Clinical Nursing Risk Assessment and Early Warning System based on Support Vector Machine

¹Prof. V. Sujatha, Dean, &Professor, Department of OBG Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP, Email: <u>Vallerusujatha@gmail.com</u>

²Prof.K. Prasanna, Professor, Department of Child Health Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP, Email: <u>Prasannak@gmail.com</u>

³**Prof. Edna Sweenie J**, Deputy Director & Professor, Department of Child Health Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP, Email: <u>ednasweenie16@gmail.com</u>

⁴Prof.S. Maha Lakshmi, Professor Department of Community Health Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP, Email: <u>Smahalakshmi@gmail.com</u>

⁵**Prof.T. Poornima**, Professor Department of Medical Surgical Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP, Email: <u>poornit@gmail.com</u>

Abstract—Clinical nursing entails several hazards. When the early warning system is really functioning, the threshold that the system sets for assessment is too imprecise, resulting in an excessively lengthy reaction time. Support vector machine-powered clinical nursing is aimed to address this problem. An early warning system and risk assessment. Combine the requirements of the early warning system, design the hardware connection circuit, use the C/S network architecture to obtain clinical care risk data, calculate the clinical care risk value, use support vector machines to set different levels of early warning thresholds, and finally design the risk evaluation signal formation hardware. The system's design has been completed. To conduct experiments, two risk assessment and early warning systems, as well as an experimental system, are employed. The planned early warning system has the fastest reaction time, according to the findings.

Keywords—*Support* vector machine; *Clinical* nursing; *Riskassessment;Early* warning(keywords).

I. INTRODUCTION

Researchers have studied the risk factors for UEX in ICU patients over the last several years and have categorised them into the following: patients, catheters, medical treatment, management and the environment. "Self-extubation by patients is the most common cause of UEX, accounting for 50% to 100% of all UEX instances. UEX is triggered by a person's inability to calm down. ICU patients' emotional state, comfort level, and illness circumstances also have a significant role in UEX's incidence. Current study findings are inconsistent, and no conclusions can be drawn. The majority of the UEX risk variables are based on retrospective study or summaries of academics' experience, thus the findings of the analysis and the real situation are congruent and reliable. There is a certain difference [11], and there is no uniform standard of

UEX risk assessment index system for ICU patients, thus it is required to develop a scientific, objective and specific UEX risk assessment index system for ICU patients.

Preventing injury without prior knowledge or preparation is the goal of early warning, which involves implementing dynamic monitoring during an activity and making real-time assessments and predictions about harmful occurrences. Research objects serve as the basis for an early warning system that gathers relevant data and information and keeps tabs on risk indicators to detect harmful situations before they arise. This system then sends warning signals to those who can make decisions so that preventative steps may be taken. When it comes to responsiveness and responsiveness, the system excels [2-3]. When compared to China's early warning information system, other nations' early warning information management began sooner. Nursing risk early warning systems in the United States and Great Britain are considered to be among the most effective in the world because of their extensive experience with risk early warning systems in other high-risk sectors. Many nations in the 1970s created early warning systems for nursing risk management. These systems included early warning systems for infusion safety, early warning systems for nursing professional risk management and early warning systems for assessing nursing risk. Medical order data extraction, adjuvant medicine and integrated health education are all examples of advanced clinical early warning systems in industrialised nations. Nursing information was first used in China in the late 1980s, and nurse workstation systems were implemented in the 1990s, resulting in continued growth. A number of pioneering and exploratory studies on the building of hospital nursing informatization have since been conducted.

II. RISK ASSESSMENT AND EARLY WARNING HARDWAREDESIGN

A. Hardwaredesignofrisksignalformation

According to the signal flow of the clinical care riskinformation chain, the information storage hardware adopts89C51 single-chip microcomputer, 74HC573 latch, memoryandclockchip.Thecircuitdiagramoftheinformationstoragemoduleis shown in the figurebelow:



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Fig.1.Signal storage hardware schematic

The information storage hardware uses an 89C51 single-chip microcomputer, 74HC573 latch, memory and clock chip, in accordance with the clinical care risk information chain's signal flow. The information storage module's circuit diagram is given in the following figure:

It is clear from the hardware circuit diagram given above that the single-chip microcomputer's external data line is linked to the address line bus in order to implement the dual transmission of scheduling address and scheduling instruction data owing to the constraint of the number of pins employed. The address bus is paralleled with the latch and the latch clock period is set to 5.0 s to guarantee that the scheduling information is effective in various situations.. Continuous input from an effectiveness assessment information source may be managed by a latch control output grounded to maintain constant output state of the latch. A microcontroller's 8-bit data line connects to the data line of the memory to retain the effective position of the geological line at various places. An inverter may be used for connection to the memory's CS terminal, and using the CS signal as the signal source, control a single-chip microcomputer to be in a high-level condition to verify that the memory is being properly stored. The clock chip is operated at a low level to boost the chip's rapid read-write function in order to achieve real-time interchange between single-chip microcomputer and clock chip.

Switch 2 is switched on in the image above, indicating that the formation circuit is in transmission mode and the related information link transmission channels 1 and 2 are disconnected. The level converter then travels via the serial port. The evaluation signal output circuit is switched on, the relay is closed, and pins 1 and 2 produce high potentials when connected to the evaluation system processor.

B. Connection circuit design

Accordingtothehardwarerequirementsoftheevaluationearlywarningsystem, atwostagemethodisused to design an amplification gate. The gate has a built-indual operational amplifier and a low-noise amplifier. Thebandwidth of the dual operational amplifier is set to 30MHz.Eachamplifierisconstantlydebugged,andtheamplification factor of the first-stage amplifier circuit iscontrolledtobe10.Theconnectioncircuitoftheamplifierisshownin thefollowingfigure:



Fig.2.Amplifiercircuit

The evaluation early warning system's amplification gate was designed using a two-stage process, which was dictated by the system's hardware limitations. Dual operational amplifiers and a low-noise amplifier are incorporated within the gate. The dual operating amplifier's bandwidth has been set to 30MHz. One of the most important aspects of the first-stage amplifier circuit is that the amplification factor is set at 10. The following diagram depicts the amplifier's wiring:

Pin 3 of the control dual operational amplifier is connected to pin 5 in the amplifier circuit described above to enhance the amplifier's gain. To prevent amplifier damage from transiently high power, a 5.5 fine resistor is attached to Pin 7. A gating circuit structure with a built-in fourchannel two-way switch is employed to limit the interference of the effectiveness assessment system, and a wave gate setting circuit is constructed. The information link signal controls the circuit gating, and control pins 1 and 2 are shorted. A single-chip timer is then connected.

III. RISK ASSESSMENT AND EARLY WARNING SOFTWARE DESIGN

A. Calculation of clinical nursingrisk value

When the clinical nursing event is poised to undergo a qualitative shift, the monitoring mechanism begins to act. A dynamic game may be used to establish acceptable thresholds for other emergency mechanisms in the following stage and prepare for the continuing development of an event by monitoring the event and using the necessary information gathered [10-11]. A two-tier C/S architecture is employed to communicate with the clinical data monitoring centre during risk detection. The data monitoring centre now operates in two distinct modes. The ZigBee WiFi gateway may be linked to the data monitoring centre as a client, and the data monitoring centre and the ZigBee WiFi gateway can interact with each other to collect and store clinical risk data.

Based on the wireless sensor network's clinical nursing risk assessment data, the application calculates the evaluation coefficient. Client gathers risk data set X based on received assessment data using the architecture described in the figure above, builds a risk analysis model using a risk

matrix and generates a risk matrix for security incidents in which risks lead to different security events. Assign 16 to each of the six possible degrees of probability and effect. This method may be used to calculate risk in a security risk matrix by multiplying the likelihood and impact degree of different security events by the risk's quantitative value:

$$F = \frac{X}{g \times h}$$
(1)

Among them, F represents the risk's value, g represents the risk's potential to cause different safety events, and h represents the risk's degree of effect on the likelihood that various incidents of safety will occur. After doing a risk assessment, the following are the results:

SYSTEM: Research Data Server with HIPAA-protected data						
Threat Event Likelihood Impact		Impact	Risk Level			
1. Loss of Confidentiality	Likely	Severe	HIGH			
2. Loss of Integrity	Possible	Significant	MODERATE			
3. Loss of Availability	Unlikely	Minor	LOW			
		OVERALL RISK:	HIGH			

Table 1 SECURITY RISK LEVEL

IV. SIMULATION EXPERIMENT

A. Experiment preparation

As stated in the table below, you should set up your system's operating environment using the software and hardware setup described there.

	Channel A		Channel B		Doppler
Тар	Relative Delay (ns)	Average Power (dB)	Relative Delay (ns)	Average Power (dB)	Spectrum
1	0	0.0	0	-2.5	Classic
2	310	-1.0	300	0	Classic
3	710	-9.0	8900	-12.8	Classic
4	1090	-10.0	12,900	-10.0	Classic
5	1730	-15.0	17,100	-25.2	Classic
6	2510	-20.0	20,000	-16.0	Classic

Table 2TEST ENVIRONMENT DATA

NLB has been chosen for network deployment to assist the clinical nursing risk assessment and early warning system, as depicted in the accompanying diagram:.



Fig.3. Network topology test

NLB has been chosen for network deployment to assist the clinical nursing risk assessment and early warning system, as depicted in the accompanying diagram:.

B. Experimental results and analysis

These three early warning systems all had lengthier reaction times than one another at various degrees of danger for a single early warning operation, as can be seen from the above table, which compares the three systems' responses to the same alert operation. The reaction time is the longest when the conventional nurse risk early warning system 1 has a danger rating of 4, clocking in at 6.1 seconds. It takes the longest time to respond to early warning instructions when all danger levels are taken into account (on average 5.1s). In terms of reaction time, the conventional nurse risk assessment and early warning system 2 is the worst at risk level 1. The average reaction time to early warning activities in the whole early warning process is roughly 3.7 seconds, which is a comparatively low response time. The reaction time of the article's nursing risk early warning system is the longest at risk level 5, and the average response time for all operations is roughly 1.4s. The risk assessment early warning system described in the article is superior than the two classic risk assessment early warning methods. Early warning operations have the shortest reaction times, making this system ideal for use in clinical care risk assessments and early warning.

The typical early warning system 1 has a throughput rate of around 100 kggs / s at various times, according to the experimental findings of the aforesaid warning system, and the rate value is tiny. A shift in the tiny rate value's direction occurs at around 1.0 s, which is too late to improve the early warning risk level. It is impractical to do an assessment based on data that is both more extensive and more complex. Traditional early warning system 2 has a variable throughput rate at various periods. Average throughput is 150ks per second. Large fluctuations in the system's throughput rate will lead to instability and jamming during assessment and early warning. There are around 350ks/s of throughput in the risk assessment and early warning system described in the article. In the real application process, there is a considerable value rate shift in the direction of improved early warning and assessment of clinical care documents with more data and more practicality.

v. CONCLUSION

Patients, medical treatment, organisation and administration, and equipment all play a role in ensuring patient safety. To ensure patient safety, researchers have shown that the use of early warning systems and early warning information may enhance early warning and quick reaction, as well as save money. Patients' nursing risks may be discovered in a timely way thanks to the use of human and material resources, enabling medical staff to "know, inform, and avoid" these risks, which is to say, "know."

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