emergency calls, on/off radio or television, etc.), automatic monitoring of vital signs, and analysis of feelings by AI tools.

In Figure 2, the resource groups can be seen, organized by the levels of the proposed technology. The second step consists of analyzing the historical data about nursing care for nonintensive care units. Figure 3 presents a boxplot for the number of patients hospitalized daily, classifying them according to their age (adult or pediatric) and risks (fall, skin damage, agitation, Broncho aspiration, nutritional, anticoagulation patients, with allergies, with isolation, dependencies, with therapies, and other risks).

Figure 3 shows high variability in patient's characteristics. We see particularly an important number of outliers in most of the features. The characteristics that have fewer outliers are associated with the risk of agitation, patients with allergies, and isolated patients. On the other hand, the most variable features (with a significant number of outliers) are the number of dependent patients for activities in daily living (ADL) and the number of anticoagulated patients. Given that these variables are directly associated with the nursing workload, the challenge is to predict them accurately and use this information to make adequate decisions.

Further, we apply a *k-means* classification model to form clusters of days according to their features, as explained in Section 2b. In preliminary tests, clustering the data into three clusters provided the best results. Figure 4 presents the clusters, mainly defined by four features. These are the number of patients with high skin damage risks (Figure 4a), agitation risk (Figure 4b), Broncho aspiration (Figure 4c), and nutritional risks (Figure 4d). The other variables did not contribute significantly to the clustering analysis. Thus, nursing requirements per day are classified, in general, into three types. These are defined in Table 2.

Finally, to test our mathematical model, the workload requirements per patient are estimated as a function of the factors that directly affect it, as presented in Eq. (1). Using the analytic hierarchic process by experts, the derived linear function is presented in Eq. (9). The reader is referred to Dolan et al. (1989) to know more about these techniques.

$$W_i = f(B_i, R_i, C_i, S_i) = 0.2 - 0.002B_i + 0.095R_i + 0.018C_i + 0.0247S_i$$

(9)

We solve the model in Eq. (1) to (8) using the commercial solver IBM ILOG CPLEX, version 12.7 and compared the solutions against experts' choice of patient assignment and a random assignment. The random assignment corresponds to the current policy in most hospitals in emerging economies, where patients are randomly assigned to beds, and each bed has a defined nurse. As a result, patients are randomly allocated to nurses in practice. Table 3 presents the comparative results for the assignment made by two expert nurses,

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Nurse Care Management Challenges



Figure 3. Number of patients per characteristic on inpatient floors Source: Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

the average results for 100 simulations of a random assignment method, and the proposed model on three cases with 20 patients, to assign to two nurses. The assessment of $B_{i}, R_{i}, C_{i}, S_{i}$ is provided for each patient i for each case. We observe that the assignment problem that considers the four variables is difficult to solve. In fact, the experts struggle with the assignment. Further, the random method could provide solutions where the workload imbalance $(W_{max} - W_{min})$ is lower than the experts' choice in two out of three cases. The results for our assignment model are very promising. For each case, we could find an assignment that has zero imbalance. That is, each nurse is assigned to the same workload. Additionally, our method minimizes the workload (W_{max}) for nurses. Naturally, this is a significant advantage for their performance and well-being.

Another important question is how to define the number of nurses per shift. Thus, we generated 15 datasets to emulate the workload for nurses according to the data analytics. Table 4 presents this comparison for cases in clusters 1-3 (five datasets per cluster) with n patients and two or three nurses. We solve these assignment problems using our model. For each case, the maximum and minimum workload is provided together with the corresponding workload imbalance. Three important conclusions are deducted from this result. First, the proposed model always computes an assignment that is near perfectly balanced. Second, as expected, the workload for a nurse when three nurses are working together is 33% lower than the case where only two nurses are working. Third, the shifts corresponding to clusters 2 and 3 have a workload that is 80% and 103% higher than cluster 1. This analysis is relevant for decision-making processes about nurse staffing.

Discussion

Nurse workload is associated with the results of the patient's care. Both the patient's characteristics and the number of patients assigned to one nurse have a great influence on the outcome. In the present study, based on the analysis of the everyday activities that nurses perform in a university hospital, significant improvement opportunities are identified using technology. We identify nonvalue-added activities that we can automate using AI to alleviate the nurse workload and automate the processes. Also, we study four variables associated with nursing workload, which are the level of dependence of patients, risks related to safety (Aiken et al., 2017; Magalhães et al., 2017), the level of complexity of the health state, and mental health. Based on these variables, there is evidence of the high variability of the characteristics of hospitalized patients. Further, a mathematical model is proposed to distribute the workload between the personnel. The aim is to guarantee more contact between nursing professionals and patients, and, ultimately, compassionate, committed care with a humane tone focused on particular needs (Su et al., 2020).

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Figure 4. Clusters of days according to the features of the patients. a) Skin damage risks, b) agitation risks, c) risk of Broncho aspiration, d) nutritional risk. Cluster 1 with "x," cluster 2 with "•," and cluster 3 with " \blacktriangle ." [Colour figure can be viewed at wileyonlinelibrary.com]

Table 2.	Clusters	of	nursing	requirem	ents
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CLUSTER	General description of the cluster
1 marked with "x"	Between 15 and 25 adult patients approximately, <16 patients with skin damage risk, less than seven patients with agitation risk.
2 marked with "•"	More than 25 adult patients, <10 patients with skin damage risk, and less than four patients with agitation risk. More than four patients with Broncho aspiration risk, and more than four patients with nutritional risks.
3 marked with "▲"	More than 30 adult patients in general, more than 10 patients with skin damage risk, more than five patients with agitation risk, less than five patients with Broncho aspiration risk, and less than five patients with nutritional risks.

Source: Own elaboration.

In this research, we corroborate that the workload of nursing depends on the combination of the individual health condition of patients, particularly when it comes to a functional state, individual needs of nursing care, and the gravity of the symptoms (Morris et al., 2007). In health institutions, the professional nurses are assigned to the hospitalized patients, not by their health conditions. The results of this study

CASE	EXPERT 1	EXPERT 2	RANDOM ASSIGNMENT	PROPOSED MODEL
1	W_{max} = 4.33 W_{min} =3.92 $W_{max} - W_{min}$ = 0.41	$W_{max} = 4.54$ $W_{min} = 3.71$ $W_{max} - W_{min} = 0.83$	$W_{max} = 4.37$ $W_{min} = 3.89$ $W_{max} - W_{min} = 0.48$	$W_{max} = 4.13$ $W_{min} = 4.13$ $W_{max} - W_{min} = 0.0$
2	$W_{max} = 5.18$ $W_{min} = 4.08$ $W_{max} - W_{min} = 1.10$	$W_{max} = 5.48$ $W_{min} = 3.79$ $W_{max} - W_{min} = 1.69$	$W_{max} = 5.20$ $W_{min} = 4.67$ $W_{max} - W_{min} = 0.53$	$W_{max} = 4.94$ $W_{min} = 4.94$ $W_{max} - W_{min} = 0.0$
3	$W_{max} = 3.77$ $W_{min} = 3.17$ $W_{max} - W_{min} = 0.60$	$W_{max} = 3.77$ $W_{min} = 3.17$ $W_{max} - W_{min} = 0.60$	$W_{max} = 3.71$ $W_{min} = 3.22$ $W_{max} - W_{min} = 0.49$	$W_{max} = 3.47$ $W_{min} = 3.47$ $W_{max} - W_{min} = 0.0$

Table 3. Comparison of results between experts' choice, random assignment, and the model

Table 4. Comparison of results for different datasets with two and three nurses

TYPE	Dataset	Two NURSES			Three NURSES			
		No. Patients	W _{max}	W _{min}	Imbalance	W _{max}	W _{min}	Imbalance
CLUSTER 1	A1	17	2,2176	2,2176	0	1,4785	1,4783	0,0002
	A2	20	2,8433	2,8433	0	1,8956	1,8955	0,0001
	A3	22	2,5433	2,5432	0,0001	1,6955	1,6955	0
	A4	23	3,0544	3,0543	0,0001	2,0363	2,0362	0,0001
	A5	25	3,5442	3,5441	0,0001	2,3628	2,3627	0,0001
CLUSTER 2	B1	28	3,9166	3,9165	0,0001	2,6111	2,611	0,0001
	B2	30	5,3516	5,3515	0,0001	3,5677	3,5677	0
	B3	32	5,3695	5,3694	0,0001	3,5797	3,5796	0,0001
	B4	34	5,3336	5,3336	0	3,5558	3,5557	0,0001
	B5	36	5,5017	5,5016	0,0001	3,6678	3,6677	0,0001
CLUSTER 3	C1	30	7,2319	7,2318	0,0001	4,8213	4,8212	0,0001
	C2	32	7,6809	7,6808	0,0001	5,1206	5,1205	0,0001
	C3	34	7,3985	7,3985	0	4,9324	4,9323	0,0001
	C4	36	8,7948	8,7947	0,0001	5,8632	5,8631	0,0001
	C5	38	9,3262	9,3262	0	6,2175	6,2174	0,0001

reflect the variability of hospital care, which not only depends on the number of hospitalized patients but also on their particular needs, which reflects the inconvenience of predetermined assignment of nursing personnel with the inevitable increase of risks of adverse events and work overload. The results of this study are coherent with those described by Carvajal Carrascal et al. (2016) in similar health institutions, in which they concluded that it is necessary to improve the working environment, as a factor that promotes the quality of care and satisfaction of the stakeholders.

Also, workload management in nursing services requires systems to classify patients according to their needs and health conditions to structure a compassionate care plan, where the level of dependence of the patient (Čiarnienė et al., 2019; Vandresen et al., 2018) and the mental health state (Nilsson et al., 2016) is explicitly considered factors.

A higher nurse workload increases the rate of adverse events associated with care (Wynendaele et al., 2019). Additionally, excessive workload also increases the rate of staff turnover, diminishes work performance, and increases the risks inpatient care (Bakhamis et al., 2019). These results prove previous findings, which emphasize the use of lean health care, analytics, and AI to improve the efficient use of resources and the safety of patients (Meyer et al., 2020; Needleman, 2013). Our study also raises new questions about the need to understand how AI-driven digital health technologies contribute to strengthening compassionate nursing care.

Limitations

Even though the direct measurement of activities of nursing personnel in the care of patients and the workload of nurses is useful, future research should

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consider the workload that is generated by other aspects of care that are not visible in this method (Ross et al., 2019). Also, the results of patients are associated with the assignment of nurses, but these vary in levels of importance depending on the type of care unit (Milstein & Schreyoegg, 2020). Taking this into account, this study focuses on the case of the inpatient floor but should consider in the future other hospital services to know whether they present similar behaviors.

Conclusions

AI tools and data analysis show promising results in freeing the workload and reducing nonvalue-added activities in nursing practice. Despite that these activities are fundamental, they are not inherent to nursing practice and distract nurses from their main purpose, which is care, safety, and helping the patient to recover. Also, the results of this study show the inconvenience of having a fixed allocation of personnel and that traditional allocation methods of human resources are insufficient to guarantee the centered attention to patients with good results in health, avoiding the risks of adverse events, and work overload. The analysis of data and lean health care has the potential to transform the decision-making processes in healthcare management in general and making efficient use of the resources. This is why we recommend the implementation of the proposed model, to make managerial decisions on assigning nurses during shifts and guaranteeing compassionate care.

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