Modified Early Warning Scorecard: The Role of Data/Information Quality within the Decision Making Process

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Abstract: Presented in this paper is the Patient Assessment-Data Quality Model (PA-DQM). It is designed to assess how patient datasets which are poor in composition can impact on the decision processes following patient assessment. The PA-DQM in particular examines four key Data Quality (DQ) dimensions: timeliness, accuracy, consistency and completeness. This DQ model is generic in nature as any number of decision making processes can be substituted to reflect the medical scenario under consideration. For example, Intensive Care Unit (ICU) admissions, Emergency Room (ER) triage systems or Modified Early Warning Scorecards (MEWS). The PA-DQM presented is evaluated using the MEWS process as an exemplar. Paper based MEWS are utilised to assist medical staff identify at risk patients with a declining health status. The calculated MEWS score is designed to trigger earlier medical interventions to avoid or reduce the potential impact of catastrophic events. In particular the existing MEWS system which (i.e. a paper based approach) is evaluated alongside an electronic-Modified Early Warning Scorecard (e-MEWS) system, which is designed and developed to reduce the number of DQ issues which continue to persist with the paper based process. To validate the assertions presented in this paper a workshop (participation of 51 medical staff) was held in St. Luke's Hospital, Kilkenny, Ireland, where the paper based MEWS has been adopted for the last 3 years. It is clear from our initial findings that the proposed e-MEWS system has the ability to greatly enhance the levels of DQ over its existing paper based counterpart.

Keywords: Information Quality, MEWS, Health Informatics and Body Area Networks.

1. Introduction

There is a growing body of evidence in the literature that many patients in hospital care become acutely ill, experience late referral to critical care, or unfortunately die due to delayed recognition of their physiological deterioration or mismanagement of patient care. Numerous studies have shown that such negative outcomes are frequently preceded by atypical vital signs in the hours prior to a catastrophic event such as coronary arrest, death, or late admission to a high dependency unit (Goldhill *et al*. 1999, McGloin *et al*. 1999, Parissopoulos & Kotzabassaki 2005). Such was the stimulus for the development of the Early Warning Scorecard (EWS) (Morgan *et al.* 1997), and later Modified Early Warning Scorecards (MEWS) (Stenhouse *et al.* 1999). Other studies, notably in the UK, Australia, and the US have reported on the value of enabling earlier referral to a Coronary Care Unit (CCU) or Intensive Care Unit (ICU) resulting in better patient outcomes and shorter stays in those units. In some cases they are also used as the primary mechanism for triggering Medical Emergency Team (MET) interventions.

The MEWS is simply a reference table which associates individual parameters for heart rate, systolic blood pressure, blood oxygen and other vital signs, with a 'score' (0, 1, 2, or 3), which is representative of the physiological derangement from a normal range. However, MEWS is not a panacea for accurate patient assessment and should be used judiciously in conjunction with clinical assessment (Roberts 2008). For the MEWS to function correctly the collection of patient vital signs needs to be at a sufficiently high frequency, accurately recorded, consistently preformed and with the complete set of patient vital signs. Within St. Luke's Hospital in Kilkenny, Ireland, the MEWS score is derived from seven vital sign parameters: Pulse, Systolic Blood Pressure, Respiratory, Blood Oxygen (SpO2), Temperature, Glasgow Coma Scale (e.g. patient level of coconscious) and Urine output.

An aggregate MEWS score on its own can only provide a snapshot of a patient's state of health. A more accurate picture or 'Known Patient Context' of a patient's state of health is obtained through the correlation of a given MEWS score with medical staff's empirical knowledge.

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As DQ issues continue to persist within the MEWS paper based approach, an electronic-Modified Early Warning Scorecard (e-MEWS) system has been developed to limit or avoid their reoccurrence. The e-MEWS system utilises wireless Body Area Network (BAN) technology to monitor patient vital signs in a consistent and regular manner to counteract the paper based DQ limitations. BANs are considered a key element for patient-centric healthcare services for the future as it can provide a very effective way to collect, monitor and manage patient's physiological parameters such as glucose levels, blood pressure, heart rate among others. A number of these devices have been developed over recent years to monitor specific patient vital signs in particular: (Lorincz et al. 2004, O'Flynn et al. 2006 and Thiemjarus et al. 2005).

To help ensure that the presented MEWS score is of a high quality, four data quality (DQ) dimensions need to be considered, these are:

- Timeliness, the frequency of patient vital signs collection.
- Accuracy, the interpretation of the collected patient vital signs and the calculation of the MEWS score.
- Consistency, vital signs collected in a consistent approach throughout the patient's stay in hospital.
- Completeness, all vital sign parameters are collected.

Judgement on patient care delivery will always reside with the medical staff. However, if the presented MEWS score is of a low quality (e.g. inaccurate or incomplete) then the medical staff, whether they have high or low levels of experience, may be ill-advised. Despite these shortcomings, the foundation of the MEWS is well grounded and has been proven to be successful. However, if the MEWS methodology is to reach its full potential, all four data quality dimensions need to be improved upon.

Many frameworks have been developed and numerous approaches taken in assessing and measuring Information Quality (IQ)/Data Quality (DQ) dimensions. Over the last number of decades researchers have addressed IQ and DQ from a number of perspectives. The role or importance of IQ/DQ frameworks vary from application to application. For example, a timeliness IQ/DQ dimension may have a higher level of importance within a medical environment than with a data warehouse reporting system. A short summary of well known IQ/DQ frameworks is presented in section 2 (cf. table 1). An explicit distinction between IQ and DQ is not applied in this paper since our findings are general and suitable for both concepts. Therefore, both terms are used in this article interchangeably.

The remainder of this paper is structured as follows: In section 2, related work, reviews existing IQ/DQ frameworks and their association with the presented PA-DQM. In section 3 the PA-DQM architecture is presented. The e-MEWS architecture is outlined in section 4 along with the initial findings of the PA-DQM in section 5. Finally a conclusion of the PA-DQM is in section 6.

2. Related work

A short overview of known significant DQ frameworks is provided. This enables a direct comparison to be made, highlighting their relationship with the presented PA-DQM. The literature has put forward a number of frameworks and classified the dimensions associated with each of these frameworks (cf. table 1). In addition to the variety of IQ frameworks, most provide their own definitions for timeliness, accuracy, consistency and completeness. The structure of table 1 extends from previous work by (Helfert, et. al., 2009). In this table, 4 DQ dimensions, timeliness, accuracy, consistency and completeness are assessed against relevant DQ frameworks.

The PA-DQM presented in this paper (cf. section 3) is generic in nature and maintains a strong underpinning with (Wang and Strong 1996, Naumann & Rolker 2000, Kahn et al. 2002 and Eppler and Muenzenmayer 2002). While a number of other DQ frameworks discuss these four DQ dimensions either directly or indirectly, their view on DQ is theoretically dissimilar and as such is viewed from a different layer of abstraction, for example, in (Leung 2001) the DQ dimension reliability, is used to measure the level to which users can rely on the system while in (Zhu and Gauch 2000) the DQ dimension popularity is used to measure the number of users who wish to use their system. For PA-DQM, the four DQ dimensions 1) timeliness, 2) accuracy, 3) consistency and 4) completeness are viewed as important indicators to ensure that the information provided to the medical practitioner is of sufficient quality to assist them make a well informed decision.

Table 1: IQ/DQ frameworks, timeliness (T), accuracy, (A), consistency (Cn), completeness (Cm)

Framework	Dimensions / Quality Category	T	A	Cn	Cm
(Wang and Strong 1996) (A Conceptual Framework for Information quality)	Believability, Accuracy, Objectivity, Reputation, Value-added, Relevancy, Timeliness, Completeness, Appropriate Amount of Data, Interpretability, Ease of understanding, Representational consistency, Concise Representation, Accessibility, Access Security.	√	√	√	√
(Zeist and Hendricks 1996) (Extended ISO Model)	Functionality, Reliability, Efficiency, Usability, Maintainability, Portability.	X	X	X	X
(Alexander and Tate 1999) (Applying a quality framework in a Web environment)	Authority, Accuracy, Objectivity, Currency, Orientation, Navigation.	X	√	-	X
(Katerattanakul et al.1999) (IQ of individual web sites)	Intrinsic, Contextual, Representational, Accessibility.	X	X	X	X
(Shanks and Corbitt 1999) (Semiotic-based framework for IQ)	Well defined / formal syntax, comprehensive, unambiguous, meaningful, correct, timely, concise, easily accessed, reputable, understood, awareness of bias.	√	X	X	√
(Dedeke 2000) (Conceptual framework for measuring IS quality)	Ergonomic Quality, Accessibility Quality, Transactional Quality, Contextual Quality, Representational Quality	X	X	X	X
(Naumann & Rolker 2000) (Classification of IQ Metadata Criteria)	Believability, Concise Representation, Interpretability, Relevancy, Reputation, Understandability, Value Added, Completeness, Customer Support, Documentation, Objectivity, Price, Reliability, Security, Timeliness, Verifiable, Accuracy, Amount of data, Availability, Consistent Representation, Latency, Response time	√	√	√	√
(Zhu & Gauch 2000) (Quality Metrics for Information retrieval on www)	Currency, availability, information to noise ratio, authority, popularity, cohesiveness	X	X	X	X
(Leung 2001) (Adapted extended ISO model for Intranets)	Functionality, Reliability, Usability, Efficiency, Maintainability, Portability.	X	X	X	X
(Kahn et al.2002) (Mapping IQ dimensions into the PSP/IQ Model)	*Product Quality:* Free-of-Error, Concise, Representation, Completeness, Consistent Representation, Appropriate Amount, Relevancy, Understandability, Interpretability, Objectivity *Service Quality*: Timeliness, Security, Believability, Accessibility, Ease of Manipulation, Reputation, Value Added	√	√	√	√
(Eppler and Muenzenmayer 2002) (Conceptual work for IQ in the Web Site Context)	Comprehensive, Accurate, Clear, Applicable, Concise, Consistent, Correct, Current, Convenient, Timely, Traceable, Interactive, Accessible, Secure, Maintainable, Fast.	√	√	√	√

3. Patient Assessment – Data Quality Model (PA-DQM)

The action protocols and decision making parameters in figure 1 can be modified to reflect the application specific scenario under review. For example, action protocols may be ICU or ER specific with adjoining ICU and ER decision making parameters. A patient's current state of health or known context is of paramount importance. It is clear from the literature that the lack of up-to-date and accurate data pertaining to the patient's state of health can lead to a delayed or incorrect reaction, with a number of negative consequences. In figure 1, the deployment of a MEWS (both paper based and electronic) within a ward environment may be grouped as follows:

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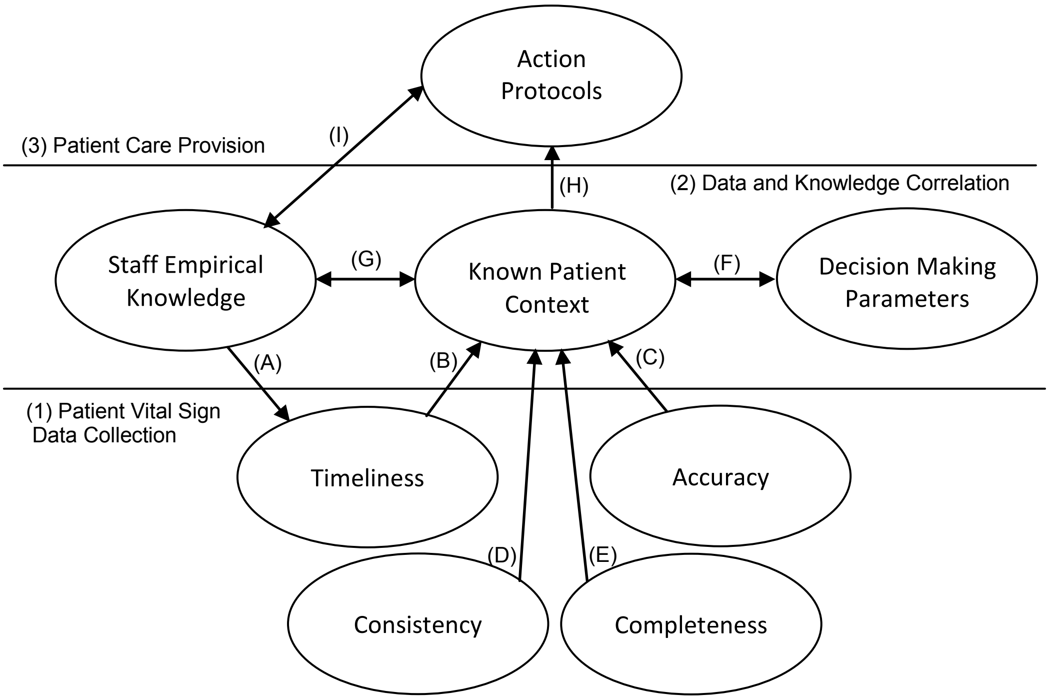

Figure 1: Patient Assessment-Data Quality Model (PA-DQM)

3.1 Patient vital sign data collection

In this subdivision the recording and collection of data is affected by four key data quality dimensions, 1) Timeliness (cf. table 2) and 2) Accuracy (cf. table 3), 3) Consistency (cf. table 5) and 4) Completeness (cf. table 6). If any of these 4 DQ dimensions contain erroneous datasets, the effect will cascade throughout the entire MEWS process.

Table 2: Timeliness DQ Dimension

Timeliness:	Definition (Leo et al. 2002): "The extent to which the data is sufficiently up-to-date for the task at hand" MEWS + e-MEWS application specific perspective: "The rate at which a patient's vital signs are measured, recorded and calculated in relation to the patient's current MEWS score" • MEWS Dependant on the medical member of staff to manually record patient vital sign parameters. Sampling frequency ranges from 15 minutes to 24 hours. As a higher sampling rate is required it directly increases the staff workload. • e-MEWS Independent of the medical staff member with a sampling frequency range from real-time to 24 hours.
Relationships:	A. Medical staff member determines the rate at which a patient's vital signs should be sampled, based on current MEWS score and their own empirical knowledge. B. This sampling rate determines the rate at which the known patient context is updated.

Table 3: Accuracy DQ Dimension

Accuracy:	Definition (Ballou and Pazer 1985): "the recorded value is in conformity with the actual value" MEWS + e-MEWS application specific perspective: "The correct calculation and display of aggregate MEWS scores. • MEWS Vital sign values are manually sampled and recorded. Individual MEWS scores for each vital sign are manually determined either at the patient bedside or at a later date. Vital sign parameters measured depend on staff member ability to accurately take a patient's reading and document it. • e-MEWS Vital sign values are automatically sampled with absolute and true MEWS scores determined. Once the sensors are attached to the patient and configured correctly the streaming data should be a consistently high level of accuracy.
Relationship:	C. Data collected either manually or electronically is in a vital sign format e.g. blood pressure 120/80 mmhg. These vital sign readings are then converted into a MEWS score. For example, vital sign readings can be converted into a MEWS score either in absolute (i.e. whole number, e.g. 1) or true numbers 1.6. (cf. table 4).

Absolute and true MEWS scores can yield outcomes with high degrees of variability. For example, in table 4, an identical set of patient vital signs generated MEWS scores of 3 and 5.2 respectively. This highlights the potential for under or over estimating a patient's true state of health through the absolute method. If a member of staff with limited experience took the absolute result at face value, the opportunity to identify the true rate of deterioration will have been missed.

Table 4: Absolute and True MEWS Scores

	SPO2	Temp	Pulse	Resp	Sys	Overall MEWS Score
Vital Sign reading	91.5	37	75	23	194	
Absolute MEWS Score	1	0	0	1	1	3
True MEWS Score	1.9	0	0	1.6	1.7	5.2

Table 5: Consistency DQ Dimension

Consistency:	Definition (Leo et al. 2002): "the extent to which data is presented in the same format" MEWS + e-MEWS application specific perspective: "The extent to which a patient's vital signs are measured, recorded and calculated in a comparable manner" • MEWS Multiple members of medical staff monitor and review an individual's state of health throughout that patient's stay. Each member of staff performs these tasks in their own unique manner. This can lead to misinterpretations as there is no consistent or unified approach taken to execute these tasks. • e-MEWS The BAN sensors are user and patient independent from the view point of performing its set of designated tasks. It will reiterate all of its duties in a clear and consistent manner over sustained periods of time without fail, thus providing the medical staff with a higher quality set of data.
Relationship:	D. Data collected either manually or electronically needs to contain the full set of vital signs in a clear and consistent manner to obtain a true picture of the "Known patient context".

Table 6: Completeness DQ Dimension

Completeness:	Definition (Leo et al. 2002): "the extent to which data is not missing and is of sufficient breadth and depth for the task at hand" MEWS + e-MEWS application specific perspective: "the availability of all known datasets to make a well informed patient decision" • MEWS Due to the inconsistent nature of vital sign capture not all relevant dataset may be present. This partial view of the known patient context may be hiding a much larger issue. • e-MEWS Once all sensors are attached and configured correctly all dataset will be present.
Relationship:	E. Complete datasets are needed at all times to guarantee an effective MEWS process.

3.2 Data and Knowledge correlation

A MEWS score on its own can only be used to assist medical staff in trying to determine a patient's state of health over a period of time. A more accurate picture (or "Known Patient Context") of a patient's state of health is obtained through the correlation of a given MEWS score allied with the staff's empirical knowledge. An experienced member of staff would have sufficient knowledge to appreciate the limits of MEWS. For example, if a patient had a MEWS score of 1 but was suffering from a myocardial infarction (heart attack) while the vital signs appear normal death occurs due to arrhythmia which tends to occur suddenly, therefore the applicability of MEWS would be of little use in this situation. Staff experience would enable them to call for further analysis of a higher rate than MEWS on its own would have suggested.

During the correlation process it was noted in (Smith and Oakey 2006) that 21.9% of Early Warning Scores (EWS) were incorrectly calculated meaning that 24.4% of those patients whose observations should have reached the trigger value did not. This incorrectly calculated score has a major impact on the combining of MEWS parameters (cf. figure 1, relationship F) with the staff empirical knowledge (cf. figure 1, relationship G) in that the "known patient context" may be incorrectly assessed. Thus triggering or lack of triggering of the associated MEWS protocol would be affected (cf. figure 1, relationship H)

3.3 Patient care provision

The provision of patient care within a MEWS environment is based on the MEWS protocol associated with the patient's MEWS score e.g. a patient MEWS score of 2 implies, that the rate of observations need to be increased to every four hours (cf. figure 1, relationship I). The triggering of a MEWS protocol is made by the member of staff based on the MEWS parameters and their own empirical knowledge. The deployment of the electronic systems e-MEWS is designed to facilitate the communication of clear concise patient context information between staff "by providing an agreed framework for assessment, increasing confidence in the use of medical language and empowering nurses", (Andrews and Waterman, 2005).

There is currently a wide range of paper based MEWSs deployed across a wide variety of hospitals. Each MEWS tends to be derived based on different sets of vital signs and relatively unique MEWS protocols. A recent systematic review of MEWS concluded that "A wide variety of [scores] were in use, with little evidence of reliability, validity and utility. Sensitivity was poor, which might be due in part to the nature of the physiology monitored or to the choice of trigger threshold" (Gao et. al. 2007). The lack of sensitivity appears to stem from the high level of inconsistencies of the MEWS deployment and maintenance. The presented e-MEWS system is designed to improve overall quality and increase the underlining MEWS philosophy.

4. Electronic-Modified Early Warning Scorecard (e-MEWS)

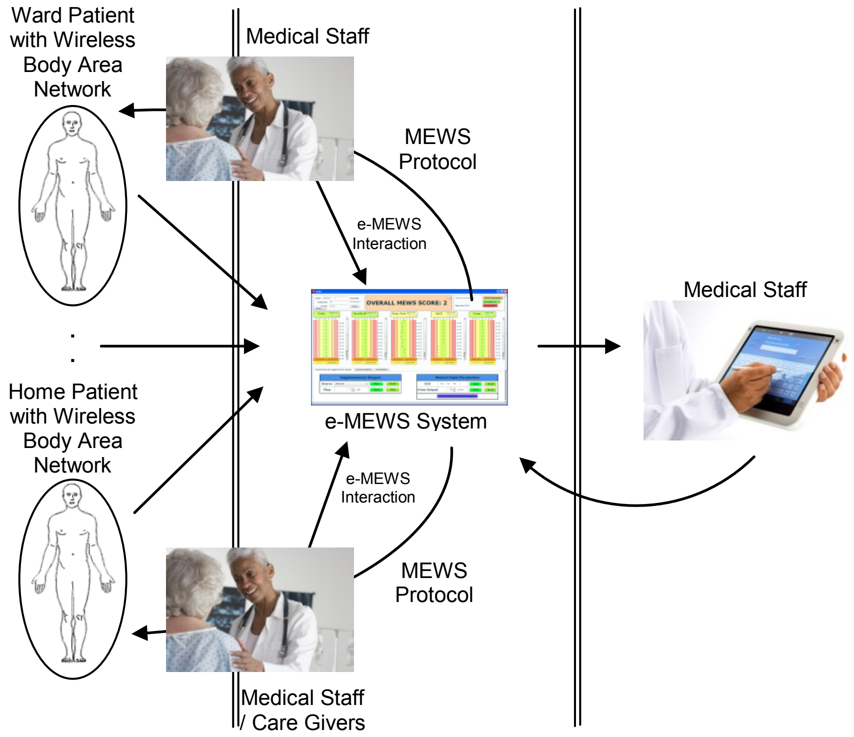

Figure 2: e-MEWS Interaction

Presented in figure 2, is a high level overview of the e-MEWS architecture and the key levels of interaction between medical staff and patients with the e-MEWS System. On the left hand side are BAN devices that communicate various vital sign data streams which feed into the e-MEWS system. These patients may be residing in a hospital ward or at home. The presented patient datasets within the e-MEWS system are accessible by medical staff within the hospital or to external consultants. Medical staff, who provide direct patient care have the capability to update the patient's medical record through the e-MEWS GUI. This global access approach helps to ensure that all medical staff, are well informed and help to obtain a higher degree of awareness regarding the "known patient context".

5. MEWS and e-MEWS Assessment

The findings for this paper were based on the results of two workshop sessions over two days (late February and early March 2010) in St. Luke's Hospital, Kilkenny, Ireland. The formation of each workshop was broken down into one hour sessions. Each one hour sitting was structured as follows (cf. table 7):

Table 7: MEWS/eMEWS workshop structure

Activity	Time (Minutes)
Power-point presentation to staff with an introduction to eMEWS	10
Medical staff were asked to calculate the overall MEWS for 6 patient datasets MEWS questionnaire (11 MEWS related questions)	20
Power-point demo of the e-MEWS system highlighting key functionality Medical staff were provided with hands on interaction with the e-MEWS system e.g. inserting data.	15
e-MEWS questionnaire (10 questions) Medical staff were asked to calculate the overall MEWS for 6 patient datasets (similar patient datasets to the MEWS exercise) however these datasets were presented in the e-MEWS graphical user interface.	15

5.1 Summary of Findings

Each MEWS questionnaire contained 6 patient datasets with each patient dataset containing seven individual physiological variables giving a total of 1974 (47 medical staff survey respondents x 6 patient datasets x7 vital signs per patient dataset) values to be processed.

In relation to the PA-DQM architecture, the four DQ dimensions were affected as follows:

- Timeliness

The BAN technology deployed within the current e-MEWS (cf. figure 2) system is capable of monitoring patient vital signs at a much higher frequency than the existing manual based approach. Given that the e-MEWS system has built in capacity to automatically increase or decrease the sampling frequency depending on the overall patient MEWS score the probability of a medical staff member missing a patient deterioration of health is greatly reduced.

- Accuracy

A basic assessment of the workshop identified 41 errors made in the calculation of the MEWS of individual vital sign MEWS scores, equivalent to an error rate of 2.08% (41/1974) which when coupled with simple arithmetic errors led to a miscalculation of 16.3% of errors in the calculation of the overall MEWS scores (46/282) or just over 1 in every 6 overall MEWS score assessments.

Of the 41 incorrect MEWS individual vital sign calculations 26 were over calculated i.e. where the medical practitioner awarded a higher MEWS score than the patient should have been. With 15 of the 41 under calculated. Over calculating tends to lead to inappropriate calling of medical teams to review a patient who does not need to be reviewed. The side effect of which takes staff away from other duties and leads to lack of confidence in the score. Underscoring leads to patients not receiving appropriate monitoring or lack of review of a patient state of health (DeVita et al. 2010).

When asked about the advantages of the e-MEWS system over the existing paper based approach 38.78% of those surveyed identified improved accuracy and maintenance of patient data. The major rational for this increase, stems from the clarity of the data presented within the e-MEWS GUI. Given that the current paper based MEWS approach contains data with is difficult to read due to personal writing styles with various writing instruments the likelihood for errors is systemic in nature. For the e-MEWS, given that the datasets are automatically communicated and processed the possibility of generating such errors will be greatly diminished.

- Consistency

DQ issues with paper based systems are well documented. The resultant errors generate various degrees of inconsistencies as members of staff begin to become unsure of its overall effectiveness. Apart from documenting the data another source of inconsistency stems from the manner in which staff physically take a patient's set of vital signs. For example, one member of staff may capture a patient's pulse at the wrist and take a full minute while another would take 15 seconds and multiply the result by 4. With the BAN technology, this ad hoc approach of recording the patient's datasets is eliminated, thus increasing the overall quality of the data within the MEWS process.

- Completeness

To achieve a correct overall patient MEWS score, all vital signs need to be measured and recorded faithfully. If anyone of these vital signs is incorrectly processed then the resulting MEWS score will be equally inaccurate. For example, with the existing paper based approach, measures such as respiratory rate take time to measure and may be estimated or not measured. In (Leuvan and Mitchell 2008) it was noted that the frequency of documentation is significantly lower for respiratory rate than for all other vital sign measurements: respiratory rate, 1 reading/day, versus blood pressure, 5 readings/day; heart rate, 4 readings/day; and temperature, 4 readings/day. This results in large inconsistencies due to incomplete and inaccurate patient datasets.

6. Conclusion

The Patient Assessment-Data Quality Model (PA-DQM) architecture presented in this paper is designed to assess how patient datasets which are poor in composition can impact on the decision processes following a patient assessment. Within a medical environment numerous decisions, across a large number of departments are made on a regular basis. Each decision tends to be based on a set of guidelines/parameters which in turn initiates an adjoining action protocol. Problems begin to arise when the decisions made by medical staff are based on poor quality datasets.

As an exemplar, the paper based MEWS approach was used to highlight the impact poor quality datasets have on the decision making process. The PA-DQM in this paper evaluated DQ from four key dimensions, which are: timeliness, accuracy, consistency and completeness. The initial findings presented in this paper support the DQ issues highlighted in previous patient monitoring assessments in particular (DeVita et al. 2010) and (Smith and Oakey 2006). It is clear from our findings that if any patient information is out-of-date, inaccurate, inconsistent or incomplete then the likelihood of over/under calculating the patient state of health will continue to persevere.

To help alleviate the DQ issues innate within the paper based approach, an electronic-Modified Early Warning Scorecard (e-MEWS) was also presented. It utilises Body Area Network technology to remove the inherent paper based vital sign data capture and recording limitations. Through the PA-DQM, we were able to demonstrate the overall effect such a system provides in delivering higher quality datasets and a higher level of understanding of the "known patient context". The PA-DQM within this paper was applied within a healthcare context; however the underlining DQM could be adapted by other DSS based applications. To further validate this model, the authors will stress test the DQM with other DQ dimensions across other application fields.

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