Adaptive Digital Encounters: An approach for reducing digital impact on outpatient flow

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***Abstract*—Healthcare service delivery has been greatly impacted by the current Covid-19 pandemic. One of the key drawbacks of the current Healthcare Management Information Systems (HMIS) is the lack of research towards improving the user's experience before, during, or after interacting with the digital system, product, or service. This has further increased the amount of cognitive load experienced by healthcare providers. Adaptive Digital Encounters (ADE) provide a mechanism for dynamically generating and upgrading the user interfaces of healthcare and wellness applications, by incorporating past histories of the patient data. It also integrates various medical devices to automate the process of collecting vital signs and reduces the burden of inserting data. This paper provides the basic building blocks which were employed to incorporate the ADE into a live application. Our results indicate an above-average score of 1.13 (-3 to +3) using the UEQ-S questionnaire, indicating a positive UX evaluation from 11 participants.**

Keywords—User Experience (UX); Healthcare; Data Interoperability

I. Introduction

The advent of COVID-19 pandemic from late 2019 has generated severe stress on healthcare providers and digital systems. While resulting in severe miseries around the world, this unfortunate situation has also shown the brighter side of human collaborations and novel initiatives towards minimizing the suffering of others. Resultantly, in under two years, the world of today is more digitally connected than before [1]. Healthcare Management Information Systems (HMIS), in the form of web portals and mobile applications have also grown in terms of their features and usage, especially in the developing world. A plethora of health and wellness management tools are available to the patients and physicians, for managing activities at various abstractions. These include patient centric activities, such as wellness and personal medication management, patient and physician inter-related activities, such as health record curation and chronic care management, and physician support activities, such as clinical decision support and diagnosis [2].

However, faced with an increase in patient inflow [3], [4, p. 19], due to the large scale of infections by coronavirus and its variants, most countries have only just started to digitize their healthcare facilities with a focus on tele-Health and mHealth services. In order to make these solutions usable and scalable in the long run it is thus, pertinent to apply modern information and communication technologies (ICT), such as big data, artificial intelligence (AI), internet of things (IoT) and many others [5], [6].

Digital input forms represent a key resource of an HMIS's user interface (UI). These are used by medical professionals to create and update patient encounters and other related data. These forms are typically bound to pre-built static interfaces that often contain a very large number of elements. The amount of training required to understand the various features and elements of the forms, along with the time required to fill them, can cause additional cognitive load for the user, causing negative user experience (UX) [7].

In order to resolve this problem a balanced digital healthcare environment with transparency, customizability and positive UX is necessary. Adaptive Digital Encounters (ADE) improve upon the traditional UI elements of HMIS, by combining static and data-driven interfaces to dynamically create and enrich medical records. Specifically the four step methodology of the ADE can greatly reduce the time and effort required by the stakeholders, through the use of data interoperability to integrate various Electronic

Medical Records (EMR) into Electronic Health Records (EHR)[8]. In this paper, we introduce the ADE methodology to create the dynamic forms based on the availability of supplementary data sources. Thus aim of this methodology is to reduce the amount of input required from the medical professional, thereby reducing erroneous data caused by an increase in their cognitive load.

II. RELATED WORK

While the adoption and improvement of current HMIS is a policy decision led by national governments and enabled by the industry, it is pertinent for the Human Computer Interaction (HCI) research community to highlight the importance of medical professional's UX. Holistic UX evaluation, before, during, and after the deployment and usage of the HMIS, can improve the positive UX of the interactive system, product, or service. Even before the Covid-19 pandemic, HMIS development suffered from a lack of UX evaluations [9]–[11], especially in public healthcare and developing countries. A multitude of factors such as lack of funding, hospital coverage, patient load, and a lack of training can lead to ineffectual usage of scarce digital resources.

A questionnaire based approach was used by the authors in [12] to evaluate the UX, in terms of Cronbach's alpha score of a military operated HMIS. The authors evaluated various factors of the UX from 85 participants after usage of the interactive system. The overall UX score of 60% indicated a need for improvement of the HMIS in terms of its usability, affect, and user value. Other effects of negative UX, in terms of attention deficit and the introduction of errors in transaction has been highlighted by authors in [13].

In [14], the authors have presented the importance of utilizing design principles in presenting information to the medical experts, which improves the overall UX of the interactive system. This improvement in UX is especially important, considering the increase in amount of text being inserted in the EMRs, annually [15]. Conversion of these EMR into information is an important aspect of any HMIS, which can be used to query records and for analysis of a patient or population’s medical history. [16] has highlighted the problems of complex data structures and the difficulty in acquiring the appropriate skills, which can enable the user to query the health data stores. The authors have presented some initial results towards creating an easy to understand and domain specific query language which can enable the medical practitioners to extract domain specific knowledge from the data store without any specific or in-depth skills in information technology. The same arguments have been applied in our research work to simplify the input interfaces for the medical practitioners and generalizing the storage of the same, to enable simple query extractions in future. [17] evaluated the level of ICT literacy among health practitioners at King Saud Medical City (KSMC), whereby most users self-characterized a high degree of familiarity with basic skills in using search engines, medical tools for research and email. It is however, imperative to note here that while these skills are useful for introducing and incorporating HMIS for digital encounter management, they also indicate that the complexity in recording and querying the HMIS can hinder its usage.

Simplifying the process of obtaining complete data from medical expert, can also enable its management and analytics, especially through the use of Big Data and Cloud Computing technologies [6], [18]. Additionally, the security of this infrastructure and compliance with privacy rules such as HIPAA (Health Insurance Portability and Accountability Act of 1996) would require the implementation of Blockchain technology, while contextual information and knowledge discovery would be achieved via cognitive computing [19].

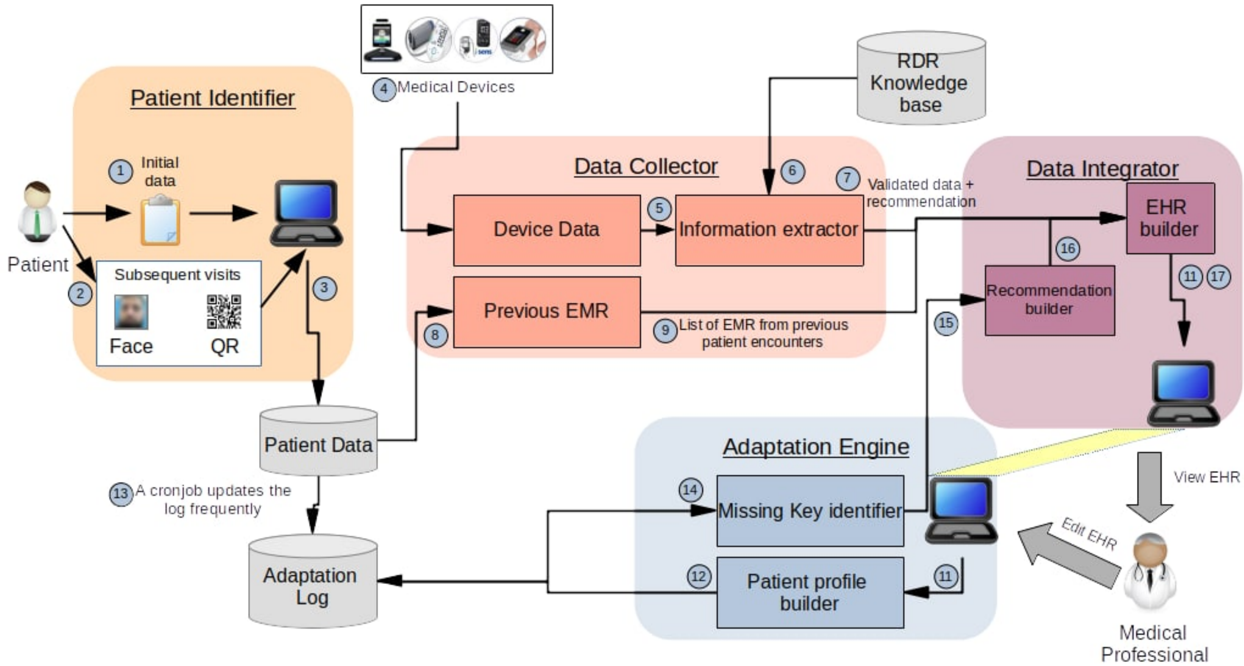

Fig. 1. The steps for building ADE (numbers indicate the general flow of data and information in the system).

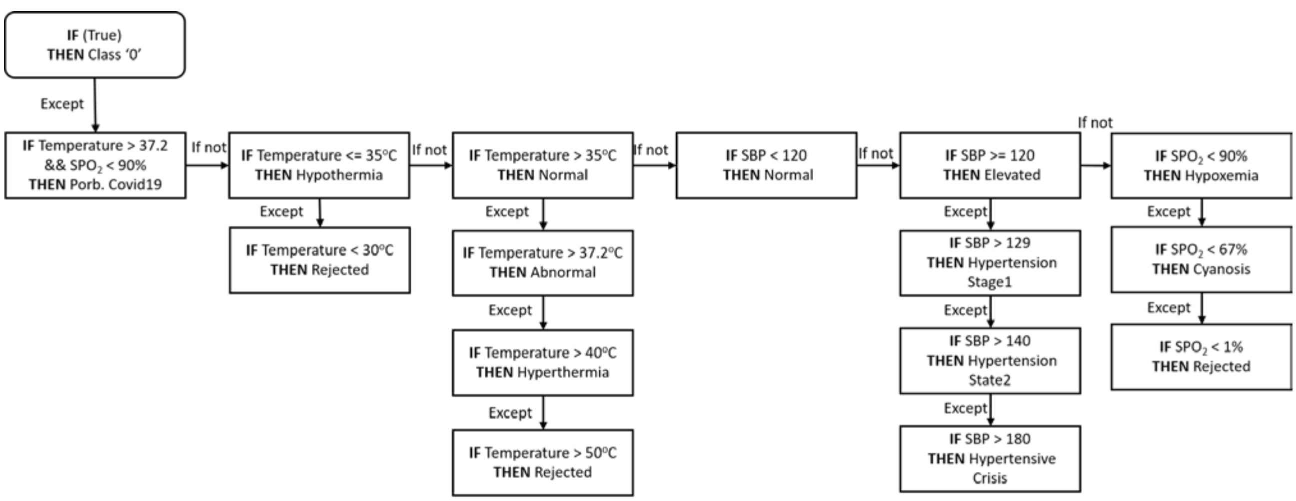

Fig. 2. Partial graph for vital sign acquisition

III. METHODOLOGY

The four steps required to create the ADE, correspond to four modules which, include Patient Identifier, Data Collector, Data Integrator, and Adaptation Engine. The detailed steps of the ADE creation and adaptation methodology are shown in Figure 1. These are further discussed in the following subsections.

A. Patient Identifier

Patient identity information such as name, date of birth, address, gender, and other demographics are an important resource to disambiguate the plethora of EMRs, collected from various sources. In traditional HMIS, and ADE, this information is collected during the first encounter using static interfaces. This data is then used to generate a Universally Unique Identifier (UUID) which, can subsequently be used to identify the patient at any stage. However, since the UUID is hard to recall, it is then pertinent to associate the UUID to a QR-code (or barcode) and/or with biometric features (such as face, finger print or others) of the patient. Such an addition would allow quick lookup of the patient, in future, with very little cognitive load required on part of the patient or medical professionals. Technological advancements have enabled the use of simple web cams to complete these two tasks, with QR-code recognition being less computationally expensive than facial recognition (FR). However, the privacy and security of the QR-code, due to its physical disassociation from the user and the ability for identity theft are a cause of concern. These can be mitigated through the use of Steganography and other techniques to mitigate these problems [20]. In our methodology we use a combination of both FR and QR-code to identify the patient (alternatively, we also provide UUID, username, name, and email based lookups).

B. Data Collector

In this step, the ADE builder identifies the integrated data acquisition resources to collect patient data. These resources include the existing "Patient Data" store that is used to collect the past medical history of the patient and other relatively stable attributes (such as family history of a disease or patient's height). Additionally, any medical IoT devices connected with the system such as a digital glucometer, blood pressure (BP) measurement device, weight machine, or others are used to collect the present vital signs of the patient. The data produced by the digital devices is highly volatile which, makes the choice of selecting the correct value difficult. ADE resolves this problem, by applying a naive anomaly removal methodology and automatic recommendation generation based on input from a medical expert. This step is achieved by the "Information extractor", which in turn utilizes a Ripple Down Rule (RDR) knowledge base, to identify the boundary values of the participating medical devices. A partial view of the RDR tree is shown in Figure 2. The tree contains rules to determine the correct values and recommendations for various vital signs, such as glucose level, body temperature, body weight, blood pressure, and others.

As a conclusion for each rule in the RDR tree, we obtain a recommendation which, discards the anomalous value and provides a recommendation for one or more metrics otherwise. As an example a valid rule within our RDR tree check if the body temperature is greater than 40 °C and SPO2 level is less than 90%, and recommends "Covid19" if true. However, if only the temperature is greater than 40 °C, then according to the RDR tree, the patient suffers from "Hyperthermia". Finally, the list of previous EMRs corresponding to past encounters of the patient and the newly obtained vital signs and their recommendations are then processed by the "Data Integrator" module.

C. Data Integrator

The data collected via various input devices produces multi-dimensional EMRs, the integration of which, is dependent on the generality of programmatic intervention. Stable patient data, such as demographics, which are also read frequently (such as during authentication and follow-up), is stored in a single relation and abstracted via a single class of the Object Relational Mapping (ORM) implementation. On the contrary, infrequently read data, such as the vital signs corresponding to patient encounters are kept in a generic data structure, represented by the entity condition, as shown in Figure 3.

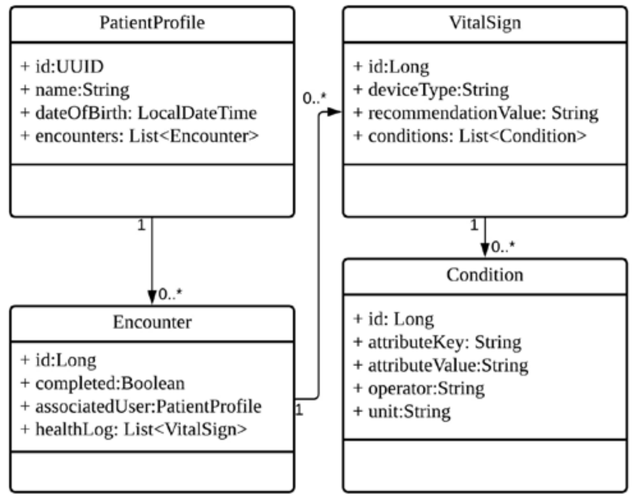

Fig. 3. Partial data structure used for storing the patient encounter and their vital signs

Here, the "attributeKey" can be set as any iterable string, such as "TEMP" for body temperature or "SBP" for systolic blood pressure, while the "attributeValue" will contain the data value obtained from the medical device. The generality of this implementation allows the physician to input any vital sign by selecting the appropriate attribute and inserting the observed patient vital sign. In this way, ADE can collect data from the medical device, or in case of its absence from the physician to update the patient's encounter. The final data is integrated across various EMRs and vital sign data for a patient to produce patient's EHR. This EHR is then presented to the medical professional, who can then interact with it. Another important feature of the Data Integrator is to collect recommendations from the Adaptation Engine, which corresponds to the next predicted value, for adding the encounter data.

D. Adaptation Engine

Predictions for missing values are built by the Adaptation Engine, using an Adaptation Log, which is periodically built from long terms "Patient Data", and comprises of a set of alphabetically sorted "attributeKey" lists, corresponding to each EMR. The set is again sorted on the size of each list in ascending order. The patient's edited record from the physician is compared with the adaptation log to identify the best matching instances with at least one additional "attributeKey". The missing "attributeKey" then becomes the recommendation for the "Recommendation builder" service of "Data Integrator". This adaptation strategy is based on the work presented in [21]. With repeated runs, the log grows to include more cases and can deal with various patient cases. The physician can also ignore the recommendation to add any attribute, not already in the previous cases. This way, any additional attribute can also evolve the recommendation log.

Fig. 4. The interfaces for ADE

IV. RESULTS

We have implemented the ADE as part of a clinical and wellness monitoring application, whereby the physician can digitize their encounters with the patient in an easy to use application. The form contains only a small set of elements, corresponding to the device type, such as one field for temperature, two for SPO2 (Oxygen and heartrate), three for blood pressure (DBP, SBP, and heartrate) and so on. The physician thus deals with contextual data on each screen. As shown in Figure 4, the physician provides a vital sign as input in the screen shown on the left hand side, which is used to evolve the form and produce the screen shown on the right hand side of the figure.

In order to evaluate the UX of these digital encounters, we collected responses from 11 experts, after they had used the ADE, atleast once. Using the shorter version of User Experience Questionnaire (UEQ-S) [22] we evaluated the pragmatic and hedonic qualities of UX. In this questionnaire the users were asked to rate their experience with the ADE, by responding on a bipolar Likert scale. The results obtained from this evaluation are shown in Figure 5.

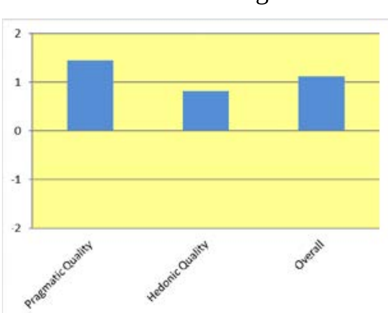

Fig. 5. Results of short UEQ scales for 11 participants after their interation with the ADE.

The results show a very positive evaluation of the pragmatic UX qualities, achieving an average score of 1.45. This indicates the user found the ADE more supportive, easy, efficient, and clear. The hedonic qualities, achieved an average score of 0.81, which represents a small positive evaluation of the ADE, in terms of the application being perceived as exciting or boring, interesting or otherwise, inventive or conventional, and leading edge or usual. Overall the UX score of 1.13, shows above average results, as shown in Figure 6, when compared with the data obtained for the full UEQ version.

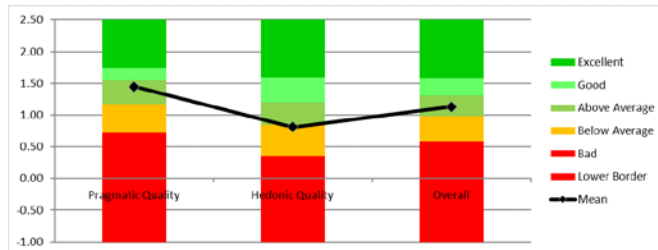

Fig. 6. Comparison of ADE UX with full UEQ benchmark.

V. CONCLUSION

Adaptive interfaces for digital encounters are necessary for reducing the negative UX of digital healthcare services. This novel methodology can generate dynamic forms and integrate various medical devices to automate the process of collecting patient data. Additionally, since this process relies entirely on existing data in the system, it is not effected by external factors and provides transparent automation. In future we shall evaluate the performance and UX of the ADE in more empirical terms.

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