An Intelligent and Efficient Rehabilitation Status Evaluation Method: A Case Study on Stroke Patients

Yao Tong[1,2], Hang Yan[1], Xin Li[3], Gang Chen[1](✉), and Zhenxiang Zhang[1](✉)

[1] Zhengzhou University, Zhengzhou 450000, Henan, China
yaotong@uw.edu, chengang@zzu.edu.cn, zhangzx6666@126.com
[2] University of Washington, Seattle, WA 98105, USA
[3] Hohai University, Nanjing 211000, Jiangsu, China

Abstract. Chronic patients' care encounters challenges, including high cost, lack of professionals, and insufficient rehabilitation state evaluation. Computer-supported cooperative work (CSCW), is capable of alleviating these issues, as it allows healthcare physicians (HCP) to quantify the workload and thus to enhance rehabilitation care quality. This study aims to design a deep learning algorithm Pose-AMGRU, a deep learning-based pose recognition algorithm combining Pose-Attention Mechanism and Gated Recurrent Unit (GRU), to monitor the human pose of rehabilitating patients efficiently. It gives instructions for HCP. To further substantiate the acceptance of our computer-supported method, we develop a multi-fusion theoretical model to determine factors that may influence the acceptance of HCP and verify the usefulness of the method above. Experiment results show Pose-AMGRU achieves an accuracy of 98.61% in the KTH dataset and 100% in the rehabilitation action dataset, which outperforms other algorithms. The efficiency running speed of Pose-AMGRU on the GTX1060 graphics card is up to 14.75FPS, which adapts to the home rehabilitation scene. As to acceptance evaluation, we verified the positive relationship between the computer-supported method and acceptance, and our model presents decent generalizability of stroke patients' care at the Second Affiliated Hospital of Zhengzhou University.

Keywords: Rehabilitation status evaluation · Deep learning · Technical acceptance

1 Introduction

Chronic diseases, such as diabetes, stroke, and heart disease, etc. are the major diseases that deteriorate the life quality of the elderly and bring our health care system high cost $199 billion per year. Efficiency and quality of caring are essential to the health of a

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nation [1–4]. Chronic illness has various long-term sequelae that need rehabilitation, and patients with chronic disease usually choose to go to hospital or community medical institutions for follow-up rehabilitation after discharge [5]. In the case of stroke patients, stroke after nerve trauma is one of the leading causes of long-term disability in adults. Up to 30% of stroke survivors experience minimal exercise recovery and rely on assistance in managing their daily activities [6]. As population aging and the trend of stroke increasing among younger people [7], there are still problems with efficiency and quality in rehabilitation care management. Delivering efficient and high-quality healthcare is complicated [8–12] since most of HCP's time is preoccupied with hunting for supplies, tracking down medications, filling out paperwork at the nursing station, and looking for missing test results [13].

Computer-supported cooperative work (CSCW) is defined that in the environment supported by computer technology, groupware cooperatively works to accomplish a common task [14]. The previous researches were focused on the behaviors of individuals at scale [15, 16]. Therefore, this kind of computer-supported method has limited generalization ability when facing a large number of users. Recently, there are many Computer-supported approaches to enhance efficiency or quality of healthcare service, such as a single application of computer algorithms to optimize and support the workflow of HCP or a mobile service app to help patients realize a better self-management [17]. However, there are few systematic theoretical studies on computer-supported healthcare services and complete process framework studies. To address the problem mentioned above, in this paper, we 1) propose the human rehabilitation movement recognition algorithm, Pose-AMGRU, which helps HCP to monitor stroke patients' state of recovery, and 2) construct a theoretical model of multi-model fusion to discuss the acceptance and adoption of our computer-supported method. Previous studies on the acceptability of relevant technologies are mostly aimed at patients [18, 19]. However, HCP is a group that needs more of such techniques because the efficiency and quality of HCP rehabilitation care management have a more direct impact on patients' rehabilitation and self-management [20].

2 Human Rehabilitation Movement Recognition Algorithm

As shown in Fig. 1, our human rehabilitation movement recognition algorithm is mainly composed of human posture estimation, preprocessing, feature extraction, and classification network, respectively.

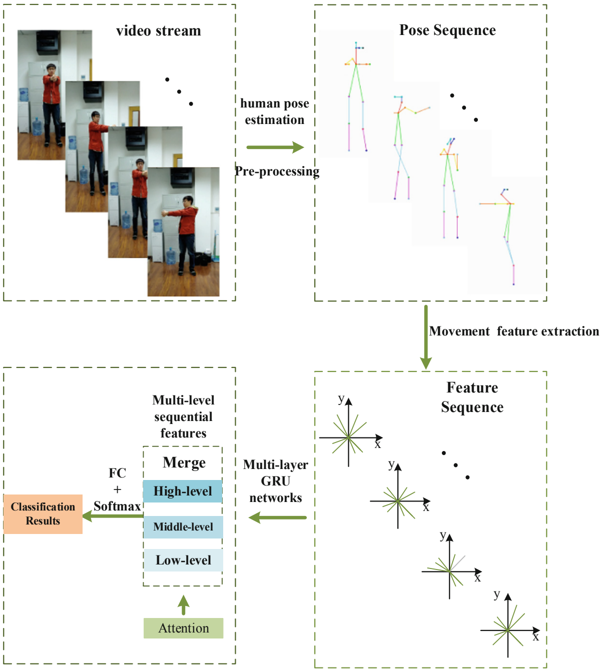
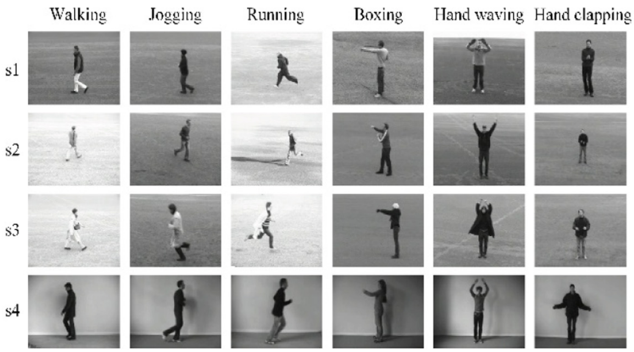


Fig. 1. Framework of pose recognization Pose-AMGRU.

2.1 Data Set

In this paper, a standardized rehabilitation action of stroke patients is referred to [21], and a rehabilitation action dataset is built under the guidance of professional physicians. Meanwhile, we chose an open data set KTH [22] to evaluate the performance of the algorithm. A data instance of KTH is shown in Fig. 2(1).

KTH is a widely-used dataset in the field of motion recognition, consisting of six movements recorded by 25 volunteers, including walking, jogging, running, clapping, waving, and boxing. The dataset consists of 599 videos, which can be subdivided into 2,391 action segments. The videos in KTH, which contain the whole target human body, is a single-person scene that can detect the complete human posture node. Therefore, we choose this dataset to do the comparison experiment.



(1) KTH dataset.

(2) Rehabilitation action dataset.

Fig. 2. Data set.

As shown in Fig. 2(2), our rehabilitation action dataset is collected by ten volunteers in 6 different environments, including a total of 2075 video segments of 6 types of behaviors, with changes in light, background, and distance. The behavior types are divided into five kinds of rehabilitation actions and one kind of daily activity. Daily activities include strolling, stretching, sitting still, and standing still. The video is 15 frames per second and lasts between 7 and 15 s.

2.2 Pose Estimate from Videos

We utilize OpenPose [23] to estimate human pose and to detect skeleton joints from videos. OpenPose is a real-time pose estimation model based on the top-down approach and deep learning, which can detect a human face, trunk, limbs, hand bone points, and maintain speed advantage in multiple scenes, as shown in Fig. 3.

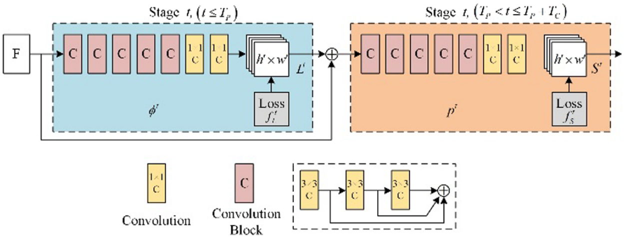


Fig. 3. OpenPose network architecture.

Latest OpenPose network architecture adopts the method of multi-stage prediction. The framework of OpenPose takes the VGG-19 model as the foundation of the top 10 layer network, transforming the input image into feature F, through multiple convolution neural network regression $L(p)$ and $S(p)$. $L(p)$ means PAFs (Part Affinity Fields), which describes the key points in the skeleton $S(p)$, represents the confidence of the joint and describes the position information of the joint. The model divides the prediction process into two different stages, such that the first T_p stage predicts the affinity vector field L^t, and the last T_c stage predicts confidence S^t.

$$L^1 = \phi^1(F), t = 1 \tag{1}$$

$$L^t = \phi^t(F, L^{t-1}), 2 \le t \le T_P \tag{2}$$

After iterations of T_p, the process is repeated for the confidence maps detection, starting from the most updated part affinity field prediction.

$$S^{T_P} = \phi^t(F, L^{T_P}), t = T_P \tag{3}$$

$$S^t = \phi^t(F, L^{T_P}, S^{t-1}), T_P < t \le T_P + T_C \tag{4}$$

At each stage, the results of the previous stage are fused with the original features to preserve both the lower-layer and higher-layer features of the image. After predicting the position and affinity vectors of the joint nodes, we leverage the Hungarian algorithm to perform optimal binary matching for adjacent joint nodes to obtain the pose information belonging to the same body.

2.3 Classification Network

In this paper, we design Pose-AMGRU, an improved GRU classification network [24] to recognize different layers of human pose and to process images. This classification network is based on convolutional neural networks fused with multilevel spatial features, such as SSD [25], DenseNet [26]. At the same time, we combine the attention mechanism to enhance the salience of features. The designed classification network is shown in Fig. 4.

The input of the model is 26 action features extracted from each frame, and the time step size is T. MK is a Masking layer used for supporting variable-length sequences. Time steps with eigenvalues all of 0 are ignored in GRU recursive computation. In the Normalization layer, to speed up the convergence process during training, we implement batch normalization to the learnable parameters with Gaussian distribution of a mean value of 0 and a variance of 1. The number of network neurons in each layer of our three-layer stacked GRU cell network is 64, and the output state h of the underlying cell network at all times is transferred to the next layer. Leveraging attention mechanism to calculate the attention weight of output features of each time step, and the space-time characteristics of each layer are obtained by the weighted sum of output features and attention weight at different moments.

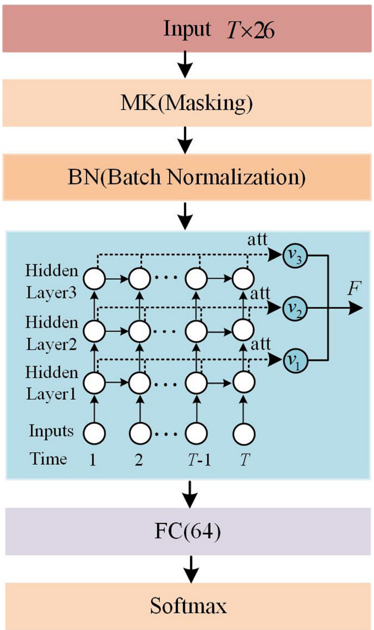


Fig. 4. Improved GRU classification network structure.

3 Construction of Theoretical Model

In this part, we utilize multi-fusion models to construct an acceptance theory, which can verify our computer-supported method is useful and efficient for healthcare management.

3.1 Technology Acceptance Model (TAM)

TAM is a classical model that applies contexts for predicting and evaluating user acceptance of information technology [27]. The model is mainly composed of four levels, which are external stimulus, cognitive, affective and behavioral response, and the validity of the model for considering the users' acceptance of information technology is verified. Many subsequent researches leveraged TAM in their studies [28–31] to explain physicians' decisions to accept telemedicine technology in the healthcare context. Moreover, with the popularity of smartphone applications, Yangil [32] utilized TAM to investigate human motivations affecting an adoption decision for the smartphone among medical doctors and nurses, and they found that HCP's attitude toward the use of smartphone technology is positive. These findings lead us to hypothesize the following:

H1: *Perceived ease of use* is positively associated with HCP's acceptance of computer-supported healthcare delivery.
H2: *Perceived usefulness* is positively associated with HCP's acceptance of computer-supported healthcare delivery.

3.2 Theory of Planned Behavior (TPB)

Realizing the limitation of TAM in explaining differences in subjectively perceived ease of use and usefulness [33], researchers combined TPB with TAM to achieve a better interpretation effect. Many researchers used the TPB to verify the behavior change of HCP or patients. TPB exists in five parts, including attitude, subjective norm, perceived behavioral control, behavior intention, and behavior, and these five variables, and all these components point to the intention of using the technology eventually. Therefore, TPB can be an excellent complement to TAM. Moreover, Patrick [34] leveraged the decomposed TPB model to predict behavioral changes in their patients to utilize TPB more flexible, such that they selected perceived usefulness and perceived ease of use as the mediating variables. Gaston [35] documented the cognitive factors most consistently associated with the prediction of healthcare professionals' intention and behaviors, and they found TPB appears to be an appropriate theory to predict behavior. Therefore, the following assumptions are made:

H3: *Subjective norm* is positively associated with HCP's acceptance of computer-supported healthcare delivery.
H4: *Intention to use* is positively associated with HCP's acceptance of computer-supported healthcare delivery.

3.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh [36] made a statistical difference analysis of previous studies and designed a unified theory of acceptance and use of technology model (UTAUT). UTAUT was formulated with four core determinants of intention and usage, and up to four moderators of key relationships (Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Performance and effort expectancy are the first shape of their belief in the design of the UTAUT theory. Moreover, simple to use is also emphasized in UTAUT, since if HCP gets sufficient technical support to perceive the ease of use of new technology, HCP's acceptance, and motivation will be improved. Similarly, if HCP can get adequate technical support to let them perceive the ease of use of new technology, HCP's acceptance and motivation can be improved. Therefore, we propose the following hypotheses:

H5a: *Expectancy* is positively associated with HCP's perceived ease of use of computer-supported healthcare delivery.
H5b: *Expectancy* is positively associated with HCP's perceived usefulness of computer-supported healthcare delivery.
H6: *Facility conditions* are positively associated with HCP's perceived ease of use of computer-supported healthcare delivery.

Moreover, UTAUT can be utilized with some additional contextual constructs that integrate specific elements of the field of use, such as social factors or personal experience [37, 38]. As shown in Cimperman's study [39], support from managers, peers, and colleagues, or other relevant people can also affect HCP's perceived usefulness of new technology. Therefore, we propose the following hypotheses:

H7: *Social influence* is positively associated with the perceived usefulness of computer-supported healthcare delivery.

However, many previous researches on the acceptance of technology focused on the psychological and behavioral factors of users. Still, there is a limited in-depth discussion of relevant technical factors. Hence, our goal is to propose a technic acceptance theoretical model on real-time human pose estimate technology that can be applied in rehabilitation care management. We select the CMT and SEIPS model fused into our novel model. After the primary interview with HCP in our hospital, we propose the following hypotheses:

H8: *Technical quality* is positively associated with HCP's acceptance of computer-supported healthcare delivery.

3.4 Care Management Technology (CMT)

CMT [40] is used by community health workers (CHWs) and care managers (CMs) working collaboratively to improve risk factor control among recent stroke survivors. It has been proved that CMT can enhance the effectiveness of the CHWs team. CMT is readily accepted by HCP and their managers, as it can support the electronic collection of clinical evaluation data, provide decision support, and obtain patients' risk factor values remotely. But as the researchers said, one weakness of CMT is the slow rate of reaction, that the gap between the electronic technic and HCP who is not familiar with the technical results to the delayed response. Therefore, in our research, we design a real-time computer-supported method to enhance both HCP and patients' experience. Moreover, if technology and HCP's work are well-compactible to each other, HCP's willingness to accept can be positively affected. Therefore, we decomposed hypotheses into two parts—quality and compatibility:

H8: *Quality* is positively associated with HCP's perceived usefulness of computer-supported healthcare delivery.
H9a: *Compatibility* is positively associated with HCP's perceived ease of use of computer-supported healthcare delivery.
H9b: *Compatibility* quality is positively associated with HCP's perceived usefulness of computer-supported healthcare delivery.

3.5 Systems Engineering Initiative for Patient Safety (SEIPS) Model

SEIPS model is anchored within the industrial engineering subspecialty of human factors [41], as it has particularly embraced three core social factors principles: system orientation, person-centeredness, and design-driven improvements [42]. Carayon [41] leveraged the SEIPS model to support processes and outcomes in the system. The model is proposed based on Donabedian's SPO model [43], which examines the clinical processes and outcomes of care. SEIPS emphasized specific individuals in a healthcare scenario, such as HCP in our research, as the center of the work system, thereby enhance and facilitate the performance of HCP as the center of the work system, thus enhance and facilitate the performance of HCP. Many researches used SEIPS to check work error and care quality or optimize healthcare work management [44]. We thus propose the following hypotheses:

H10: *Safety* is positively associated with HCP's perceived usefulness of computer-supported healthcare delivery.

3.6 The Proposed Theoretical Research Model

Based on the above theoretical framework, we propose a conceptual model (shown in Fig. 5) from multi-models by five different hierarchies corresponding to three different levels of problem analysis, including cognitive, technical, and personal levels. The three cognitive factors are self-efficacy, expectancy (including performance expectancy and effort expectancy), and facility conditions. The two technical factors, which are quality, and compatibility, are measured by three factors, including recordable, real-time, and feedback. The three personal factors are social influence, safety, and intention to use. Furthermore, three factors - expectancy, facility conditions, and compatibility affect HCP's perceived ease of use of the computer-supported method. And five factors - expectancy, compatibility, assistant quality, social influence, and safety affect HCP's perceived usefulness of the computer-supported method. Finally, perceived ease of use and usefulness, self-efficacy, and intention to use are the predictive factors to determine HCP's acceptance of the computer-supported method.

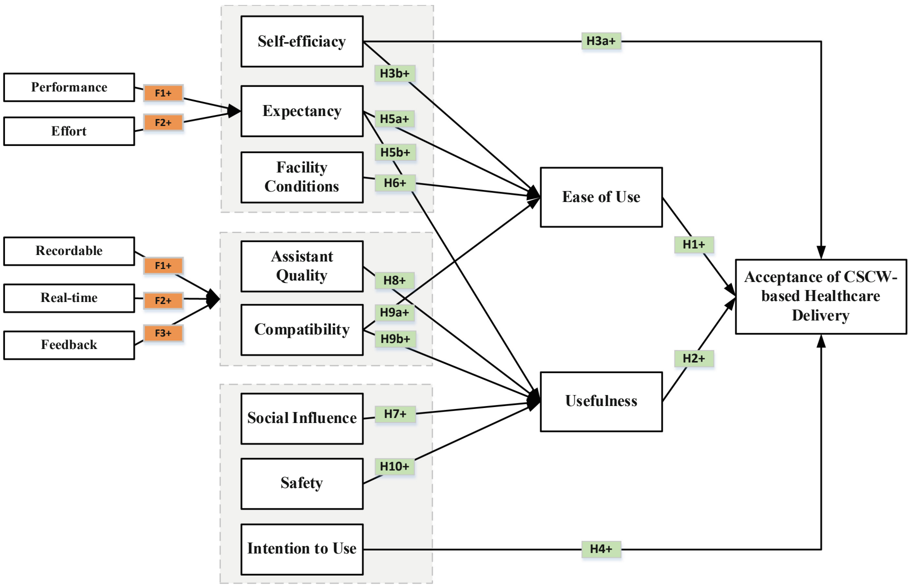


Fig. 5. Theoretical model of technology acceptance.

4 Methods

4.1 Pose-AMGRU Algorithm Application

We implement our Pose-AMGRU algorithm in the rehabilitation departments of two hospitals and two community hospitals and explain how the algorithm works. We use high precision 1080P monocular camera to collect real-time monitoring video streams for online real-time behavior recognition. Smartphones and surveillance cameras are used to collect rehabilitation action data. The critical point information of each skeleton is extracted frame by frame from the video by a multi-human pose estimation method. In the course of the demonstration, the behavior types are divided into three kinds of rehabilitation actions and one kind of regular activities, including upper and lower arm exercises, left and right arm exercises, and sitting up exercises. Regular activities include standing still, sitting still, strolling, stretching, and other daily activities. The resolution of each video is 1280 * 720 or 1920 * 1080, the frame rate is 15 frames per second, and the duration of the video segment is between 8 and 15 s. Based on the traditional method, we have realized the function of real-time online recognition, with an average recognition rate of 90.66%. We can independently deterimine the rehabilitation action of each target in the monitoring flow, and output the position, type, and probability of action in real-time, as shown in Fig. 6.

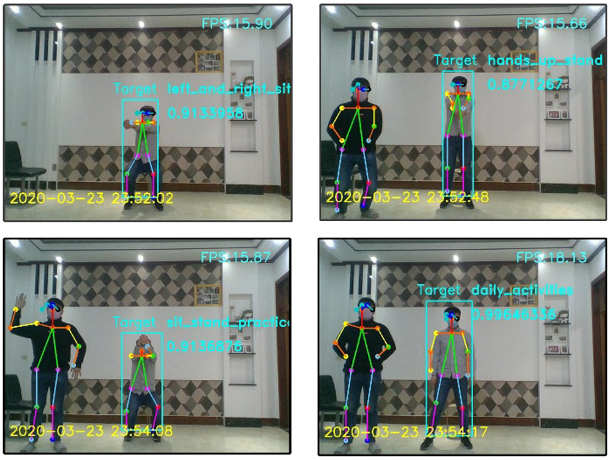


Fig. 6. Real-time online human-pose recognization.

4.2 Conducting a Questionnaire Survey

For our technology acceptance model, we design a questionnaire about influence factors including perceived ease of use (PEOU), perceived usefulness (PU), self-efficiency (SE), expectancy (EXP), facility conditions (FC), compatibility (COM), assistant quality (AQ), social influence (SI), safety (SAF), intention to use (ITU). To ensure the validity of all measures, the measurement items of the latent constructs in the model are developed from previous studies. The detailed items of each construct are listed in Table 2.

The concept of technology acceptability was first proposed in the literature [27], in which the authors gave sufficient reasons to prove that perceived ease of use (PEOU) and perceived usefulness (PU) are the major factors positively associated with user's acceptance of new technology, and hence these two variables are widely used in models related acceptance. Our theoretical model takes inspiration from the questionnaires from the literature [45], and the results show excellent reliability. Literatures [34] summarizes factors that affect user's cognition, and they designed path model of TOE–TAM and a decomposed TPB Model based on TAM, which both mentioned that both PEOU and Self efficacy (SE) could affect users' cognition and mentioned one new concept, ITU, which is another factor could affect acceptance of users directly, in our research, we used questionnaires from the literature [46] and [21]. Moreover, the literatures mentioned above indicated that subjective norm and COM could affect PEOU and PU of users. According to the literature [39], behavioral intention to use is influenced by four primary constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). In the subsequent actual investigation, we include all four indicators in our survey due to the mutual complement between subjective norm and SE. We combined the two variables Performance Expectancy (PE), Effort Expectancy (EE), according to the expert consultation. As for PU, apart from considering the cognitive of users, the quality of new technology also needs to be included. Literature [47] summarized a system that could encourage the active and adaptive role of HCP and hence can deliver high-quality healthcare for patients, and the principle of this work system is simply constructed with man-machine cooperation. We revise the questionnaires from literatures [45] and [48], summarize the variable as assistant quality (AQ). After interviewing with HCP, we find that the healthcare management core is person-centered. This is also in line with the concept of human engineering [42], which mentions that the perception of the behavior of people in daily work has a direct impact on the products, equipment, environment, and safety. There were more than four variables used in our questionnaire at first, and after the reliability test, we removed two low-reliability factors and added the action recognization tools to the AQ-related questions. We use Social influence (SI) according to the research [49]. We revised the questionnaires from the literature [50] to design questions about factor Safety (SAF).

To verify the reliability and validity of the theoretical model, we design a questionnaire about the model of influence factors on a total of 28 variables. Among the 300 sent questionnaires, we obtain 263 valid recycling copies, and we use the Likert scale, which ranges from 1 (strongly disagree) to 5 (strongly agree), to score each question (Table 1).

Table 1. The questionnaire form.

Construct		Variables	Measurement items	Source
Perceived ease of use (PEOU)		PEOU1	It is easy to operate action recognization tools	[27, 45]
		PEOU2	Learning how to use a new action recognization tools would be easy for me	
		PEOU3	It is easy to monitor patients' statements with action recognization tools	
		PEOU4	Interacting with action recognization tools is often frustrating	
Perceived usefulness (PU)		PU1	Appling action recognization tools in my job would enable me to accomplish tasks more quickly	[33]
		PU2	Appling action recognization tools improve my job performance	
		PU3	Appling action recognization tools would make it easier to do my job	
		PU4	Overall, action recognization tools are useful in my job	
Self-efficacy (SE)		SE1	I can use action recognization tools without much time and energy	[21]
		SE2	I get the best value from using action recognization tools Assistant work	
Expectancy (EXP)	Performance (PE)	PE1	I will increase the quality of the output of my job	[36]

(*continued*)

Table 1. (*continued*)

Construct		Variables	Measurement items	Source
		PE2	My coworkers will perceive me as competent	
	Effort (EE)	EE1	I will spend less time on routine job tasks	
		EE2	I will increase the quantity of output for the same amount of effort	
Facility conditions (FC)		FC1	I believe the guidance will be available to me when deciding whether to use action recognization tools	[39]
		FC2	I believe specific persons (or a group) will be available for assistance with action recognization tools difficulties	
Compatibility (COM)		COM1	Using action recognization tools is compatible with all aspects of my work	[34]
		COM2	Using action recognization tools fits into my work style	
		COM3	Using action recognization tools fits with my service needs	
		COM4	Using action recognization tools does not fit with my practice preferences	
Assistant quality (AQ)		AQ1	Action recognization tools can provide useful information about patients' rehabilitation information	[45, 48]

(*continued*)

Table 1. (*continued*)

Construct		Variables	Measurement items	Source
		AQ2	Using action recognization tools will improve the quality of healthcare services in my city	
Social influence (SI)		SI1	People who are essential in assessing my patient care and management think that I should use action recognization tools	[49]
		SI2	People who influence my behavior would think that I should use action recognization tools	
Safety (SAF)		SAF1	A better self-management can be available with action recognization tools	[50]
		SAF2	Action recognization tools can help me to keep a good nurse-patients relationship	
Intention to use (ITU)		ITU1	Given the opportunity, I would like to use action recognization tools	[21, 46]
		ITU2	I would consider using action recognization tools continuously	

5 Results

5.1 Results on Pose-AMGRU Algorithm

In our dataset, skeleton joints are first extracted from the video and preprocessed, and then compared with various timing relation models based on pose features. The running speed is the total predicted time of all test samples, excluding the calculation time of pose estimation and preprocessing.

We test our model both on the KTH dataset and our dataset. At the same time, we compare our model with four other methods tested on KTH. The experimental result is shown in Table 2 and Table 3. The performance of the cyclic neural network series model is superior to the traditional hidden Markov model, while our model achieves the best recognition results; however, our model requires more computation and hence can affect the real-time performance in practice.

Table 2. Results on the KTH dataset.

Methods	Accuracy (%)
3D CNN [51]	90.20
SVM [52]	94.39
YOLO + CNN & LSTM [53]	96.63
CNN + SVM & KNN [54]	98.15
Our model	98.61

Table 3. Results on the rehabilitation action dataset.

Methods	Accuracy (%)	Time (ms)
HMM	77.52	911
RNN	94.06	673
LSTM	98.39	1128
IndRNN	99.19	709
SRU	98.07	741
Our model	100	2633

5.2 Theoretical Model Validation

We use indicator reliability and composite reliability (CR) and to validate the reliability of our model. The CR of PEOU, PU, SE, EXP, FC, COM, AQ, SI, SAF, ITU are 0.8928, 0.8221, 0.8774, 0.8698, 0.9413, 0.8801, 0.9039, 0.9115, 0.9347, respectively. The values are all higher than the recommended value of 0.70 [55].

We use the average variance extracted (AVE) to confirm the convergent validity. The AVE of PEOU, PU, SE, EXP, FC, COM, AQ, SI, SAF, ITU are 0.8100, 0.7511, 0.6930, 0.7054, 0.8870, 0.6588, 0.7836, 0.8243, 0.8330, 1.0000, respectively. All of our values was higher than 0.5, which is the standard threshold.

6 Discussion

6.1 Principal Findings

The purpose of this paper is to use the theoretical derivation process to construct a theoretical model framework of chronic disease healthcare service management. We develop an improved algorithm to enhance healthcare management. From reviewing healthcare literature and exploring the preliminary reliability and validity of our models, we find sufficient evidence to show that the computer-supported method can provide effective theoretical support and exploratory guidance for the development of chronic disease healthcare service management systems in the future.

This study highlights several challenges in previous studies. First, in the research on applying computer algorithms to the field of health services, it is necessary to pay attention to the unique nature of health services – people-centered, such as the HCP satisfaction in this model, which can directly or indirectly affect the service quality and efficiency. Second, studies on healthcare management need to consider multiple impact factors instead of focusing on a single factor. In terms of the effectiveness of use, a multi-model integration method should be adopted to balance the influence of multiple factors and to simplify the workflow.

6.2 Limitations

This study is still in the preliminary exploratory stage. Due to the small sample size of data and the absence of long-term investigation and analysis, further improvement and factor exploration are needed. At the same time, the purpose of this study is to provide theoretical support for the other design of a chronic disease health management system based on computer-supported methods. Therefore, it is necessary to explore and analyze the feasibility of system design and implementation in practice. Furthermore, as this study focused solely on HCPs, it is also essential to include patients as research subjects.

7 Conclusion

This study explores the relationship between computer-supported methods and chronic disease healthcare service management. We improve the algorithm pose-AMGRU and construct a theoretical model to verify the acceptance of our model. We have shown that the computable and multi-model fusion healthcare service model can provide academic guidance for improving the work efficiency and quality of HCP, and provide a theoretical basis for future computer technical support.

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References

1. Enthoven, A.C., Tollen, L.A.: Competition in health care: it takes systems to pursue quality and efficiency. Health Aff. (Millwood). Suppl Web 420–433 (2005)
2. Owens, G.M.: Gender differences in health care expenditures, resource utilization, and quality of care. J. Manag. Care Pharm. **14**, 2–6 (2008)
3. Parekh, A.K., Goodman, R.A., Gordon, C., Koh, H.K.: Managing multiple chronic conditions: a strategic framework for improving health outcomes and quality of life. Public Health Rep. **126**, 460–471 (2011)

4. Wennberg, J.E., Fisher, E.S., Baker, L., Sharp, S.M., Bronner, K.K.: Evaluating the efficiency of california providers in caring for patients with chronic illnesses. Health Aff. (Millwood). Suppl Web 526–543 (2005)
5. Kischka, U., Wade, D.T.: Rehabilitation after stroke. Handb. Cerebrovasc. Dis. Second Ed. Revis. Expand. 231–241 (2004)
6. Jørgensen, H.S., Nakayama, H., Raaschou, H.O., Vive-Larsen, J., Støier, M., Olsen, T.S.: Outcome and time course of recovery in stroke. Part I: outcome. The Copenhagen stroke study. Arch. Phys. Med. Rehabil. **76**, 399–405 (1995)
7. Teasell, R.W., McRae, M.P., Finestone, H.M.: Social issues in the rehabilitation of younger stroke patients. Arch. Phys. Med. Rehabil. **81**, 205–209 (2000)
8. Enthoven, A.C., Vorhaus, C.B.: A vision of quality in health care delivery. Health Aff. **16**, 44–57 (1997)
9. Feder, J., Komisar, H.L., Niefeld, M.: Long-term care in the United States: an overview. Health Aff. **19**, 40–56 (2000). https://doi.org/10.1377/hlthaff.19.3.40
10. LAST: Role of Effective Teamwork and Communication in Delivering Safe, High-Quality Care. Medicine (Baltimore), pp. 15–21 (2007)
11. Waters, T.M., Kaplan, C.M., Graetz, I., Price, M.M., Stevens, L.A., McAneny, B.L.: Patient-centered medical homes in community oncology practices: changes in spending and care quality associated with the COME HOME experience. J. Oncol. Pract. **15**, e56–e64 (2019)
12. Feo, R., Rasmussen, P., Wiechula, R., Conroy, T., Kitson, A.: Developing effective and caring nurse-patient relationships. Nurs. Stand. **31**, 54–63 (2017)
13. Lee, W., Park, J., Park, C.H.: Acceptability of tele-assistive robotic nurse for human-robot collaboration in medical environment, pp. 171–172 (2018)
14. Wang, Z.W., An, Y.: The analysis on the construction of CSCW system and group collaborative mode. Adv. Mater. Res. **756–759**, 2966–2970 (2013)
15. Stahl, G.: Theories of collaborative cognition: foundations for CSCL and CSCW together. In: Goggins, S., Jahnke, I., Wulf, V. (eds.) Computer-Supported Collaborative Learning at the Workplace. Computer-Supported Collaborative Learning Series, vol. 14, pp. 43–63. Springer, Boston (2013). https://doi.org/10.1007/978-1-4614-1740-8_3
16. Reddy, M.C., Bardram, J., Gorman, P.: CSCW research in healthcare: past, present, and future. Work. 615–616 (2010)
17. Hood, M., Wilson, R., Corsica, J., Bradley, L., Chirinos, D., Vivo, A.: What do we know about mobile applications for diabetes self-management? A review of reviews. J. Behav. Med. **39**(6), 981–994 (2016). https://doi.org/10.1007/s10865-016-9765-3
18. Kowitlawakul, Y.: The technology acceptance model: predicting nurses' intention to use telemedicine technology (eICU). CIN - Comput. Informatics Nurs. **29**, 411–418 (2011)
19. Moon, B.C., Chang, H.: Technology acceptance and adoption of innovative smartphone uses among hospital employees. Healthc. Inform. Res. **20**, 304–312 (2014)
20. Matthias, M.S., et al.: Self-management support and communication from nurse care managers compared with primary care physicians: a focus group study of patients with chronic musculoskeletal pain. Pain Manag. Nurs. **11**, 26–34 (2010)
21. Dou, K., et al.: Patients' acceptance of smartphone health technology for chronic disease management: a theoretical model and empirical test. JMIR mHealth uHealth. **5**, e177 (2017)
22. Schüldt, C., Laptev, I., Caputo, B.: Recognizing human actions: a local SVM approach. Proc. - Int. Conf. Pattern Recognit. **3**, 32–36 (2004)
23. Cao, Z., Simon, T., Wei, S.E., Sheikh, Y.: Realtime multi-person 2D pose estimation using part affinity fields. In: Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, vol. 2017-Janua, pp. 1302–1310 (2017)
24. Rowe, N.C., Chan, A.L.: On the properties of neural machine translation: encoder–decoder approaches. In: Proceedings of 2011 International Conference on Image Processing, Computer Vision, Pattern Recognition, IPCV 2011, vol. 1, pp. 317–322 (2011)

25. Liu, W., et al.: SSD: Single shot multibox detector. In: Leibe, B., Matas, J., Sebe, N., Welling, M. (eds.) ECCV 2016. LNCS, vol. 9905, pp. 21–37. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-46448-0_2
26. Huang, G., Liu, Z., Van Der Maaten, L., Weinberger, K.Q.: Densely connected convolutional networks. In: Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017. 2017-Janua, 2261–2269 (2017).
27. Davis, F.D., Bagozzi, R.P., Warshaw, P.R.: User acceptance of computer technology: a comparison of two theoretical models. Manage. Sci. **35**, 982–1003 (1989). https://www.jstor.org/stable/2632151
28. Yarbrough, A.K., Smith, T.B.: A new take on TAM. Med. Care Res. Rev. **64**, 650–672 (2007)
29. Ooi, K.B., Tan, G.W.H.: Mobile technology acceptance model: an investigation using mobile users to explore smartphone credit card. Expert Syst. Appl. **59**, 33–46 (2016)
30. Müller, J.M.: Comparing technology acceptance for autonomous vehicles, battery electric vehicles, and car sharing-a study across Europe, China, and North America. Sustain. **11**, 4333 (2019)
31. Hu, P.J., Chau, P.Y.K., Sheng, O.R.L., Tam, K.Y.: Examining acceptance model using physician of acceptance telemedicine technology. J. Manag. Inf. Syst. **16**, 91–112 (2012)
32. Park, Y., Chen, J.V.: Acceptance and adoption of the innovative use of smartphone. Ind. Manag. Data Syst. **107**, 1349–1365 (2007)
33. Lee, Y., Kozar, K.A., Larsen, K.R.T.: The technology acceptance model: past, present, and future. Commun. Assoc. Inf. Syst. **12**, 50 (2003)
34. Chau, P.Y.K., Hu, P.J.-H.: Information technology acceptance by individual professionals: a model comparison approach. Decis. Sci. **32**, 699–719 (2007)
35. Godin, G., Bélanger-Gravel, A., Eccles, M., Grimshaw, J.: Healthcare professionals' intentions and behaviours: a systematic review of studies based on social cognitive theories. Implement. Sci. **3**, 1–2 (2008)
36. Venkatesh, M., Davis, D.: User acceptance of information technology: toward a unified view. MIS Q. **27**, 425 (2003). https://doi.org/10.2307/30036540
37. Jewer, J.: Patients' intention to use online postings of ED wait times: a modified UTAUT model. Int. J. Med. Inform. **112**, 34–39 (2018)
38. Krishnan, G., Mintz, J., Foreman, A., Hodge, J.C., Krishnan, S.: The acceptance and adoption of transoral robotic surgery in Australia and New Zealand. J. Robot. Surg. **13**(2), 301–307 (2018). https://doi.org/10.1007/s11701-018-0856-8
39. Cimperman, M., Makovec Brenčič, M., Trkman, P.: Analyzing older users' home telehealth services acceptance behavior-applying an Extended UTAUT model. Int. J. Med. Inform. **90**, 22–31 (2016)
40. Ramirez, M., Wu, S., Ryan, G., Towfighi, A., Vickrey, B.G.: Using beta-version mhealth technology for team-based care management to support stroke prevention: an assessment of utility and challenges. JMIR Res. Protoc. **6**, e94 (2017)
41. Carayon, P., et al.: Work system design for patient safety: the SEIPS model. Qual. Saf. Heal. Care. **15**, 50–58 (2006)
42. Dul, J., et al.: A strategy for human factors/ergonomics: developing the discipline and profession. Ergonomics **55**, 377–395 (2012)
43. Rublee, D.A.: The quality of care: how can it be assessed? JAMA J. Am. Med. Assoc. **261**, 1151 (1989)
44. Wooldridge, A.R., Carayon, P., Hundt, A.S., Hoonakker, P.L.T.: SEIPS-based process modeling in primary care. Appl. Ergon. **60**, 240–254 (2017)
45. Zhou, M., Zhao, L., Kong, N., Campy, K.S., Qu, S., Wang, S.: Factors influencing behavior intentions to telehealth by Chinese elderly: an extended TAM model. Int. J. Med. Inform. **126**, 118–127 (2019)

46. Yu, P., Li, H., Gagnon, M.P.: Health IT acceptance factors in long-term care facilities: a cross-sectional survey. Int. J. Med. Inform. **78**, 219–229 (2009)
47. Carayon, P., et al.: Human factors systems approach to healthcare quality and patient safety. Appl. Ergon. **45**, 14–25 (2014)
48. Razmak, J., Bélanger, C.H., Farhan, W.: Development of a techno-humanist model for e-health adoption of innovative technology. Int. J. Med. Inform. **120**, 62–76 (2018)
49. Todd, P.A., Taylor, S.: Understanding information technology usage: a test of competing models. Inf. Syst. Res. **6**, 144–176 (1995). https://www.jstor.org/stable/23011007. Understanding Models Usage
50. Schoot, T., Zuyd, H.: Client-centred care balancing between perspectives (2015)
51. Ji, S., Xu, W., Yang, M., Yu, K.: 3D Convolutional neural networks for human action recognition. IEEE Trans. Pattern Anal. Mach. Intell. **35**, 221–231 (2013)
52. Megrhi, S., Jmal, M., Souidene, W., Beghdadi, A.: Spatio-temporal action localization and detection for human action recognition in big dataset. J. Vis. Commun. Image Represent. **41**, 375–390 (2016)
53. Yuxi, M., Li, T., Dong, X., et al.: Action recognition for intelligent monitoring. J. Image Graph. **24**(02), 128–136 (2019)
54. Sargano, A.B., Wang, X., Angelov, P., Habib, Z.: Human action recognition using transfer learning with deep representations. In: Proceedings of International Joint Conference on Neural Networks, vol. 2017-May, pp. 463–469 (2017)
55. Guo, X., Sun, Y., Wang, N., Peng, Z., Yan, Z.: The dark side of elderly acceptance of preventive mobile health services in China. Electron. Mark. **23**, 49–61 (2013)