A Two-Echelon Responsive Health Analytic Model for Triggering Care Plan Revision in Geriatric Care Management

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ABSTRACT

Due to the increasing ageing population, how can caregivers effectively provide long-term care services to meet the older adults’ needs with finite resources is emerging. In addressing this issue, nursing homes are striving to adopt smart health with the internet of things and artificial intelligence to improve the efficiency and sustainability of healthcare. This study proposed a two-echelon responsive health analytic model (EHAM) to deliver appropriate healthcare services in nursing homes under the internet of medical things environment. A novel care plan revision index is developed using a dual fuzzy logic approach for multidimensional health assessments, followed by care plan modification using case-based reasoning. The findings reveal that EHAM can generate patient-centred long-term care solutions of high quality to maximise the satisfaction of nursing home residents and their families. Ultimately, sustainable healthcare services can be within the communities.

KEYWORDS
Care Plan Modification, Case-Based Reasoning, Fuzzy Logic, Geriatric Care Management, Internet of Medical Things

1. INTRODUCTION

In an attempt to address the challenge of how to handle the growing global ageing population best, the adoption of effective geriatric care management (GCM) is now being emphasised in nursing homes for delivering the best quality of care (QoC) to older individuals who show difficulties in daily living or who have chronic diseases (Thambusamy & Palvia, 2020; Schubert et al., 2016). However, resource shortages have been proven to affect the service quality in nursing homes (Leung et al., 2020; Berridge et al., 2018; Bratt & Gautun, 2018). As such, nursing homes continue to search for...
better use of limited healthcare resources. The resources include in terms of capital and staffing, and facilities. So that customised care plans for serving older individuals can be established. In the meantime, how can caregivers generate effective care plans under the constraints of limited resources and a limited time frame has become a key consideration for nursing homes to explore. To address this issue to alleviate pressures on caregivers, the adoption of smart health and the integration of ubiquitous computing and ambient intelligence has drawn significant attention in the healthcare context for analysing health information, assisting in clinical decision-making and selecting the most appropriate healthcare services (Hong et al., 2021; Khanra et al., 2020; Pramanik et al., 2017; Sicari et al., 2017). The opportunities available in this area have triggered a wide response in both research and the community that focuses on continuously advancing and implementing health technologies using information technology and responsive artificial intelligence to increase their economic, social, and sustainable impacts in the field of GCM.

According to Franceschi et al. (2018), ageing increases vulnerability to age-associated diseases, which causes vision change, hearing, muscular control, bone strength, immunity and nerve function, called ageing pathology. In socially responsible nursing homes, care planning is a critical activity in providing long-term care services to the elderly residents for maintaining their health. As shown in Figure 1, a care plan refers to the elderly needs and corresponding actions to address them through care planning. It provides both standardised and individualised interventions and needs to continuously monitor and review at a specific period as changes in the elderly conditions occur (Mariani et al., 2017). However, a comprehensive care plan review process is currently executed at fixed time intervals to assess older individuals’ overall health performance. Since they have different levels of health deterioration, this fixed time-interval approach may not be suitable for application to every older patient in a nursing home to satisfy their individual needs, particularly in cases of acute illness. Notably, serious health effects may emerge if inappropriate healthcare services are delivered. Therefore, modifying the care plan at dynamic time intervals according to changes in the health state should be considered in nursing homes for providing timely and accurate healthcare services.

On the other hand, to prevent acute illness from appearing, caregivers must perform a daily review of vital signs and biometric data to monitor the health status. However, caregivers in nursing homes should not only be aware of any preceding abnormalities in biometric data. Still, they should also consider functional problems, including physical status, subjective well-being or happiness, mental depression and social abilities. Deterioration in these chronic aspects may significantly affect older

Figure 1. Typical GCM operations in nursing homes
individuals’ capacity to perform basic daily activities and the arrangement of resources in nursing homes available for aiding them. Thus, it is critical to developing a systematic approach to (i) determine the triggering point for care plan modification (CPM) at dynamic time intervals and (ii) measure both the acute and chronic health deterioration patterns of older individuals to inform CPM processes. To date, however, studies covering these aspects are still rare, and the importance of GCM in nursing homes is neglected in the literature. Specifically, current research related to healthcare is more focused on short-term and urgent treatment in hospitals in the area of disease diagnosis, disease prevention, and drug reaction detection (Kumar et al., 2021; Shen et al., 2018; Sathya & Kumar 2017). However, the target customers for hospitals and nursing homes are fundamentally different. Hospitals mainly provide acute care and treatment to patients in all age groups, and these types of patients usually need to receive urgent treatments in a short time. On the contrary, nursing homes are more emphasised in providing long-term care services for around-the-clock GCM to the elderly with chronic diseases or disabilities. Also, the health status of the elderly will progressively decline associated with their age. Hence, multidimensional health assessment needs to be performed regularly to maintain their health in nursing homes. Therefore, comparing to the functions and responsibilities between hospitals and nursing homes, it is impossible to directly adopt the existing smart health solutions from hospitals to nursing homes. The lack of customised smart health solutions in multidimensional health assessment and dynamic care planning modification generates the research gap for the GCM in nursing homes.

This paper proposes a two-echelon responsive health analytic model (EHAM) to narrow the above research gap. The Internet of Medical Things (IoMT) integrates dual fuzzy logic and case-based reasoning (CBR) for activating CPMs at dynamic time intervals. The adoption of the IoMT would allow caregivers to capture and monitor biometric data automatically. Further, instead of only assessing instances of acute health deterioration, a novel care plan revision (CPR) index was designed using the dual fuzzy logic approach. With this, the measurement of acute and chronic health deterioration can be aggregated and considered in the CPR index to analyse the overall health performance and determine an intelligent triggering point for CPM. Based on the outputs of the CPR index, a severity factor was used to define the weightings of the corresponding attributes and, hence, CBR can be adopted for supporting decision-making in the CPM processes for generating customised care solutions. The rest of this paper is organised as follows. A literature review covering healthcare in nursing homes, IoMT and AI is reviewed in Section 2, while the architecture of the proposed EHAM is described in Section 3. A case study is described in Section 4 to illustrate the implementation of EHAM in a particular nursing home. Then, the results and discussion are presented in Section 5. Finally, Section 6 outlines the conclusions and recommendations for future work.

2. LITERATURE REVIEW

As individuals today continue to live longer lives than their ancestors, increasingly despite morbidities, the expanding global ageing population is placing significant pressure on modern healthcare systems to meet significant demands for healthcare resources, including both in the short- and long-term (Hold et al., 2019). Further, due to ongoing shortages of healthcare resources faced by caregivers in nursing homes, reports of a lack of time and equipment to provide an adequate amount of healthcare services to older individuals persist (Scott et al., 2018). This situation significantly affects the quality of GCM concerning their assessment, planning and monitoring, and the delivery of corresponding healthcare services to older individuals. Evidently, an intelligent solution is required to maintain the QoC given to older individuals, thereby relieving pressure on the nursing homes. The emergence of smart health has been identified as a potential solution that might support delivering quality healthcare services. Smart health encompasses the integration of ubiquitous computing and ambient intelligence to predict potential health concerns, in effect seeking to prevent rather than simply react to diseases, personalise diagnoses, and select the most suitable services available in existing healthcare systems (Röcker et al., 2014). Through the IoMT, i.e. one of the ubiquitous computing technologies, different types of
healthcare devices such as medical sensors and monitoring cameras can be seamlessly combined to collect the medical data and hence boost the effectiveness of healthcare systems (Srinivasa et al., 2018; Tang et al., 2019; Tsang et al., 2021). In other words, this approach allows disease diagnostics, health monitoring and treatment to occur in a more timely and cost-effective manner (Swaroop et al., 2019). Due to the benefits offered by smart health, it has already been widely adopted in hospitals and by home care providers for improving the QoC (Shen et al., 2018). Considering the need to deliver healthcare services in a cost-effective and resource-efficient manner, it is worthy of exploring expanding and adapting the concept of smart health in nursing homes to enhance the outcomes of GCM.

In GCM, accurately measuring the overall health performance is essential for caregivers to prevent health deterioration. Caregivers are required to assess each patient’s medical and physiological conditions, including parameters related to acute illnesses, physical functioning, mental functioning, and social well-being (Cho et al., 2018). Currently, qualitative approaches have been established, such as the early warning scores (EWS) and the adult deterioration detection system (ADDS). These approaches highlight any acute decline that may have recently appeared through daily checking of relevant parameters, such as vital signs and ensuring interventions are provided in a timely fashion to older individuals (Challen & Roland, 2016; Preece et al., 2012). Rather than simply offering short-term fixes, the provision of consistent residential and supportive care is emphasised more in nursing homes to support patients’ basic activities in daily living. Caregivers are also required to consider the residents’ physical, mental and social functioning, where different quantitative measurements can be adopted to assist, as shown in Table 1.

According to the functionalities and cultures in nursing homes, appropriate measurements must be selected uniquely to assess the residents’ health. From the above literature, while a large cache of quantitative measurements has been established for assessing the functional abilities of older individuals, caregivers continue to face the problem of how to carry forward the scores generated into feasible recommendations (Roedl et al., 2016). There remains a lack of an aggregated measurement method for analysing results from the acute and chronic categories and triggering corresponding short- and long-term actions. To address this issue, it is crucial to develop an intelligent decision support system for caregivers to use that can translate the amount of care required by an individual and their functional limitations gleaned from various assessments into customised care actions.

In the healthcare context, intelligent decision support systems assist caregivers in disease diagnosis and healthcare management (Iancu, 2018). Different kinds of uncertainty, vagueness, and imprecision are always present in handling medical data because of the varied responses among individual patients (Luukka, 2009). Fuzzy logic is a promising AI technique for generating acceptable reasoning from ambiguous variables into linguistic forms (Wang & Zhang, 2020; Lamrani Alaoui & Tkiouat, 2019). In practice, fuzzy logic has been applied to date to handle the uncertainty of medical data and improve the performance of nursing staff (Choy et al., 2018; Das et al., 2016). However, in using simple fuzzy logic with one fuzzy controller, it is challenging to handle multidimensional input and output parameters, particularly when aiming to measure the health performance of older individuals across various dimensions. Consequently, a dual fuzzy logic approach involving two fuzzy different fuzzy controllers has been proposed to determine two distinct targets according to two sets of parameters (Wu et al., 2015). It may be feasible to extend this dual fuzzy logic approach to measure the level of health deterioration in both acute and chronic aspects among older individuals to trigger the pursuit of CPMs at dynamic time intervals.

For older individuals showing significant health deterioration, immediate action should be taken by caregivers. To effectively formulate the most up-to-date care plan, past care records and prior healthcare knowledge become important components, acting as reliable references to drive decision-making. CBR is a process that requires the cognitive capability to solve a new problem by referencing the solutions of past similar cases (Kolodner, 1993). In the healthcare context, CBR is recognised as an ideal methodology to support medical diagnosis and planning (Valencia et al., 2018). With its use of an automatic cognitive process for finding solutions, CBR helps to reduce the length of
Table 1. Common quantitative measurements for assessing physical, mental and social functions

<table>
<thead>
<tr>
<th>Category</th>
<th>Area</th>
<th>Measurement</th>
<th>Items involved in the measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Function</td>
<td>Activities of Daily Living (ADL)</td>
<td>Katz Index of Independence in Activities of Daily Living (Katz et al., 1963)</td>
<td>Bathing, dressing, toileting, transferring, continence and feeding</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Barthel Index (Mahony &amp; Bathel, 1965)</td>
<td>Feeding, moving to the bed, grooming, toileting, bathing, walking, stair-climbing and bladder control</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Physical Self-maintenance Scale (Lawton &amp; Brody, 1969)</td>
<td>Toileting, feeding, dressing, grooming, locomotion and bathing</td>
</tr>
<tr>
<td>Mental Function</td>
<td>Cognitive Functioning</td>
<td>Mental Status Questionnaire (Kahn et al., 1960)</td>
<td>Contains ten items covering fundamental aspects of short-and long-term memory and orientation (e.g., age, week, month, year and community)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Short Portable Mental Status Questionnaire (Duke University, 1978)</td>
<td>Contains ten items that are similar to those of the Mental Status Questionnaire</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Philadelphia Geriatric Center Mental Status Questionnaire (Fishback, 1977)</td>
<td>Contains 35 items such as orientation items concerning age, week, month, year and community and items related to the location of various places in the nursing home</td>
</tr>
<tr>
<td>Affective Functioning</td>
<td>Zung Self-rating Depression Scale (Zung, 1965)</td>
<td></td>
<td>Contains 20 items that users rate as applicable to themselves</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Beck Depression Index (Beck et al., 1961)</td>
<td>Contains 21 items with four to five graded statements designed to reveal increasing depression</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hopkins Symptom Checklist (Derogatis et al., 1974)</td>
<td>Contains 13 symptoms that users rate according to the degree of their symptoms from “not to all” to “extremely”</td>
</tr>
<tr>
<td>Social Function</td>
<td>Social Interaction and Resources</td>
<td>Role Activity Scales (Havinghurst &amp; Albrecht, 1953)</td>
<td>Measures 13 social roles of older individuals</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Social Dysfunction Rating Scale (Linn et al., 1969)</td>
<td>Contains 21 questions in three areas of self-esteem, interpersonal area and performance area</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OARS Social Resource Scale (Duke University, 1978)</td>
<td>Contains ten questions related to family composition, personal and telephone contacts and the availability of care</td>
</tr>
<tr>
<td>Subjective Well-Being and Coping</td>
<td></td>
<td>Cavan Attitude Inventory (Cavan et al., 1949)</td>
<td>Contains eight areas of health, friendship, work, finances, religion, usefulness, happiness and family</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Life Satisfaction Index (Neugarten et al., 1961)</td>
<td>Contains 22 questions in five areas of zest versus apathy, congruence between desired and achieved goals, resolution and fortitude, self-concept and mood and tone</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Philadelphia Geriatric Center Morale Scale (Lawton, 1975)</td>
<td>Contains 22 questions in three areas of agitation, attitude, lonely dissatisfaction and opinions of one’s own ageing experience</td>
</tr>
<tr>
<td>Environment Fit</td>
<td></td>
<td>Satisfaction with Nursing Home Scale (McCaflree &amp; Harkins, 1976)</td>
<td>Contains 22 items concerning life in the nursing home</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ward Atmosphere Scale (Moos &amp; Houts, 1968)</td>
<td>Contains 100 questions in 10 areas of involvement, support, spontaneity, autonomy, practical orientation, personal problems, anger and aggression, order and organisation, program charity and staff control</td>
</tr>
</tbody>
</table>
time and complexity experienced in making a particular decision. However, few studies to date have focused on linking health deterioration to the weighting of health attributes in CBR for enhancing case retrieval performance. To generate effective long-term care solutions for older individuals, this factor should be considered in care planning.

In summary, the above studies indicate that the adoption of smart health is crucial for nursing homes to improve outcomes in the execution of the GCM. The numerous categories encompass both acute and chronic aspects required to be measured in the GCM. There is a need to develop aggregated measurement processes to effectively analyse such results and, hence, deliver accurate and timely healthcare services based on health deterioration. Therefore, an EHAM is proposed in this paper that explores the novel CPR index for evaluating the level of health deterioration. The CPM can then be activated using dual fuzzy logic and CBR. In addition, the IoMT application is deployed to achieve better data capture and health monitoring.

3. METHODOLOGY

According to Hevner et al. (2004), there are seven guidelines to design information systems for solving specific problems, including (i) Design as an artefact, (ii) Problem relevance, (iii) Design evaluation, (iv) Research contribution, (v) Research rigour, (vi) Design as a search process and (vii) Communication of research. This study follows these seven guidelines in establishing the proposed information systems artefact. With the increasing demands for long-term care services, this study purposes developing a two-echelon responsive health analytic model (EHAM) to enhance the operation of GCM in nursing homes, integrated the IoMT, dual fuzzy logic and CBR. The contribution of the proposed EHAM is to (i) purpose the qualitative method for evaluating the health deterioration of the patients in terms of acute and chronic aspects through the CPR index, and (ii) trigger the CPM at the dynamic time interval according to the result of CPR index. The case study has been conducted in the Comfort Nursing Home to validate the performance of the proposed EHAM. The discussion on the case study reveals the system performance evaluation in terms of quality, effectiveness and efficiency. In addition, this study provides useful insight into the critical foundations of the GCM regarding theoretical and managerial implications and its details in Section 5.

In the following section, the methodology of the proposed EHAM is described as follows. An EHAM is proposed to capture real-time health data and evaluate the health deterioration level to trigger a CPM proactively. The architecture of EHAM is shown in Figure 2. It involves the following three modules: (i) an IoMT data-collection and monitoring module, (ii) a CPR index–determination module and (iii) a nursing CPR module.

As shown in Figure 2, the first module is the IoMT data-collection and monitoring module, which uses the IoMT to collect the older patients’ real-time biometric data. Analysis of health data in acute and chronic aspects is performed to calculate the CPR index and measure the level of health deterioration through the dual fuzzy logic approach. This information is then used to trigger the needs of CPM and support knowledge manipulation using CBR. By adopting the proposed system, a customised care plan can be generated to fulfil the individual needs of older patients. Details of each module are discussed in the following section.

3.1 IoMT Data Collection and Monitoring Module

Four layers are involved in this module: a sensor layer, a gateway layer, a data-processing layer and an application layer. Figure 3 shows the IoMT framework of EHAM. First, various wireless sensors are provided in nursing homes for caregivers to capture residents’ biometric data. Seven types of biometric data, including four typical vital signs [i.e., blood pressure (mmHg), heart rate (bpm), respiratory rate (bpm) and body temperature (°C)] and three additional data types [i.e., blood glucose level (mmol/L), oxygen saturation (%) and body mass index (BMI)] are collected within the IoMT environment. For example, residents are equipped with wearable devices for collecting blood pressure and heart rates in
In this context, through the wireless local area network (WLAN) using Wi-Fi or Bluetooth, such data are transmitted from the sensors to the gateway and then to customised LAMP (Linux, Apache, MySQL and PHP/Python) servers acting as a centralised cloud-based platform through the gateway. By constructing different user interfaces in the LAMP servers, authorised users can easily obtain...
and monitor the health status of the patients under observation. Once an abnormal signal occurs in the biometric data, a pop-up alert notification is delivered so that the caregivers can take emergency actions to prevent further deterioration. Apart from the dynamic biometric data, static data such as the historical health record information and staff and equipment numbers in nursing homes stored in the local database are also extracted and transferred to the LAMP server for further analysis and decision-making in the CPR index–determination and CPM modules.

3.2 CPR Index–Determination Module

In nursing homes, caregivers must perform regular reviews of the content of the care plan based on changes in the health statuses of residents. In this part, the CPR index–determination module is designed to compute and trigger the CPM’s needs, which requires the manipulation of data collected from patients. Figure 4 shows the flow in the CPR index–determination module. A dual fuzzy logic approach is adopted in this module, allowing caregivers to consider uncertain information such as vital sign data and functioning assessment scores for data analysis. On the one hand, the dynamic biometric data gathered using the IoMT data-collection and monitoring module generate the Acute Health Deterioration Score (AHDS). On the other hand, the absolute changes in the scores of individual measurements related to physical, mental and social functioning are used to determine the Chronic Care Deterioration Score (CCDS). Two fuzzy outputs are then converted and presented in the CPR index to (i) generate instant actions and guidelines for preventing further health deterioration and (ii) confirm the need to pursue CPM processes for supporting long-term care.

Three processes are involved in the dual fuzzy logic approach: fuzzification, fuzzy inference engine, and defuzzification. In fuzzification, biometric data are treated as inputs for determining the AHDS as the output. At the same time, information related to the functional, mental and social status is defined to measure the CCDS as the output. All input and output parameters are converted into fuzzy sets ranging from 0 to 1, with their relationship expressed in Equation 1:

\[
F = \sum_{i=1}^{n} \frac{\mu_F(U_i)}{U_i}
\]

where \( F \) is the fuzzy set in a universe of discourse \( U \), \( U_i \) represents the data set of all elements \( \{u_1, u_2, u_3, \ldots u_n\} \) and \( \mu_F(U_i) \) is the membership function of \( F \). For example, the fuzzy set of the

Figure 4. The flow of the CPR index–determination module

[Diagram showing the flow of the CPR index–determination module with various parameters and processes.]
heart rate parameter includes Excellent (EX), Good (GO), Average (AV), Not Good (NG) and Poor (PO). An older patient with an average heart rate per minute above 84 bpm in the specific period under assessment is classified as ‘poor’ in the fuzzy membership functions. The fuzzy inputs are then transmitted to the fuzzy inference engine. Besides the fuzzy input values, fuzzy rules are also stored in this engine to stimulate the reasoning actions to calculate the AHDS and CCDS. Such fuzzy rules are used to present the relationship between the input and output parameters. The Mamdani fuzzy model (Cordón, 2011), i.e., a max-min method, can be adopted to define the fuzzy rules in the fuzzy inference engine by capturing the professional knowledge of domain experts for obtaining the output value, \( O_i \). Equation 2 shows the mathematical expression for deriving the overall output fuzzy set:

\[
\mu_{A_i}(O_i) = \max \left\{ \min \left\{ \mu_{F_{i_1}}(U_1), \mu_{F_{i_2}}(U_2), \ldots, \mu_{F_{i_n}}(U_n) \right\} \right\}
\]

Regular discussion among domain experts is required to drive updates and adjustments to the content of the rules as required. These discussions ensure the quality of the fuzzy rules. Finally, the output fuzzy sets are defuzzified into a corresponding universe of discourse values using the centre of area method. Equation 3 presents the mathematical expression for calculating the centroid of the area of the combining regions of the output fuzzy membership functions:

\[
\bar{O}_i = \frac{\int \mu_{A_i}(O_i) \cdot o \cdot do}{\int \mu_{A_i}(O_i) do}
\]

The output parameters in the defuzzification process are used to determine the CPR index. The index ranges from one to five points and from which caregivers can systemically design appropriate instant and long-term care actions to prevent further health deterioration. Equation 4 shows the calculation of the CPR index value:

\[
\text{CPR index} = \prod_{i=1}^{n} s_i, \quad \forall i \in I
\]

where \( n \) is the total number of health performance aspects, and \( s_i \) is the value of AHDS \( (i=1) \) or CCDS \( (i=2) \). According to the defined scale discussed by domain experts, two outputs from the fuzzy system are arranged as a two-dimensional space with four regions. Figure 5 shows the conversion of the fuzzy output into the CPR index value.

The four regions represent different levels of health deterioration appearing in older individuals, and the description of these four regions is shown in Table 2. Such information guides caregivers to design and apply corresponding instant actions to assist older individuals concerning different aspects. On the other hand, the results of the CPR index can be further used to activate the actions of the CPM module and, hence, create a severity factor for adjusting the weighting of related attributes in the case-retrieval process. This process is helpful for caregivers seeking to select the most relevant past case to use as a reference to generate optimally customised care plans based on changes in a patient’s health status.

### 3.3 CPM Module

The care plans falling in regions I, II and III of the CPR index were selected and sent to the CPM module to re-evaluate current healthcare services using the CBR. This step reduces the degree of
complexity in forthcoming CPM processes. Information concerning the input problems of the care plan encompasses the basic historical health records of older individuals, such as heart rate; details of their physical, mental and social status; biometric information; and expected costs. Based on the above information, caregivers revise five components in the output solutions of the care plan, i.e., basic healthcare services, customised daily activities, staffing, equipment and diet to meet their needs. Figure 6 shows the relationships between the components involved in the care plan.

Table 2. The four regions in the CPR index

<table>
<thead>
<tr>
<th>Region</th>
<th>AHDS</th>
<th>CCDS</th>
<th>CPR index</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region I</td>
<td>High</td>
<td>High</td>
<td>16–25</td>
<td>Severe health deterioration in the overall health performance of older individuals</td>
</tr>
<tr>
<td>Region II</td>
<td>High</td>
<td>Low</td>
<td>5–15</td>
<td>Severe/significant health deterioration in the biometric information of older individuals</td>
</tr>
<tr>
<td>Region III</td>
<td>Low</td>
<td>High</td>
<td>5–15</td>
<td>Severe/significant deterioration in the physical, mental and social status of older individuals</td>
</tr>
<tr>
<td>Region IV</td>
<td>Low</td>
<td>Low</td>
<td>1–4</td>
<td>No change/acceptable change in the overall health performance of older individuals</td>
</tr>
</tbody>
</table>

* High = 4–5 points for AHDS/CCDS; Low = 1–3 points for AHDS/CCDS
Abbreviations: AHDS: Acute Health Deterioration Score; CCDS: Chronic Care Deterioration Score; CPR: care plan revision.

Figure 5. Conversion of the output of fuzzy logic into CPR index value (Abbreviations: CPR: care plan revision)
When constructing the CBR engine, a list of attributes is required for retrieving the potentially relevant past care records from the case library. Subsequently, an indexing method is applied to group past care records into different clusters following a tree-type structure. This tree contains five levels (i.e., mobility, self-care ability, neuropsychiatric problem, communication ability and age), and the most critical attribute is placed on the highest indexing level. Along the searching path of the tree, a list of past care records with the corresponding attributes can be generated from the numerous care records. The nearest-neighbour method is applied for determining their degree of similarity relative to the new case to select the optimal past care records from among the selected care records. Caregivers are required to define the weighting of attributes considered. A value of the CPR index of greater than five points implies that there is significant health deterioration, and the severity factor is considered to adjust the weighting of corresponding attributes for calculating the total similarity value using Equation 5:

\[
\text{Total similarity value} = \frac{\sum_{i=1}^{n} w_i \cdot \varphi_j \cdot \text{sim}(f_{i}^{\text{new}}, f_{i}^{\text{old}})}{\sum_{i=1}^{n} w_i \cdot \varphi_j} \tag{5}
\]

where \( w_i \) is the weight of particular attributes; \( \text{sim} \) is the function for calculating the similarity value; \( f_{i}^{\text{new}} \) and \( f_{i}^{\text{old}} \) are the values of attributes \( f_i \) in the new and past cases, respectively; and \( \varphi_j \) is the severity factor to adjust the weighting by considering \( 1 + s_i / \max(s_i), \forall i \in I \). According to the similarity value, the selected case records are then ranked in descending order automatically. The past case showing the highest similarity value is considered the reference most significant to the new input problem. Any necessary modifications, such as adding customised rehabilitative activities according to the health status, are undertaken during a new case’s solution stage to determine the appropriate healthcare services to pursue. After formulating a new care plan for solving the new problem, the care plan is sent and stored in the case library for continuously updating and improving the quality of the care records. Hence, fast responsiveness and accuracy healthcare services can be delivered to older individuals to enhance their satisfaction level.

4. CASE STUDY

A case study was conducted in the Comfort Nursing Home located in Taichung, Taiwan, to validate the performance and feasibility of the proposed EHAM.

4.1 Background of the Comfort Nursing Home

The Comfort Nursing Home was founded in 1987. It is one of the largest private nursing homes located in Taichung, Taiwan. It aims to provide a comfortable and safe living environment by offering a wide range of healthcare services to more than 200 older individuals with chronic diseases and disabilities to fulfill their daily living needs. It has approximately 100 staff to deliver healthcare services, including personal care, residential care, nursing care, rehabilitative care, and daily activities. Figure 7 shows the existing workflow in daily routine processes. Currently, a regular review of established care plans is performed every six months. Caregivers must extract the relevant biometric data and conduct basic functioning assessments to re-evaluate residents’ health performance. However, due to the long time intervals between two re-evaluations, caregivers may, at times, overlook abnormalities that may ultimately affect the health of residents. In addition, the complexity inherent in considering the numerous data available during the review process increases the difficulty of and time to delivery of appropriate healthcare services. These factors have resulted in many complaints and poor service satisfaction in the case nursing home.
To deliver QoC to older individuals, the Comfort Nursing Home decided to implement EHAM to facilitate the execution of GCM and enhance the degree of efficiency in assessing the level of health deterioration by measuring the CPR index and triggering actions for short- and long-term care solutions. Four phases were established to implement the EHAS: (i) development of the IoMT health monitoring application, (ii) deployment of health measurements using a dual fuzzy approach, (iii) establishment of the CPR index and (iv) execution of CPM processes using CBR. The details of each phase are described in Sections 4.1 through 4.4.

4.2 Development of IoMT Health Monitoring Application

As mentioned previously, various sensors are used to automatically capture biometric data to facilitate the daily checking processes in nursing homes, as shown in Figures 8 and 9. In most nursing homes, wearable devices are given to each resident to collect data on blood pressure, heart rate and oxygen saturation. In addition, other devices such as thermometers and glucometers with the ability for transmitting data under the IoMT environment are provided in each ward. A smart device is selected as an edge router to facilitate data synchronisation and transmission between the various sensors and the LAMP server. By configuring the MySQL database in the LAMP server, biometric data can be stored in EHAM (Tang et al., 2019). In addition, the alert function in EHAM enables caregivers to monitor the health statuses of residents in real-time. Apart from the data used for health monitoring purposes, static data, including the details of available resources in nursing homes and chronic data related to physical, mental and social functioning, are also stored in the MySQL database. Figure 10 shows dynamic and static data flow from wearable sensors to EHAM under the IoMT environment. The sensing devices collect all the relevant data from the patients. The data is then transmitted and stored to the proposed system through the gateway. The integration of such dynamic and chronic data then supports measurements of health deterioration and CPR index values to trigger CPMs where appropriate.

4.3 Deployment of Health Measurement Using a Dual Fuzzy Logic Approach

The dual fuzzy logic approach was developed using the Python programming language (Python Software Foundation, Wilmington, DE, USA) to measure the level of deterioration in both acute and chronic aspects of health. Caregivers must define the input and output parameters, their fuzzy membership function and the fuzzy rules. In this case, there were seven input and one output parameters included in the acute category, including average systolic blood pressure (avgSBP), average heart rate (avgHR), average respiratory rate (avgRR), average body temperature (avgBT), average oxygen saturation (avgOS), average blood glucose level (avgBG), BMI and AHDS. For chronic aspects, the input parameters concern the absolute score changes in the functioning measurements. Through meetings with nursing home managers and caregivers, it was found that different measurements were being adopted for assessing physical, mental and social abilities, respectively. These measurements have previously been proven to have reliability and validity in assessing older adults. Specifically, six
input parameters—that is, absolute scores change in the Katz Index of Independence in Activities of Daily Living (Katz Index), the Philadelphia Geriatric Center Mental Status Questionnaire, the Beck Depression Inventory, Social Dysfunction Rating Scale, the Philadelphia Geriatric Center Morale Scale and the Satisfaction with Nursing Home Scale—and one output parameter (i.e., CCDS) were selected for determining the level of chronic health deterioration. Figure 11 presents the input and output parameters for both acute and chronic aspects.

All parameters were then fuzzified by their corresponding membership function. In this case, only trapezoidal and triangular membership functions were considered to reduce the complexity in calculating the fuzzy inference engine. The input parameters’ fuzzy set was judged by domain experts such as doctors and nurses utilising professional health knowledge to ensure the suitability of the parameters.
parameters’ fuzzy characteristics. Regarding the fuzzy rules stored in the fuzzy inference engine, valuable knowledge was extracted after meetings and discussions with a group of caregivers and is presented in an if-then format. Through the discussions, the rules could be adjusted to minimise any inconsistencies appearing due to knowledge variations among the caregivers.
An older patient (patient no. 0030) was selected to help illustrate the mechanism of the dual fuzzy logic approach in EHAM. Table 3 shows the values of the input variables for both the acute and chronic aspects for this individual. The historical medical records stored in the proposed model found that they have various chronic diseases. Also, in these two days, his avgSBP increased from 132 mmHg to 160 mmHg, while, among other biometric data, the avgHR was 82 bpm, the avgRR was 19.2 bpm, the avgBT was 37.2°C, the avgBG was 5.3 mmol/L, the avgOS was 97%, and the BMI was 18.5 kg/m². Among physical, mental and social data, it was found that the score change in the Katz Index was two points. The score change on the Philadelphia Geriatric Center Mental Status Questionnaire (PGCMSQ) was nine points. The score changes in the Beck Depression Inventory, the Social Dysfunction Rating Scale, the Philadelphia Geriatric Center Morale Scale (PGCMS) and the Satisfaction with Nursing Home Scale were 14, 15, 15 and four points, respectively in this week.

The quantitative value of such parameters is then converted into fuzzy value as the input for the dual fuzzy logic through the fuzzification process. The details of the fuzzification process are presented in the paper written by Hendiani & Bagherpour (2019). By doing so, all input parameters can be fuzzified according to their fuzzy set and membership functions.

With the fuzzy input value, the corresponding rules can be identified in the fuzzy inference engine. The fuzzy output value can be determined based on the compositing membership values in the corresponding rules. Figure 12 presents the evaluation process of the fuzzy influence engine for calculating the AHDS. With aggregation processes, the results from each rule can be fused for generating the value of the output variable (i.e., AHDS). The fuzzy output value is finally converted into a crisp value using Equation 3 to determine the centre of the area in each fuzzy region. In this case, it was found that the centre of the area (i.e., AHDS) is 2.31, which implies that the level of acute health deterioration is low. By following similar procedures, the CCDS can be determined to have a value of 3.7 points, implying that the level of chronic health deterioration is medium.

### 4.4 Establishment of the CPR Index

Based on the dual fuzzy logic processes results, the CPR index can be determined using Equation 4. With scores of 2.31 points for AHDS and 3.7 points for CCDS, the CPR index for patient no. 0030 was 8.55 points. Since the score of CCDS is higher than that of AHDS, the patient no. 0030 can be classified into region III of the CPR index, which implies severe/significant physical, mental and social deterioration. The instant actions to take for each region in the CPR index are provided to prevent further health deterioration, as shown in Table 4.

Such instant actions are formulated according to the information offered in previous studies and provided during discussions with health professionals (Challen & Roland, 2016; Preece et al., 2012; Evashwick, 2005; Morris et al., 1997). In this case, three instant actions are suggested before re-modifying the long-term care solutions in the care plans. First, a comprehensive assessment
following the standard criteria should be conducted to diagnose the functional problems of patient no. 0030 fully to facilitate a better understanding of the current situation for their caregivers. Second, social workers and caregivers should begin to pay more attention to the patient no. 0030. In addition to closely monitoring their mood and behaviours related to mental and social functioning, a score sheet distributed for assessing their feelings social workers and caregivers should complete each day. Apart from instant actions such as these, the output of the CPR index also triggers CPM processes.

**Table 4. Instant actions for caregivers to serve older individuals in different regions of the CPR index**

<table>
<thead>
<tr>
<th>Category</th>
<th>Immediate action</th>
</tr>
</thead>
</table>
| Region I | • Take emergency/ immediate action if necessary, such as transfer to the hospital  
• Have the medical team with critical care competencies conduct an emergency assessment  
• Conduct continuous monitoring of patient vital signs and emotions |
| Region II | • Take emergency/immediate action if necessary, such as transfer to hospital  
• Inform the registered nurse/medical team caring for the patient of the findings  
• Conduct the ‘ABCDE’ assessment* and document results in the medical notes  
• Increase the frequency of monitoring biometric data (e.g., review at minimum hourly)  
• Update the clinical setting if needed to facilitate ongoing care |
| Region III | • Consider the need for further assessment (such as conducting full diagnostic interviews/appropriate investigations that follow the standard criteria)  
• Increase the frequency of monitoring the patient’s mood and behaviours within a specific period (e.g., require older individuals to provide a summary score each day for how they are feeling)  
• Inform social workers/caregivers supporting the patient of the findings  
• If necessary, make a referral to appropriate professionals to treat the related problems |
| Region IV | • Continue to follow the original care plan |

* ABCDE stands for airway, breathing, circulation, disability and exposure
for generating customised long-term care solutions and affects the weights of various attributes in calculating the total similarity value in the case-retrieval engine of CBR.

4.5 Execution of CPM Processes Using CBR

The results obtained from the CPR index triggers an immediate CPM process to begin rather than waiting to execute the necessary processes in a fixed time interval. CBR is adopted in this part for facilitating decision-making in revising the content of the care plan by reference to past care records (Aamodt & Plaza, 1994). Past care records are loaded into the LAMP server to support the construction of the case library. In this case, the care plan for patient no. 0030 was treated as a new problem. The inductive indexing approach and the nearest-neighbour method were first adopted into the case-retrieval engine for extracting the most relevant past care records. For the inductive indexing approach, a five-level decision tree was built as follows: (i) level 1, mobility; (ii) level 2, self-care ability; (iii) level 3, neuropsychiatric problem; (iv) level 4, communication method; and (v) level 5, age. Figure 13 shows the structure of this decision tree in more detail. Along the searching path of these five levels, a small group of past care records with the same attributes as the new problem was identified and extracted for determining their similarity value using the nearest-neighbour method.

Sixteen attributes were defined to calculate the similarity value: the biometric data collected in the first phase, any diseases that the patient has, and the expected costs that the patient can afford. According to the corresponding services provided for these attributes, different weights are initially assigned by the domain experts to present their importance. Since it was found that there is a significant change in the physical, mental and social functioning of patient no. 0030, the weights of the attributes related to the individuals’ physical, mental and social abilities are increased. Taking social attributes as an example, originally, the weighting of the social attribute was 0.7. Considering the severity factor, this weight rose from 0.7 to 1.218, indicating increased importance in calculating the total similarity value. By using Equation 5, the total similarity value can be calculated. The past care records are then ranked in descending order. Hence, caregivers can easily distinguish the past care record with the highest similarity value and consider it the most significant reference for generating solutions to the new problem. Finally, the case of patient no. 0094 with an 89.3% similarity rate is retrieved and acted as the reference for care solutions generation.

Figure 13. Structure of the decision tree in the case-retrieval engine
5. FINDINGS AND ANALYSIS

5.1 Findings

From the case study, it was found that CPR index for the patient no. 0030 is 8.55 points with scores of 2.31 points for AHDS and 3.7 points for CCDS. Instant actions are needed to prevent further health deterioration. Based on the information provided by Table 4, three actions are taken, which includes (i) the conduction of complete diagnosis, (ii) closely monitoring their mood and behaviour, and (iii) the collection of the score sheet every day. It is essential to keep track of the patient feeling and emotions before modifying the care plan. The CPR results also trigger care plan modification for reviewing and assessing their needs accordingly. The CBR engine can identify the past case with the highest similarity value to the new problem. Figure 14 shows the results of the retrieved case with consideration of the severity factor. In this scenario, case 0094 has the highest similarity value, which is 89.3%.

Therefore, customised long-term care solutions for older individuals are generated based on the retrieved case. Caregivers also make modifications, such as adding up-to-date supportive care for rehabilitation with sufficient healthcare knowledge. In this case, tailor-made range-of-motion (ROM) exercises and outings were decided to increase patients’ self-esteem and distraction them from their worries and concerns. Furthermore, the caregivers inform family members of such events and encourage them to participate in the treatment protocols. In addition, since there was a significant increase in the blood pressure of the patient no. 0030 under observation, a low sodium diet should be provided to reduce blood pressure. Besides, the caregivers need to inform the patient’s doctor of the necessity to conduct further assessments and potentially adjust drug dosages. New long-term care solutions are formulated with these and other similar actions, and corresponding healthcare services can be determined and provided for maintaining the QoC. Finally, the new case is transferred and stored in the case library to support continuous quality improvement in GCM.

5.2 Sensitivity Analysis of the Dual Fuzzy Logic Approach

A sensitivity analysis was conducted to evaluate the effectiveness of the dual fuzzy logic approach in EHAM to determine how sensitive the model is about different combinations of fuzzy settings. From the literature, factors including implication methods, rule-aggregation methods and
defuzzification methods are selected for the sensitivity of the fuzzy logics (Geramian et al., 2019; Poveda & Fayek, 2009; Mahabir et al., 2003). In this case, eight system configurations, including two implication methods (minimum or product), two rule-aggregation methods (maximum or sum) and two defuzzification methods (centre of the area or mean of maximum), were selected to predict the AHDS and CCDS of 10 patients in the case nursing home. Different combinations of the eight system configurations of EHAM are shown in Table 5.

These results were then compared to the actual deterioration score, ranging from one to five points, provided by senior caregivers with ten years of working experience. Through the comparison, the errors involving each patient were located, while the average percentage change of the error (avg. % error) of each system configuration was computed accordingly using Equation 6:

\[
\text{Average percentage change of error} = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n} \times 100\% 
\]

where \(x_i\) is the output value of AHDS or CCDS, \(y_i\) is the actual deterioration score provided by senior caregivers, and \(n\) is the number of system configurations. The input data for the ten patients and the sensitivity analysis results of the eight-system configuration for determining the values of AHDS and CCDS are shown in Tables 6 and 7, respectively. The higher value of average % errors in Tables 6 and 7 indicates the higher difference between the actual and the predicted value in AHDS and CCDS. Moreover, Figures 15 and 16 show the percentage changes of each patient’s error (% error) and the avg. % error values for the eight system configurations involving AHDS and CCDS, respectively. The bars in Figures 16 and 17 indicate the error difference between predicted and actual values. For example, in system configuration 1 (#1) in Figure 16, the first bar shows the error difference of AHDS between the predicted and actual value for patient 1.

From Tables 6 and 7, it can be seen that system configuration 1 has the lowest avg. % error for both AHDS and CCDS with values of 0.82 and 0.94 points, respectively. These findings imply that, when the implication method is the minimum, the rule-aggregation method is the maximum, and the defuzzification method is the centre of the area, the proposed EHAM can generate the results of AHDS and CCDS close to the actual deterioration scores of senior caregivers with less variability among individuals and with the least avg. % error possible. System configuration 5 involves the same rule-aggregation and defuzzification methods but a different implication method

<table>
<thead>
<tr>
<th>System configuration</th>
<th>Implication method</th>
<th>Rule-aggregation method</th>
<th>Defuzzification method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Minimum</td>
<td>Maximum</td>
<td>Centre of area</td>
</tr>
<tr>
<td>2</td>
<td>Minimum</td>
<td>Maximum</td>
<td>Mean of maximum</td>
</tr>
<tr>
<td>3</td>
<td>Minimum</td>
<td>Sum</td>
<td>Centre of area</td>
</tr>
<tr>
<td>4</td>
<td>Minimum</td>
<td>Sum</td>
<td>Mean of maximum</td>
</tr>
<tr>
<td>5</td>
<td>Product</td>
<td>Maximum</td>
<td>Centre of area</td>
</tr>
<tr>
<td>6</td>
<td>Product</td>
<td>Maximum</td>
<td>Mean of maximum</td>
</tr>
<tr>
<td>7</td>
<td>Product</td>
<td>Sum</td>
<td>Centre of area</td>
</tr>
<tr>
<td>8</td>
<td>Product</td>
<td>Sum</td>
<td>Mean of maximum</td>
</tr>
</tbody>
</table>

Table 5. Different combinations of system configurations of EHAM
Table 6. Sensitivity analysis and error of different system configurations for AHDS

<table>
<thead>
<tr>
<th>Patient</th>
<th>Input parameters</th>
<th>AHDS in different system configurations</th>
<th>Actual deterioration score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SBP</td>
<td>HR</td>
<td>RR</td>
</tr>
<tr>
<td>1</td>
<td>160</td>
<td>82</td>
<td>19.2</td>
</tr>
<tr>
<td>2</td>
<td>125</td>
<td>88</td>
<td>17.5</td>
</tr>
<tr>
<td>3</td>
<td>112</td>
<td>72</td>
<td>16</td>
</tr>
<tr>
<td>4</td>
<td>132</td>
<td>77</td>
<td>21</td>
</tr>
<tr>
<td>5</td>
<td>122</td>
<td>83</td>
<td>18.5</td>
</tr>
<tr>
<td>6</td>
<td>110</td>
<td>84</td>
<td>19.5</td>
</tr>
<tr>
<td>7</td>
<td>128</td>
<td>80</td>
<td>14.2</td>
</tr>
<tr>
<td>8</td>
<td>145</td>
<td>82</td>
<td>21</td>
</tr>
<tr>
<td>9</td>
<td>130</td>
<td>79</td>
<td>16.9</td>
</tr>
<tr>
<td>10</td>
<td>115</td>
<td>72</td>
<td>15.1</td>
</tr>
<tr>
<td>Average % error</td>
<td>0.82</td>
<td>1.63</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Table 7. Sensitivity analysis findings and errors of different system configurations for CCDS

<table>
<thead>
<tr>
<th>Patient</th>
<th>Input parameter</th>
<th>CCDS in different system configurations</th>
<th>Actual deterioration score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>KI</td>
<td>PGCMSA</td>
<td>BDI</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>9</td>
<td>14</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>8</td>
<td>15</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>16</td>
<td>13</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>9</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Average % error</td>
<td>0.94</td>
<td>1.49</td>
<td>0.99</td>
</tr>
</tbody>
</table>

relative to system configuration 1. The average % error of the CCDS for system configuration 5 was 0.95 points, which is relatively near to the avg. % error of the CCDS for system configuration 1 (0.94 points). However, in this sensitivity analysis, the product implication method was not considered as the best choice for the system configuration due to the higher avg. % error values apparent in all system configurations, including this attribute — for example, the avg. % error for system configuration 2 was lower than the avg. % error for system configuration 6 (1.63 points vs 1.84 points). Therefore, based on the above results, it is recommended that the minimum implication method, maximum aggregation method and centre of area defuzzification method should be adopted to establish the proposed EHAM for accurately determining levels of health deterioration among older individuals.
Figure 15. Error differences in the sensitivity analysis for AHDS

![Sensitivity Analysis of AHDS](image)

Figure 16. Error differences in the sensitivity analysis for CCDS

![Sensitivity Analysis of CCDS](image)

6. DISCUSSION, LIMITATIONS AND FUTURE RESEARCH

A prototype was developed and implemented in the Comfort Nursing Home for three months, i.e. January 2020 to March 2020, to verify the significance of the proposed EHAM and assist the process of GCM. Based on the functionality of the proposed EHAM, caregivers can (i) revise the care plan at dynamic time intervals and (ii) consider both acute illnesses and functional abilities in assessing the health performance of older individuals.
6.1 Discussion on Case Study

To measure the performance of the proposed EHAM, two key performance indicators, operational efficiency and older satisfaction, were chosen. With the aid of the proposed EHAM, it was found that significant improvements occurred in these two indicators.

1. Improvement in the efficiency in executing the GCM.

The implementation of the proposed EHAM had a positive influence on the execution of GCM in the case nursing home. Table 8 shows the improvement in operational efficiency of GCM after adopting the proposed model. With the adoption of the IoT, biometric data can be captured automatically and stored in the cloud database. Caregivers can easily visualise such data by logging in to the proposed EHAM. Compared with the previous manual data-collection and documentation approach, the time required for the daily checking processes with the new method is reduced by 88.9%, which led to a significant improvement in the data-documentation process (zero minutes).

Furthermore, the use of dual fuzzy logic and CBR in EHAM improves the operational process for CPM. Caregivers can easily assess the total health performance in terms of acute illness and functional abilities. Based on the CPR index results, long-term care solutions can be formulated by extracting past similar care records for reference. Caregivers no longer need to spend long periods assessing the total health performance, reviewing health records, and revising the care plan manually. Therefore, the time for CPM was significantly reduced by 69.1%.

2. Improvement in the satisfaction level.

Before the launch of EHAM, caregivers at the case nursing home often overlooked abnormalities appearing and delayed delivering appropriate healthcare services to the residents. This issue resulted in a high number of complaints from residents’ families and low levels of satisfaction. EHAM allows caregivers to monitor the biometric data in real-time and distinguish any abnormalities with the aid of the alert function. In addition, a comprehensive health assessment involving both acute and chronic aspects can be conducted for triggering CPMs at dynamic time intervals rather than fixed time intervals to limit or avoid further deterioration. By doing so, proactive and accurate healthcare services can be delivered to the residents, satisfying their needs. Consequently, the number of complaints per month in the case nursing home was reduced from eight to two, while the satisfaction level increased from 6.8 to 8.5 points after implementing EHAM for two months.

### Table 8. Improvements in the operational efficiency of GCM

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>After (with EHAM)</th>
<th>Percentage of improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time for daily checking processes</td>
<td></td>
<td></td>
<td>88.9%</td>
</tr>
<tr>
<td>- Collect biometric data</td>
<td>5 min</td>
<td>2 min</td>
<td></td>
</tr>
<tr>
<td>- Document data into the database</td>
<td>13 min</td>
<td>0 min</td>
<td></td>
</tr>
<tr>
<td>Time for CPM</td>
<td></td>
<td></td>
<td>69.1%</td>
</tr>
<tr>
<td>- Assess the total health performance</td>
<td>20 min</td>
<td>15 min</td>
<td></td>
</tr>
<tr>
<td>- Review health records</td>
<td>30 min</td>
<td>2 min</td>
<td></td>
</tr>
<tr>
<td>- Revise the content of a care plan</td>
<td>18 min</td>
<td>4 min</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>86 min</td>
<td>24 min</td>
<td></td>
</tr>
</tbody>
</table>
6.2 Research and Managerial Implications

This study proposes a new paradigm of GCM that identifies the research gap regarding nursing homes. The theoretical foundation of this study was based on a literature review to identify common quantitative measures for evaluating the physical, mental, and social functions of the elderly (Cho et al., 2018; Challen & Roland, 2016). In addition, previous studies proposed to execute a care plan review process for patients at a fixed time interval rather than based on the level of health deterioration and individual needs. The research gap in GCM has been filled through this study by proposing the two-echelon responsive health analytic model (EHAM), integrating the IoMT, dual fuzzy logic, and CBR. The novel Care Plan Revision (CPR) index explores the use of the aggregated measurement method for evaluating the level of health deterioration concerning the acute and chronic health aspects. Moreover, the results of the CPR index open a novel research domain to determine dynamic time intervals for implementing the care plan review and, hence, facilitating the formulation of customised care solutions. This study also provides insights for studies on enhancing service quality and operational effectiveness in nursing homes. In the digitalisation era, this study can be treated as a valuable reference for nursing homes to implement responsive AI techniques and emerging technologies, impacting research in GCM. Adopting the proposed EHAM impacts the use of GCM in health monitoring, health assessment, and care plan modification. Instead of traditional physical health monitoring, the remote health monitoring process is applied by using sensing devices. Caregivers can quickly notice abnormalities occurring in the elderly to take proactive actions to prevent further health deterioration. This change helps improve the quality of life of the elderly and further relieves pressure on caregivers through the efficient operation processes in GCM.

Delivering high QoC in nursing homes is crucial to improving and maintaining older individuals’ desired health outcomes. However, because the ageing population is growing, how can caregivers effectively provide long-term care services to meet the increasing and potentially limitless needs of older adults with finite staff numbers, facilities, and funding is emerging and might highly affect the QoC. Nursing homes strive to adopt smart health to generate accurate and responsive healthcare solutions in addressing this issue. The integration of ubiquitous computing and ambient intelligence in the context of smart health offers caregivers the ability to intelligently manipulate a large volume of health data and improve operational efficiency, transparency, and traceability among stakeholders. Family members expect that relatives living in nursing homes will receive the best QoC. With the adoption of the smart healthcare platform, families can now become more involved in the care planning process through the interactive platform to reduce their dissatisfaction and enhance the understanding of their expectations and goals. From a management perspective, big data analytics offer a boundless improvement to leverage the benefits of current GCM under the constraints of limited healthcare resources (Wang et al., 2018). Through data integration and sharing among different stakeholders, managers can better organise and allocate staff and equipment to increase healthcare process efficiency and productivity. In addition, knowledge discovery and retention will allow managers to use valuable knowledge to formulate strategic directions in GCM to achieve operational excellence in nursing homes as socially responsible healthcare organisations. Ultimately, by utilising resources and assets within communities and taking responsible approaches to employment and production of sustainable healthcare services, the proposed EHAM using AI can attain long-term economic and social value for healthcare organisations. Hence, patient-centred long-term care solutions of high quality can be generated in a timely way to maximise the satisfaction of nursing home residents and their families.

6.3 Limitations and Future Works

In this study, there are three limitations: (i) the willingness of the elderly to wear wireless devices, (ii) information security for handling sensitive data, and (iii) the accuracy of fuzzy logic. It is understood that some elderly may feel discomfort or difficulty in wearing the IoT equipment. In this situation, traditional health monitoring by caregivers would be performed for this group of patients. In addition, caregivers would communicate with the elderly and their families to clearly explain the importance
of using the new information system in performing daily health monitoring and health assessment activities. Even though implementing the proposed EHAM improves the operation efficiency in the GCM, the caregivers still play a crucial role in care planning (Song et al., 2021). For example, once a continuous alert is received from wireless sensors, caregivers must verify the patient’s health status using standard health assessment methods.

In some cases, the alert may occur due to sensor failure or misdetection by the wireless sensors. Some studies have pointed out that information systems may decrease contact between caregivers and the elderly and, hence, create loneliness (Lee et al., 2015; Goldkuhl, 2013). Especially in the Hong Kong environment, most of the nursing homes adopted the open-plan layout design. The proposed system integrated the IoT technology and AI techniques to facilitate the delivery of proactive healthcare services through the dynamic health assessment and reduce direct contact with the patients through remote health monitoring. This approach can reduce the chance of inflexion from epidemics such as human swine, avian, and coronavirus disease 2019 (Shiau et al., 2021; Chow, 2020). Future research could focus on information system design and the social impacts of using such systems in the healthcare industry. Secondly, since patients’ data is sensitive, high data security is required in data transmission, data storage, and redundancy control of the equipment. To ensure data security in the proposed system, only authorised users, including the families of the elderly, caregivers, and managers, can log in to the data storage system and access the data. Besides, firewall and regular testing are essential for reducing system vulnerabilities and the chances of insecure interfaces occurring in the proposed system. In the future, we intend to adopt blockchain technology to facilitate the secure transfer of patients’ medical records among healthcare stakeholders from nursing homes, daily health centres, clinics to hospitals. Lastly, three factors, i.e., the implication method, the rule aggregation method, and the defuzzification method, were adopted in the sensitivity analysis at this stage. Future research could consider more factors, such as the shape of membership functions and the input-aggregation method in the sensitivity analysis, to optimise the fuzzy logic configuration further.

7. CONCLUSION

Although healthcare is an essential part of life, the rapidly expanding ageing population and the related rising demands for resources place significant stress on nursing homes that affect the QoC being delivered to residents. The concept of smart health has been recognised as a potential solution to alleviate pressure and maximise the quality of healthcare services. Traditional GCM in nursing homes, which uses a fixed time interval for assessing the health performance of older individuals, is inappropriate since different patients may have different levels of health deterioration. In addition, only considering the biometric data collected from daily checking processes are insufficient for caregivers to conduct a comprehensive health analysis. Without a systematic approach to addressing these problems, residents may receive inappropriate healthcare services from caregivers, resulting in serious health effects and death. Therefore, this study developed an EHAM, integrating the IoMT, dual fuzzy logic approach and CBR, to enhance the performance of GCM. The adoption of IoMT would enable caregivers to collect and store biometric data for better health monitoring automatically. A novel CPR index was designed to establish a comprehensive health performance assessment. The index is given by the dual fuzzy logic approach to intelligently analyse the triggering point according to the level of health deterioration in both acute and chronic aspects. This triggering point yields a directive for caregivers to pursue instant actions for preventing further deterioration. Simultaneously, it activates the process of CPM using CBR. With the CPR index output, the severity factor is considered in the case-retrieval engine for selecting the most significant past care record to support decision-making in generating long-term care solutions. The significance of this study is to link up the processes involved in the GCM, starting from the automatic daily checking process to the aggregating assessment of
the health deterioration and the modification of care plans based on such health deterioration. By launching EHAM, caregivers can detect abnormalities so that appropriate healthcare services can be delivered to nursing home residents on time. Furthermore, managers can use such valuable knowledge extracted from EHAM to support better use of available resources, including staffing and equipment, to improve the QoC continuously delivered cost-effectively.

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REFERENCES


Chow, L. (2020). Care Homes and COVID-19 in Hong Kong: How the lessons from SARS were used to good effect. *Age and Ageing*. Advance online publication. doi:10.1093/ageing/afaa234 PMID:33035300


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