SeVA: An AI Solution for Age Friendly Care of Hospitalized Older Adults

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Abstract: As a dangerous syndrome, delirium affects more than 50% of hospitalized older adults and has an economic burden of 164 billion US dollars per year. It is crucial to prevent, identify and treat this syndrome systematically on all hospitalized patients to prevent its short and long-term complications. Currently, there are no AI-based tools being utilized at a large scale focused on delirium management in hospital settings. The advancement of the Internet of Things in the medical arena can be leveraged to help clinical teams managing the care of patients in the hospital. The renaissance of Artificial Intelligence brings the chance to analyze a large amount of monitoring data. Deep neural networks like Convolutional Neural Network and Recurrent Neural Network revolutionize the fields of Computer Vision and Natural Language Processing. Deep learning tasks like action recognition and language understanding can be incorporated into the routine workflow of healthcare staff to improve care. By leveraging AI and deep learning techniques, we have developed a chatbot based monitoring system (that we refer to as SeVA) to improve the workload of the medical staff by using an Artificial Emotional Intelligence platform. The SeVA platform includes two mobile applications that provide timely patient monitoring, regular nursing checks, and health status recording features. We demonstrate the current progress of deploying the SeVA platform in a healthcare setting.

1 INTRODUCTION

Delirium affects more than 25% of hospitalized patients and can be seen in more than 50% of hospitalized older adults, impacting long-term survival, and quality of life (Marcantonio, 2017). The continuous and objective monitoring of delirium similar to blood pressure checks can help medical staff identify, prevent, and treat delirium and its many compilations.

The Internet of Things (IoT) technology has the potential of improving healthcare quality. It empowers clinicians (physicians and nurses) to review vast amounts of clinical data efficiently and meaningfully for clinical decision making by improving their workflows. Xu et al. present an IoT-based system for emergency medical service by providing data access timely and ubiquitously in a cloud and mobile computing platform (Yu, Beam, and Kohane, 2018).

As healthcare systems increasingly adopt Artificial Intelligence (AI) in their decision making, we are seeing a renaissance of AI in the field of Healthcare. For example: in the case of patient monitoring in the intensive care unit or emergency rooms, an AI-assisted alert system can be helpful to process a large amount of data generated by routine monitoring devices (Xu et al., 2014). The vital signs and Modified Early Warning Score systems can be used to build a prediction model for cardiac arrest (Churpek et al., 2012; Szep, Akoglu, Hariri, & Moukabary, 2018).

The advancement of Natural Language Processing makes it possible to create an expert knowledge system to provide ubiquitous service. Microsoft released the Healthcare Bot service to empower healthcare organizations to build and deploy the conversational health care experience at scale (Microsoft, 2020). It combines medical intelligence with natural language capabilities. The

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IBM question-answering computer system Watson is utilized to help physicians with the treatment of patients as a “diagnosis and treatment advisor” (IBM, 2020). Extracting the knowledge broadly and returning the results promptly is an inherent feature of the AI healthcare knowledge engines. It provides a significant advantage compared to traditional medical processes, especially in areas with limited medical resources.

Healthcare data is very sensitive and requires security protection. Secure identification is one of the measures to mitigate the risk of identity theft. Pacheco et al. propose an IoT security framework for smart infrastructures against cyber-attacks (Pacheco and Hariri, 2016). When conducting user group estimation, local differential privacy can protect user information without the assumption of the trusted data server (Gu, Li, Cao, and Xiong, 2019；Gu, Li, Cheng, Xiong, and Cao, 2020).

By analyzing data coming from monitored patients we can create a system that can respond to patient's needs in a timely manner. In this paper, we present an Age-Friendly patient care platform connecting seniors, caregivers, healthcare, and community by leveraging AI and ML techniques: SeVA (Senior’s Virtual Assistant). With the support of a Natural Language Processing platform, the SeVA platform achieves real-time and continuous monitoring of the patient status as well as capturing patient intent from the human-computer interactions.

The remaining sections of the paper are organized as follows: Section II introduces the related research of artificial intelligence application in the medical field; In section III, we present the system design of the SeVA platform; Section IV shows the implementation details of the platform; Section V summarizes the work in this paper and discusses future research plan.

2 BACKGROUND AND RELATED RESEARCH

2.1 Delirium: Insidious and Dangerous Syndrome

Delirium is a dangerous syndrome commonly seen in hospitalized patients. More than half of hospitalized older adults (> 65 years of age) are affected (around 7 million patients annually) and most of them remain undiagnosed. Delirium in hospitalized patients leads to higher hospital length of stay, higher mortality rate, loss of physical function requiring long term care, and can even be a precursor to dementia. It costs more than 164 billion US dollars per year to healthcare (Inouye et al., 2016). There is no mandatory prevention program as well as no reporting to the Centres of Medicare & Medicaid Services (CMS). As a comparison, around 24 billion dollars are lost due to sepsis, and every hospital carries a mandatory sepsis alert program and pathway (Paoli, Reynolds, Sinha, Gitlin, & Crouser, 2018). The data for sepsis is also reported to CMS as an adverse event. The gaps in delirium care include delayed recognition, inadequate risk modification and prevention, and ineffective treatment. The major reason for this is the lack of a standardized multidisciplinary approach for the management of delirium across hospital systems. The Hospital Elder Life Program (HELP) developed by Inouye is a system that relies on volunteer healthcare workers to engage patients (Inouye et al., 1999); however, it has only been implemented in a few hospitals. There certainly is a need for a system that can be easily implemented, customized and is scalable across all hospitals that can provide timely screening, assessment, and recognition, so that the cause or precipitating factors for delirium can be removed, and the patient can receive appropriate and early treatment.

2.2 Gaps in Patient Monitoring

Despite best efforts by nursing staff in hospital systems, to decrease the risk of falling, management of uncontrolled pain, even addressing basic patient needs like using the bathroom, can be easily missed. For the patient who has cognitive impairment either as delirium or dementia, this risk becomes even more profound. Best nursing practices include a systematic approach to addressing these care needs, e.g. performing timed nurse rounding checks or checking for the 4 Ps (Pain, Position, Potty, Periphery). However, these practices require dedicated nursing staff and strict protocols which can be difficult to implement at a large scale due to limited resources and cost issues. The “Unsupervised Care Windows” created due to lack of these practices or between the hours of timed nurse rounding can lead to serious events like falls. Patient falls have an enormous cost on the healthcare system according to the data reported by the National Database of Nursing Quality Indicators (NDNQI) (AHRQ, 2020; Mitchell, Lavenberg, Trotta, and Umscheid, 2014).

Prevention of these adverse events by integrating technology for the detection of unexpected patient behaviors like unintended falls is the subject of significant research over the last several years.

Various detection systems have been developed and can be broadly divided into wearable based, non-wearable based, and fusion-based systems (Chaccour, Darazi, El Hassani, and Andres, 2016).

The wearable based systems can be placed on different body parts like feet, knee, waist, etc. To measure the body motion parameters like acceleration, the sensors must be tied to the body. The typical sensors include accelerometer, gyroscope, magnetometer, etc. With the universal acceptance of mobile devices, the smartphone-based solution could be a very competitive alternative to the conventional dedicated fall detection and prevention tools (Habib et al., 2014). The shortcomings of wearable based systems are that they are relatively inflexible and uncomfortable.

2.3 AI-based Assistant in Healthcare

Many researchers and companies have introduced artificial intelligence into their mobile medical applications to make interactions with the patient easier. The applications can be further categorized as healthy lifestyle assistants, remote diagnosis systems, and medical advisors.

Healthy lifestyle assistant applications will perform more on disease prevention so that the suggestion will be more general. Pact Care is a startup that provides a patient-centric healthcare data solution. Their mobile product Florence is a chatbot based personal health assistant with medication reminders and health trackers. It does not provide medical advice and is only for personal usage (PACT, 2020). Fadhil et al. propose an AI-chatbot scenario for healthy lifestyle promotion with nutrition education and behavior change interventions (Fadhil and Gabrielli, 2017).

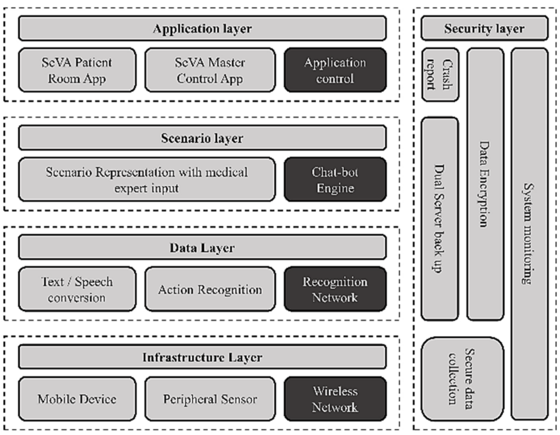


Figure 1: SeVA System Framework.

Remote diagnosis applications will connect the patient and the physician remotely to mitigate the medical resource imbalance distribution. The AI part of the application is focused more on assisting patients to find the correct doctor. Babylon Health is a health service provider that offers remote doctor diagnosis. Their artificial intelligence platform uses a probabilistic graphical model and natural language processing to interpret medical questions (Babylon health, 2020).

Medical advisor applications will give medical suggestions based on their knowledge base. Buoy Health makes a digital assistant application that helps patients self-diagnose and triage for the selection of appropriate care. The chatbot will ask a series of medical questions to diagnose customer symptoms (Buoy Health, 2020). Chung et al. propose a chatbot-based service with a knowledge base (Chung & Park, 2019). The patient could consult the system with the picture or text input from the mobile devices. It gives a fast treatment plan in response to accidents as well as the change of conditions of a patient with chronic disease. Comendador et al. develop a pediatric generic medicine consultant chatbot. It acts as a medical consultant to suggest generic medicine for children (Comendador, Francisco, Medenilla, & Mae, 2015).

Our patient care platform SeVA brings the AI technologies by leveraging Natural Language Processing and the real-time monitoring of peripheral sensors. SeVA can be classified as a combination of the medical advisor and the remote diagnosis system which is different from the other AI health platforms which search for often unreliable solutions from the Internet or other databases, SeVA allows clinicians to design personalized conversations directly within the platform. The user interaction in SeVA is easy to use for older patients who might have limited proficiency in using technology, or for patients with cognition issues like dementia or delirium who might not be able to use plain text-based interactions. It uses simple gestures like hand waving or simple voice conversations. This communication mode allows for the recognition of emotion which can, in turn, allow interventions like soothing music to mitigate the risk of delirium. The modular system design provides the possibility for the integration of additional extra sensors to accommodates the system in different environments.

3 SYSTEM DESIGN

3.1 SeVA Framework

As shown in Figure 1, the SeVA platform consists of a five-layer framework: infrastructure layer, data layer, scenario layer, application layer, and security layer. This framework provides a general methodology for building a chatbot-based healthcare system by utilizing patient real-time data and medical expert knowledge.

The infrastructure layer provides the basic hardware requirement of the data collection unit. It includes the minimum requirement for deploying SeVA platform to a different environment because most of SeVA functions are provided as cloud services. The wireless network block works as a communication module for real-time data transmission. The mobile device, such as the tablet or cell phone, shows the user interface and conducts the conversation. The peripheral sensor collects patient movement data to infer the patient's position status without infringing user privacy. The voice data and movement data will then be transferred to the upper layer.

The data layer processes the incoming raw data from the infrastructure layer. The main task here is text-to-speech conversion, speech-to-text conversion, and action recognition. Hence, we need the neural network as the backbone technique to implement task functions. For a sequence to sequence problem, the RNN will provide the majority solution. For the action recognition which is based on the temporal movement data, we use a long-short-term memory neural network to process it. The output of this layer will be the conversation plain text and the result of the user action classification.

The scenario layer contains the scenarios provided by the professional medical expert and returns the proper conversation to the user. It requires a chatbot engine to support the scenario representation. More specifically, the medical expert predefines the scenario representation with the related incoming conversation plain text or action class, then it will provide the conversation and trigger the other program in the application layer.

The application layer consists of two mobile applications: the SeVA Patient Room (SPR) application and the SeVA Master Control (SMC) application. The first application will work as the main interface for the patient. It does not only supply the conversation but also has a predefined workflow for a regular medical check. The second application is designed for the medical staff to receive the notification from the patient room and return quick feedback to the patient. Behind the user, the mobile application is the application control system, which is connected to the SeVA backend server. It manages the user account database for the authentication process and controls the communication between different user applications.

The security layer serves as the auxiliary component of our system. It protects user data security and privacy and guarantees SeVA system robustness. In the infrastructure layer, all the data collection is compliant with the privacy policy and with the consent of the user. The data transmission and storage will be encrypted to guarantee data confidentiality. We also set up a crash report in the application layer and system monitoring server to enable us to achieve a quick response to any anomalous behavior of the SeVA platform functions.

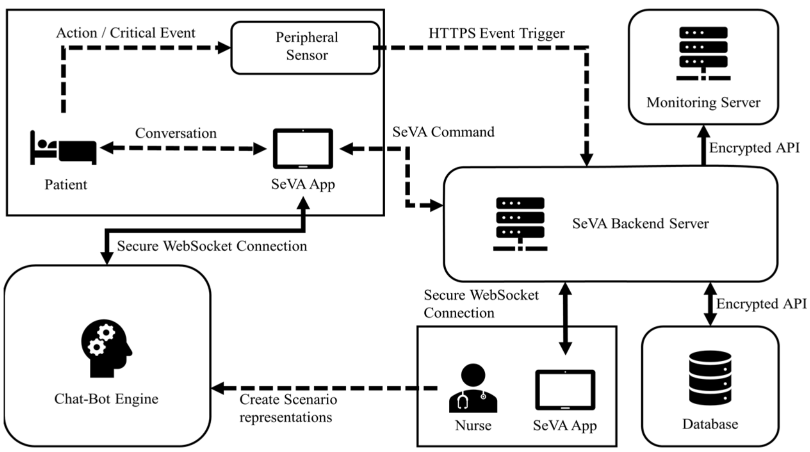


Figure 2: System Architecture of SeVA.

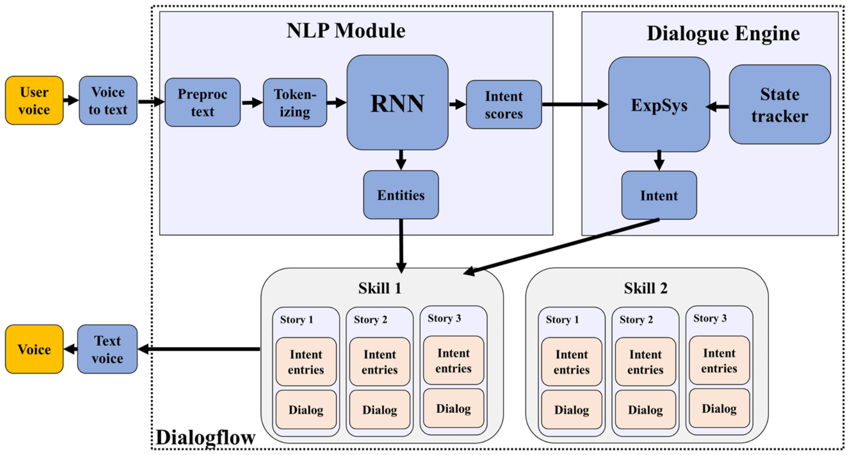


Figure 3: Chatbot Engine skill and story design.

3.2 Components

The SeVA system architecture is shown in Figure 2. It shows the connection between the main SeVA components. The arrow represents the information flow direction. The Chat-bot engine scenario is defined by the medical staff. Let us consider the "Waving Hand" event as an example. When a patient has a request, he/she just waves a hand and then the peripheral sensor recognizes the action and sends an HTTPS request to the SeVA backend server. The request is parsed and fetches the necessary information, like the room number, from the database then triggers the chatbot engine to start the conversation. The SeVA patient room application has a WebSocket connection with the chatbot engine, then the conversation will be launched. The conversation result will be sent to the SeVA backend server as the format of SeVA Command, which will be further sent to the SeVA Master Control application in the nurse room. Then the nurse can make timely interventions if a critical event happens. The system running status is monitored by the Monitoring Server, which guarantees system reliability.

3.2.1 Peripheral Sensor

We use peripheral sensors to monitor the patient's status and provide timely interventions in case of any emergency or critical events. The currently available sensor is a smart wristband that can detect user movement sending out the event trigger.

3.2.2 Chatbot Engine

The Chatbot engine architecture is shown in Figure 3. We build the engine by using the Google NLP platform Dialogflow. The user's voice is transformed into plain text and is processed in the NLP module. The text is first being pre-processed and tokenized, which result in discrete word and sent to the RNN. The output of the RNN can be entries, which is the matching word candidates, or the intent score. The intent score then is being sent to the expert system module in a dialogue engine and gives out the final intent. The intent and the entries serve as the input of the predefined skills and the skill logic decides the key content of the conversation. The skill can be triggered by a request or determined by the intent.

3.2.3 SeVA Backend Server

The SeVA backend server processes the incoming requests and manages the user data. As a centralized processing center, it facilitates the management of the user account as well as providing the API for the mobile application, database, and monitoring server. The data sent to the SeVA backend server are encrypted. When the user tries to use the application, it must submit the login request to the SeVA backend server and wait for the authentication token stored in the database. With the token, it starts the service of the chatbot engine. The SeVA backend is listening to the event trigger from the peripheral sensor, which will be routed to the Chatbot engine to start the conversation or directly to the SeVA mobile application.

3.2.4 SeVA Mobile Applications

We have developed two applications: SeVA Patient Room App (SPR) and SeVA Master Control App (SMC). As the name indicates, SPR is deployed in the patient room. SPR uses the Apple built-in Speech framework for both the Speech-to-Text and Text-to-Speech conversion. It has the authorization and user

Table 1: SeVA skills in the Dialogflow.

Type	Skill	Story	Description
Movement Response	Sensor Response	Fall Detection	Response to patient and notify nurse by recognize patient movement.
		Wave	
Regular Check	Hourly Rounding	Feeling Check	Perform regular hourly check to fulfil patient needs actively.
		Restroom Check	
		Brace Check	
		Heat pack Check	
	Delirium Check	What day is today	Perform regular delirium check to evaluate patient cognition ability.
		Spell weekdays in reversed order	
Relaxations	Soothing Music	Play Music	Use music, jokes, and small talk to improve patient's mental state.
	Small Talk	Random Talk	
	Joke	Tell me a joke	
		More jokes	

configuration pages for customizing user service. The SMC app is deployed in the nurse room. It monitors the status of all patients by receiving the messages regularly from SPR and provides feedback to the nurse immediately.

3.2.5 Monitoring Server

The SeVA backend server provides the monitoring service. It monitors the API availability, the number of connected nurses and patients, as well as the backend server running status. Any abnormal behaviors, such as backend server API unavailable or no nurse online, will be reported to the operator through the email service in the notification module.

4 IMPLEMENTATION

The mobile applications are written using Apple iOS native program language Swift on Xcode 11, which runs on the iOS device with iOS 13. The SeVA backend server has 4 dedicated ARM processors with 2GB memory and the Ubuntu Xenial system.

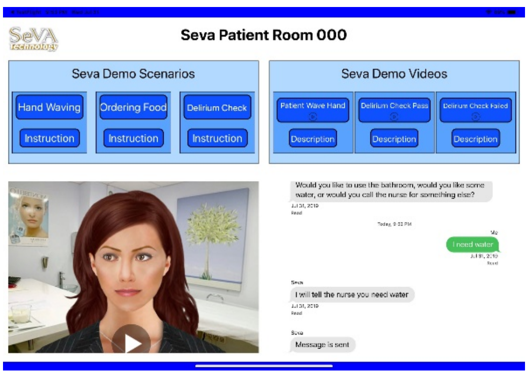
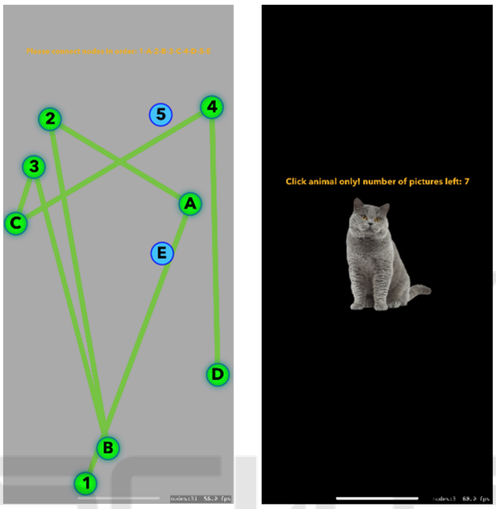


Figure 4: SPR application user interface.

We use the Chatbot engine Dialogflow developed by Google, LLC (Google, 2020). Dialogflow is a UI-based platform for creating smart and proactive chatbots. Our team's medical experts define the skills by setting the intent, trigger, and replies. A skill is composed of inputs, slots, replies, actions, and stories. Inputs define events that a bot can react to. Slots are the memory of the bot for remembering some information during the conversation. Replies are all the possible sentences that a bot can reply to a user. Stories define the logic behind a skill. The input is classified by the RNN which has been trained with the sample inputs we supplied. Once the intent matches, it will continue the conversation in a predefined way.

As shown in Table 1, the SeVA skill set includes "Sensor Response", "Hourly Rounding", "Delirium Check", etc. Each skill contains multiple stories. Regarding the stories of the "Sensor Response" skill, when the patient is waving a hand for help, the story "wave" will be triggered by the HTTPS post, and then the chatbot engine will send the sentence to the story part. The story part may contain the trigger of the next story part, which will facilitate the program reuse. For the story part of "Morning Check": when the chatbot engine receives the trigger, it will send the first sentence to the SPR, then waits for the returning sentence. The patient response will then be classified as the intent "Yes" or "No", which will continue to different conversations.

The SPR provides the interaction between the SeVA platform and the user. The user interface is shown in Figure 4. Every user is required to register so the personal profile will be created. After logging in, the SPR will connect to the SeVA Backend server through a WebSocket for communication. The conversation can be initiated by hand waving, using the wake-up word, and simply touching the screen. For privacy consideration, the SPR microphone is turned off when there is no conversation and the wake-up word feature is optional. The SPR will ask a question every hour (except for the rest hour) to make sure patient needs are satisfied. The SPR also can play some of the music selected by the therapist which will create a calm atmosphere for the patient and relieve anxiety.



(a) Game “Connect Nodes” (b) Game “Click Animal”

Figure 5: The sample delirium check games embeded in the SPR. (a) Game “Connect Nodes” for testing patient visuospatial and executive functions, it require patient connect numbered nodes in a given order. (b) Game “Click Animal” for testing patient attention, it require patient click the animal image which will disappear quickly.

When triggered, SPR starts checking the patient delirium status by asking questions or launching the delirium check game. For example, we use a modified version of Alternating Trail Making from the Montreal Cognitive Assessment for mental status assessment in older adults (Julayanont & Nasreddine, 2017). In Figure 5, we display two delirium check games. The first game “Connect Node” is used for testing the visuospatial and executive ability. In this game, the patient is required to connect nodes in a certain order. If the patient fails the test, a message will be immediately sent to the SMC. The second game “Click Animal” tests the patient’s attention. Pictures will be prompted and then they disappear. The patient must click at all the animal picture. The results of the test will also be sent to the SeVA Master Control application.

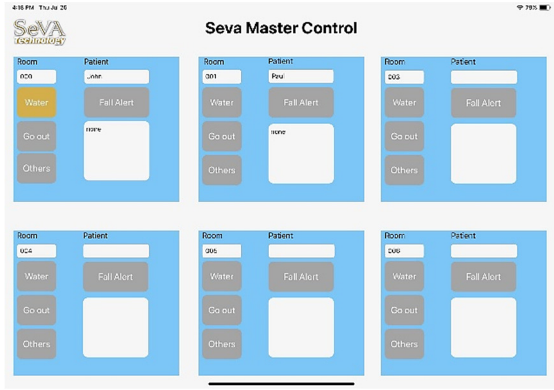


Figure 6: SeVA Mater Control application user interface.

The SMC lets the nurse monitor the status of multiple patient rooms and process the incoming request, as shown in Figure 6. The SMC shows 6 sub-panels on the screen. Each sub-panel contains buttons and a textbox. It will display the request by flashing the displayed buttons, and the nurse could click the button to send back the acknowledge message. For preventing the patient from falling, the SMC will display the critical movement information like “Patient is sitting up” on the textbox. Then the nurse could make a timely intervention.

This system is being deployed at the Banner - University Medicine Rehabilitation Institute. It has gotten the approval of the Institutional Review Board (IRB) and also obtained positive feedback from the nursing staff at preliminary demonstrations.

5 CONCLUSION

The IoT architecture and AI-based SeVA platform can improve healthcare quality and nursing workflows by automating traditional standard clinical and nursing practices in hospital settings. SeVA platform implementation uses Artificial Emotional Intelligence to build a monitoring and diagnosing system. The system features include: starting a conversation with the patient to check for delirium; perform regular round checks to improve nursing workflows and provide actionable items for nursing care; detect critical events such as falls, detect gestures and patient’s motion like walking, waving for help, detecting emotion and providing interventions like playing relaxing music. The system reduces gaps from “Unsupervised Care Windows” and provides a customized healthcare experience catered to Age-Friendly Care. We are currently testing and evaluating the feasibility of the current

SeVA platform implementation in a hospital setting. We are also investigating innovative methods to quantify cognition and emotion with the goal to recommend non-pharmacological interventions to reduce stress during the hospital stay. We will evaluate the system with patient and nurse surveys as well as the alarm statistical metrics including True Positive Rate, False Positive Rate, and False Negative Rate.

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