



Digital Innovation in Nursing in China

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Johannesburg, South Africa, Oct. 21, 2026

AI-enabled care should be human-centered, nurse-led, and clinically useful.

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Brief Background: Why Digital & AI Nursing Now



Four Forces Driving Digital Nursing

01

Policy: Clear direction

- 💧 **Healthy China 2030**
- 💧 **Promoting High-Quality
Development of Nursing Services**
- 💧 **“Smart Hospital” pilot initiative**



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02

Demand: Large care needs

- 💧 **Aging population**
- 💧 **Acute & NCD patients ↑**
- 💧 **Continuous care needs ↑**



Four Forces Driving Digital Nursing

01 **Policy:** Clear direction

- 💧 Healthy China 2030
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- 💧 “Smart Hospital” pilot initiative

02 **Demand:** Large care needs

- 💧 Aging population
- 💧 Acute & NCD patients ↑
- 💧 Continuous care needs ↑

03 **Realities:** Nurse Shortage

- 💧 6M RNs / 1.4B population
- 💧 Workforce shortage & inequity
- 💧 Need scalable support



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01 **Policy:** Clear direction

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- 💧 Acute & NCD patients ↑
- 💧 Continuous care needs ↑

03 **Realities:** Nurse Shortage

- 💧 6M RNs / 1.4B population
- 💧 Workforce shortage & inequity
- 💧 Need scalable support

04 **Capital:** Rapid growth

- 💧 NIS investment: 8.2B RMB
- 💧 NIS use: 96%–98% hospitals
- 💧 Digital foundation established



Digital Nursing: Gaps & Challenges



**Many nursing
tasks remain
partly or fully
manual (only
~12% of
workflows fully
digitized)**



Digital Nursing: Gaps & Challenges



Many nursing tasks remain partly or fully manual (only ~12% of workflows fully digitized)



Fragmented systems and lack of nurse input in design have led to poor workflow fit



Digital Nursing: Gaps & Challenges



Many nursing tasks remain partly or fully manual (only ~12% of workflows fully digitized)



Fragmented systems and lack of nurse input in design have led to poor workflow fit



Nurse feedback has often been lacking, so digital tools sometimes disrupt rather than streamline care



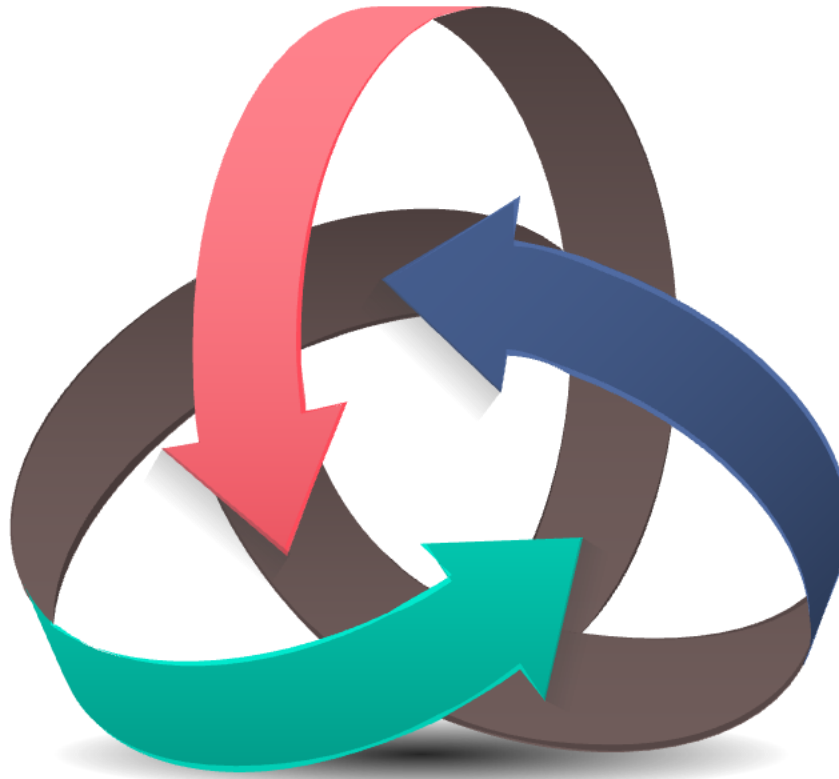
Nurses: the Main Force to Close the Gap



Nurse-led innovation



Digital nursing systems reduce burden and enhance patient care





Nurses: the Main Force to Close the Gap



Nurse-led innovation



Digital nursing systems reduce burden and enhance patient care



Nurses are the primary caregivers



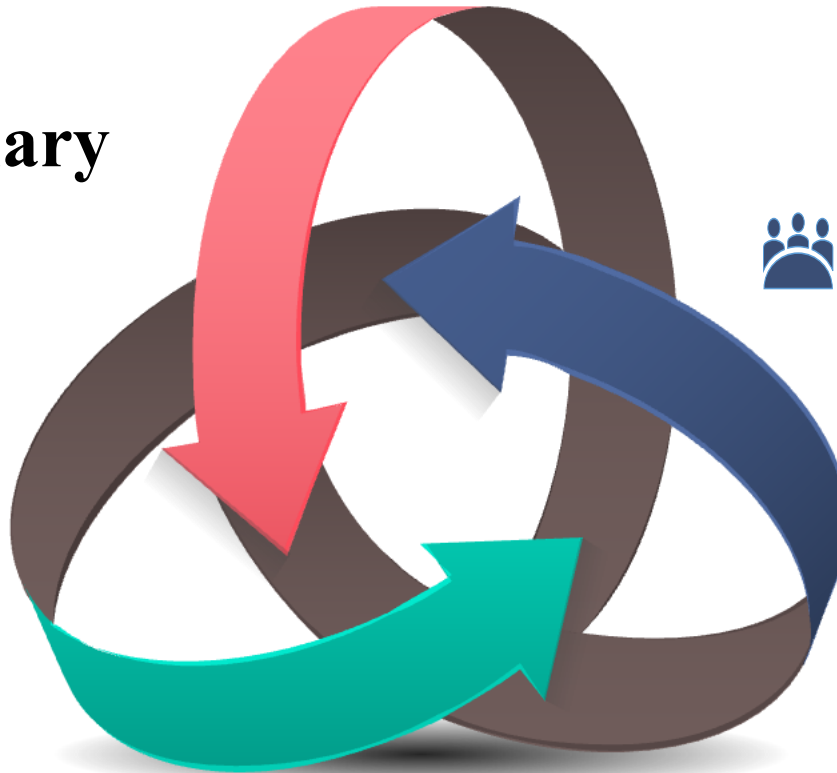
Their frontline insights ensure tech truly fits real care workflows



Involving nurses in system design



Making tools more user-friendly and boosts adoption by staff





Nurse-Led Smart Hospital Nursing Systems



(1) Smart Pediatric IV Medication Safety System

- ❑ Medication dosing errors account for a large proportion of IV-related adverse events, especially under conditions of limited staffing

- 🍒 **Personalized dose**
 - ◆ Doses change with rapid clinical status variation
- 🍒 **Frequent Adjustments**
 - ◆ Doses change with rapid clinical status variation





(1) Smart Pediatric IV Medication Safety System

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Personalized dose

- ◆ Doses change with rapid clinical status variation



Frequent Adjustments

- ◆ Doses change with rapid clinical status variation



Complex Calculation

- ◆ Multiple Medications, High intensity



Error Rate: 28% — 34.5%



Root Cause Analysis

Pre-Admin

Dosage Retrieval and Calculation Errors

医嘱内容	组	规格	频次	剂量	单位	途径	说明
★多巴胺注射液	┐	20mg	qd	60	mg	微泵	5ug/kg/min
5%葡萄糖针	┘	50ml	qd	50	ml	微泵	



Root Cause Analysis

Pre-Admin

Dosage Retrieval and Calculation Errors

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5%葡萄糖针	┘	50ml	qd	50	ml	微泵	

❑ Complex conversion from dose to infusion rate

单位	流速计算公式 (流速)	启用量计算公式 (药物剂量率)
ug/kg.min	流速 = (启用量 * kg * 60) / [(mg/ml) * 1000]	启用量 = [流速 * 1000 * (mg/ml)] / (60 * kg)
ug/kg.h	流速 = (启用量 * kg) / [(mg/ml) * 1000]	启用量 = [流速 * 1000 * (mg/ml)] / kg
mg/kg.h	流速 = (启用量 * kg) / (mg/ml)	启用量 = [流速 * (mg/ml)] / kg
ng/kg.min	流速 = (启用量 * kg * 60) / [(mg/ml) * 1000000]	启用量 = [流速 * 1000000 * (mg/ml)] / (60 * kg)
u/kg.h	流速 = (启用量 * kg) / (u/ml)	启用量 = [流速 * (u/ml)] / kg

Admin Phase

Infusion Pump Setup Errors



One of the top 6 globally recognized medical hazards

Dose-rate order entered as pump rate
→ microinfusion pump errors



Root Cause Analysis

Pre-Admin

Dosage Retrieval and Calculation Errors

医嘱内容	组	规格	频次	剂量	单位	途径	说明
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Dosing or Rate?

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ng/kg.min	流速 = (启用量 * kg * 60) / [(mg/ml) * 1000000]	启用量 = [流速 * 1000000 * (mg/ml)] / (60 * kg)
u/kg.h	流速 = (启用量 * kg) / (u/ml)	启用量 = [流速 * (u/ml)] / kg

❑ Confusing units: e.g., µg/kg/min vs. mL/h

- ❖ “Is the rate 5 µg/kg/min or 5 mL/h?” – A common and dangerous misunderstanding

Admin Phase

Infusion Pump Setup Errors



One of the top 6 globally recognized medical hazards

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→ microinfusion pump errors

Manias E. Medication errors in hospitalised children[J]. J Paediatr Child Health
Tully MP. 用药安全[M]. 科学技术文献出版社, 2019



The Pediatric IV Safety System Developed

Dose Calculation Display

药物名称:	Dopa		
计算类型:	药物启用量 药物走速	5	
药物单位:	ug/kg.min		
患儿体重:	5	kg	
药物剂量:	60	mg +	60 ml
计算结果		重置输入	
结果	药物走速: 1.5ml/h		
分析提示	走速= (启用量*kg*60)/[(mg/ml)*1000]		
护理常规	操作要点	监测要点	
	无	心率、心律、血压*qh	



The Pediatric IV Safety System Developed

Dose Calculation Display

药物名称:

计算类型:

药物单位:

患儿体重: kg

药物剂量: mg + ml

结果: 药物走速: 1.5ml/h

分析提示: 走速= (启用量*kg*60)/[(mg/ml)*1000]

	操作要点	监测要点
护理常规	无	心率、心律、血压*qh

Rate Verification

The Rate Verification interface includes a 7-segment display showing '0.1234' and '5.6789', a diagram of a drip chamber with labels 'a' through 'g', and a verification table.

	a	b	c	d	e	f	g
1							
2	0	✓	✓	✓	✓	✓	✓
3	1		✓	✓			
4	2	✓	✓		✓	✓	✓
5	3	✓	✓	✓	✓		✓
6	4		✓			✓	✓
7	5	✓		✓	✓	✓	✓
8	6	✓		✓	✓	✓	✓
9	7	✓	✓	✓			
10	8	✓	✓	✓	✓	✓	✓
11	9	✓	✓	✓		✓	✓



The Pediatric IV Safety System Developed

Dose Calculation Display

药物名称:

计算类型:

药物单位:

患儿体重: kg

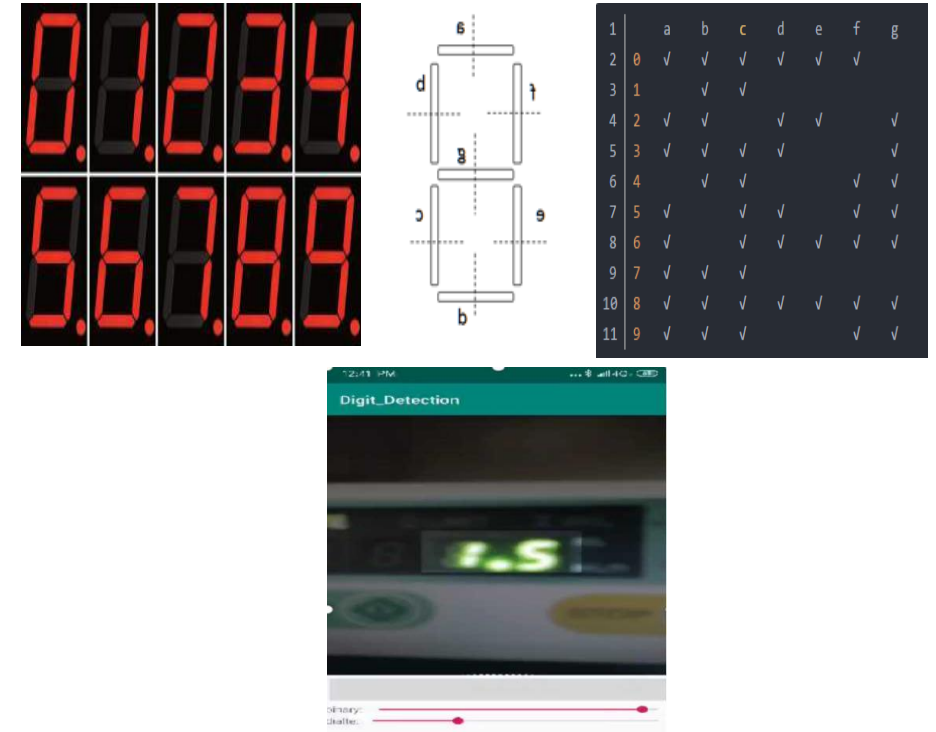
药物剂量: mg + ml

结果: 药物走速: 1.5ml/h

分析提示: 走速= (启用量*kg*60)/[(mg/ml)*1000]

	操作要点	监测要点
护理常规	无	心率、心律、血压*qh

Rate Verification



Clinical Value

Standardized quality & Safe medication

Economic Value

Efficiency↑
Accuracy↑

Social Value

Protects vulnerable populations



Clinical Value

Comparison of Accuracy and Efficiency Between Traditional and New AI-Based Methods n(%)

	DRA	DCA	IRSA	Total Time (sec)	Novice Time (sec)	Experienced Time (sec)
Traditional	141 (94%)	133 (89%)	144 (96%)	17.09±5.22	20.07±5.19	14.11±3.14
New AI-Based	150 (100%)	150 (100%)	150 (100%)	15.15±2.74	15.85±2.79	14.13±2.66
χ^2 Value	9.278	18.021	6.122	3.451	5.459	-0.038
P Value	0.003	< 0.001	0.03	0.001	< 0.001	0.970

Note: DRA = Dose Retrieval Accuracy; DCA = Dose Calculation Accuracy; IRSA = Infusion Rate Setting Accuracy



Clinical Value

Comparison of Accuracy and Efficiency Between Traditional and New AI-Based Methods n(%)

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χ^2 Value	9.278	18.021	6.122	3.451	5.459	-0.038
P Value	0.003	< 0.001	0.03	0.001	< 0.001	0.970

Note: DRA = Dose Retrieval Accuracy; DCA = Dose Calculation Accuracy; IRSA = Infusion Rate Setting Accuracy

Accuracy↑

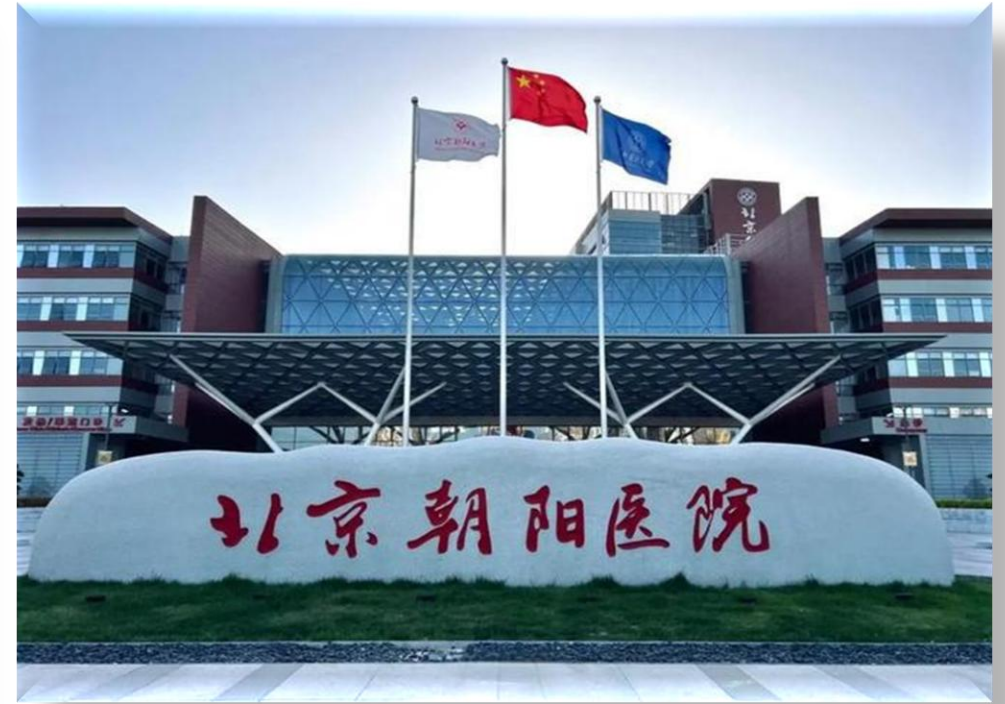
Efficiency↑

Nursing Time Saved

For every 10,000 infusion operations, This system saves approximately **6.95 hours** of nursing labor.



(2) AI-based Delirium Nursing System (AI-AntiDelirium)





(2) AI-based Delirium Nursing System (AI-AntiDelirium)

Background

ICU Delirium



**Incidence Varies
20%~87%**

Prolonged Mech Ventilation

Prolonged In-hospital Stay

Complication Increased

Mortality Increased

Medical Costs Increased



(2) AI-based Delirium Nursing System (AI-AntiDelirium)

Background

ICU Delirium



Incidence Varies
20%~87%

Prolonged Mech Ventilation

Prolonged In-hospital Stay

Complication Increased

Mortality Increased

Medical Costs Increased

Pharmacological

Non-
Pharmacological
ABCDEF bundle

Complicated

Poor Adherence

Poor
Effectiveness



Modules of AI-AntiDelirium

Delirium Assessment



Tools

Items

Results



Checklist



Reminder



History

Intervention Checklist

Risk Factor Assessment



Assess Form

Results

History

Initial Status Care Plan

History

AI-Generated Care Plan



Delirium Assessment



Tools



Items



Results



Risk Factor Assessment

返回 危险因素评估单

1008床 张山山 25岁

2020/03/31 15:56

危险因素评估表 2020-04-01 15:42

内容	结果
疼痛评估:	3
使用约束:	☒ 无 ☐ 有
机械通气:	☒ 无 ☐ 有
留置尿管:	☒ 无 ☐ 有

目前用药情况: 苯二氮卓类镇静催眠药

☒ 无 ☐ 狄喜班 ☐ 密达伦索 ☐ 氯化钠 ☐ 其他

Richard Campbell 睡眠问卷得分: 6

家属陪伴: ☒ 无 ☐ 有

确认

Assess Form

返回 谵妄危险因素 历史2

1008床 张山山 25岁

2020/03/31 15:56

谵妄发生风险预测值 2020-04-27

患者王小波, 2020-04-27日
目前的谵妄发生风险预测值为 9.9%

修改 确认

危险因素评估结果 2020-04-27

1. 视力减退
2. 疼痛
3. 感染
4. 机械通气
5. 留置尿管 (≥24h)
6. 视力减退
7. 疼痛
8. 感染
9. 机械通气

谵妄评估 危险因素 护理计划 执行单

Results



History



Initial Status screen showing patient information (1008床, 张山山, 25岁) and a list of nursing measures (护理措施) for 2020-04-01. The screen includes a '返回' (Back) button, a '历史5' (History 5) button, and a '导出' (Export) button. The nursing measures are listed in a table with columns for '护理措施' (Nursing Measures) and '执行频率' (Execution Frequency).

Initial Status

Care Plan screen showing a detailed list of nursing measures (护理措施) and their frequencies (执行频率) for 2020-04-01. The screen includes a '返回' (Back) button, a '历史5' (History 5) button, and a '导出' (Export) button. The nursing measures are listed in a table with columns for '护理措施' (Nursing Measures) and '执行频率' (Execution Frequency).

Care Plan

History screen showing a calendar view of nursing measures (护理措施) and their frequencies (执行频率) for 2020-04-01. The screen includes a '返回' (Back) button, a '历史5' (History 5) button, and a '导出' (Export) button. The nursing measures are listed in a table with columns for '护理措施' (Nursing Measures) and '执行频率' (Execution Frequency).

History

AI-Generated Care Plan

Checklist screen showing a list of nursing measures (护理措施) and their frequencies (执行频率) for 2020-04-01. The screen includes a '返回' (Back) button, a '历史5' (History 5) button, and a '导出' (Export) button. The nursing measures are listed in a table with columns for '时间' (Time), '护理措施' (Nursing Measures), and '执行人' (Executor).

Checklist

Reminder screen showing a clock (08:34) and a list of nursing measures (护理措施) for 2020-04-01. The screen includes a '返回' (Back) button, a '历史5' (History 5) button, and a '导出' (Export) button. The nursing measures are listed in a table with columns for '时间' (Time), '护理措施' (Nursing Measures), and '执行人' (Executor).

Reminder

History screen showing a bar chart of nursing measures (护理措施) and their frequencies (执行频率) for 2020-04-01. The screen includes a '返回' (Back) button, a '历史5' (History 5) button, and a '导出' (Export) button. The nursing measures are listed in a table with columns for '时间' (Time), '护理措施' (Nursing Measures), and '执行人' (Executor).

History

Intervention Checklist



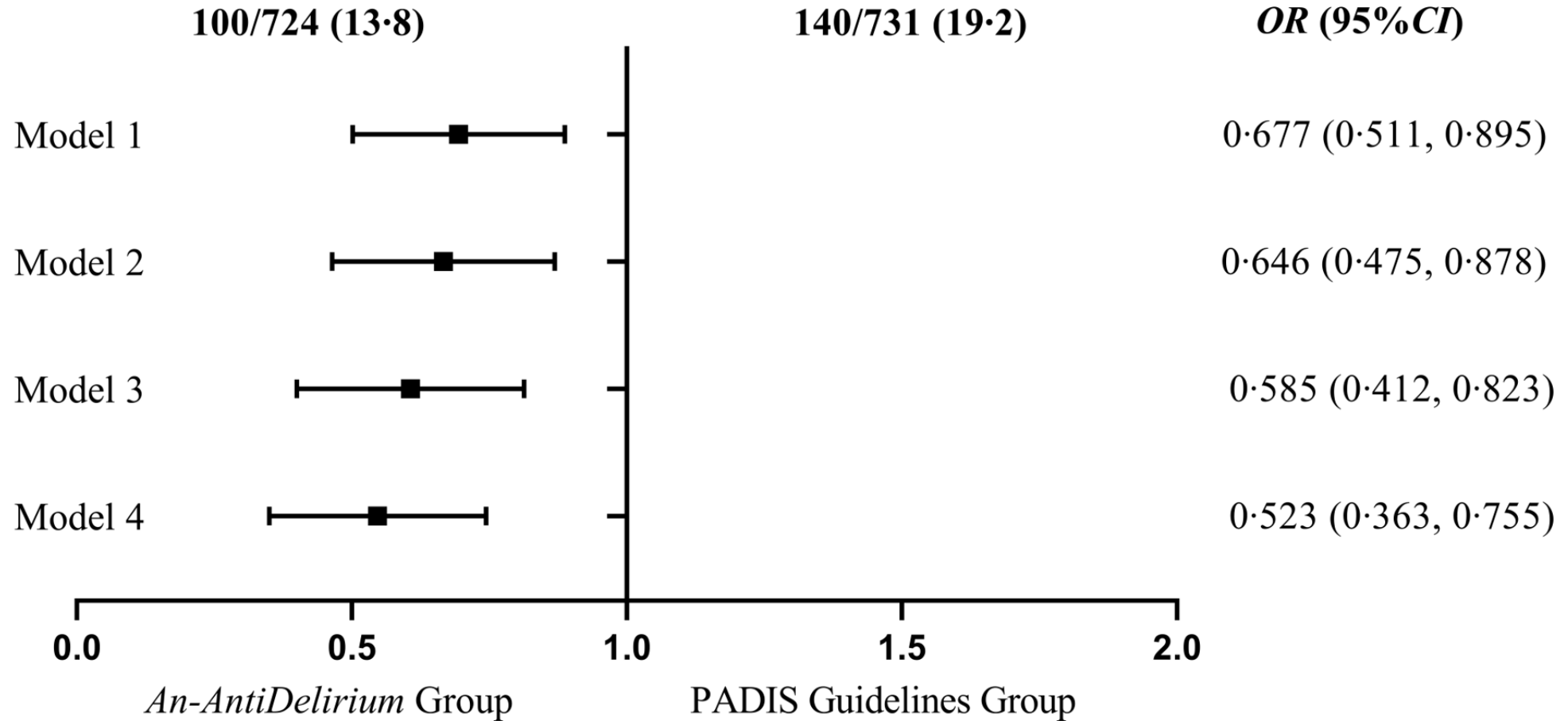
Accuracy of the Smart Delirium Assessment Tool (iMoBILE)

Rater	Positive N (%)	Sensitivity (95% CI)	Specificity (95% CI)
Phase I (n=181)			
Nurse Investigator A	68 (37.6%)	95.2 (92.0-98.5)	93.3 (88.3-96.3)
Nurse Investigator B	67 (37.0%)	93.7 (90.0-97.4)	93.2 (88.3-96.3)
Phase II (n=192)			
Bedside Nurses	55(28.6%)	86.7(81.9-91.5)	97.7(95.6-99.8)



The AI-AntiDelirium Reduces Incidence

Incidence of ICU Delirium (%)



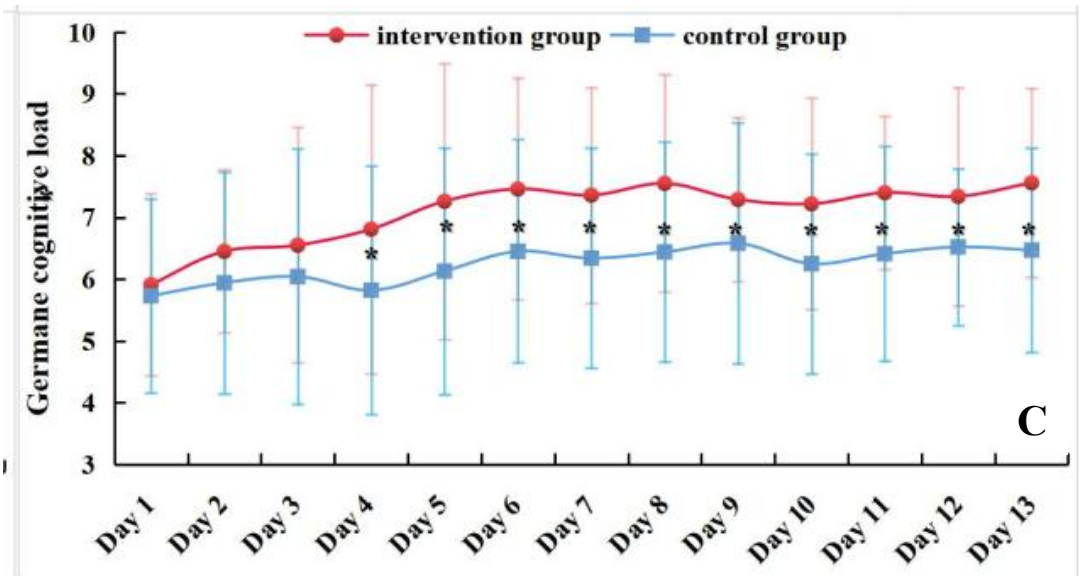
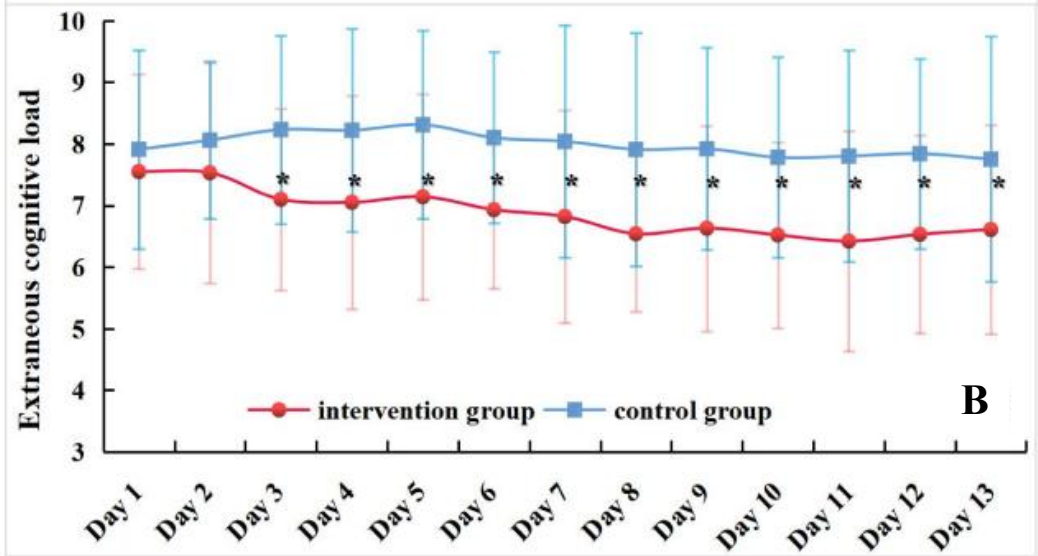
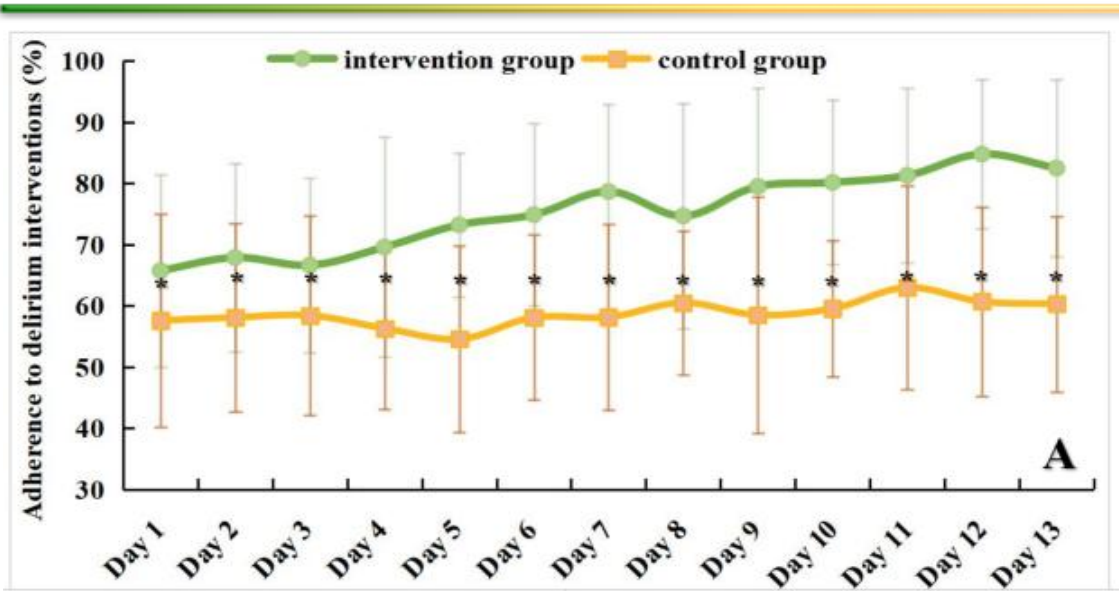


The AI-AntiDelirium Significantly Improved Outcomes

Outcome	Mean (SD) [No. of participants]		Relative Effect of AI-AntiDelirium (95% CI)	P value
	Intervention Group	Control Group		
Duration of ICU delirium, days ^a	1.9 (0.9) [100]	2.3 (1.1) [140]	-0.52 (-0.83, -0.22)	.001
Length of ICU stays, days ^a	2.9 (1.8) [724]	3.0 (1.8) [731]	-0.16 (-0.34, 0.03)	.10
Length of hospital stays, days ^a	11.9 (4.0) [724]	12.6 (4.2) [731]	-0.80 (-1.29, -0.30)	.002
MMSE scores at ICU discharge ^a	25.9 (3.8) [694]	24.9 (4.0) [727]	0.16 (-0.27, 0.60)	.46
Barthel Index at ICU discharge ^a	42.5 (19.7) [694]	34.3 (9.9) [727]	5.34 (3.63, 7.05)	<.001
severe (≤ 40) to severe (≤ 40) dependence, No. (%) ^b	462 (73.8) [626]	628 (88.5) [710]	0.29 (0.19, 0.43)	<.001
severe (≤ 40) to moderate (41-60) dependence, No. (%) ^b	78 (12.5) [626]	70 (9.9) [710]	2.52 (1.55, 4.09)	<.001
severe (≤ 40) to mild (≥ 61) dependence, No. (%) ^b	86 (13.7) [626]	12 (1.7) [710]	3.01 (1.42, 6.38)	.004
ICU mortality, No. (%) ^c	8 (1.1) [696]	6 (0.8) [728]	1.86 (0.32, 10.69)	.49
Unplanned extubation, No. (%) ^b	3 (0.4) [696]	2 (0.3) [728]	1.13 (0.18, 7.17)	.90

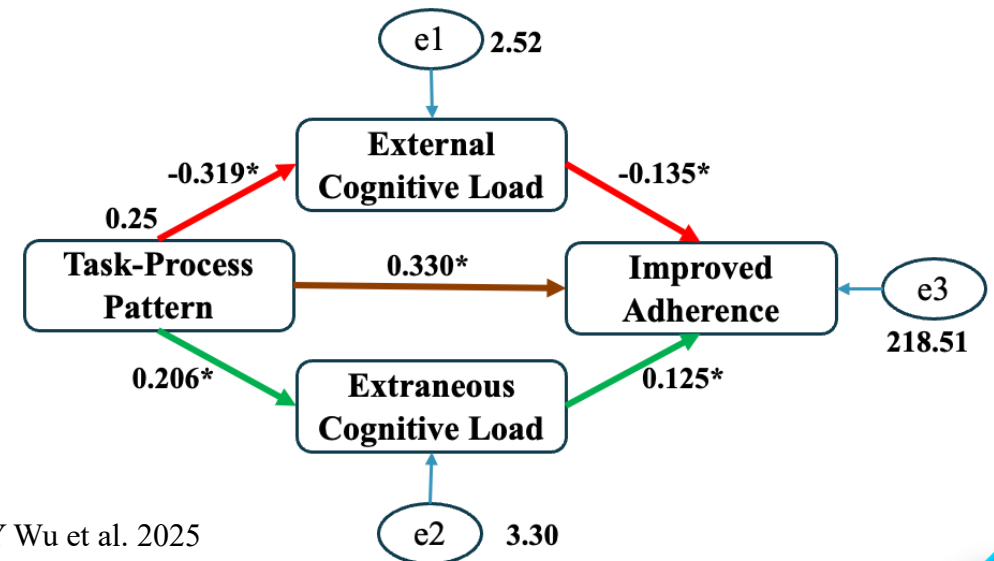
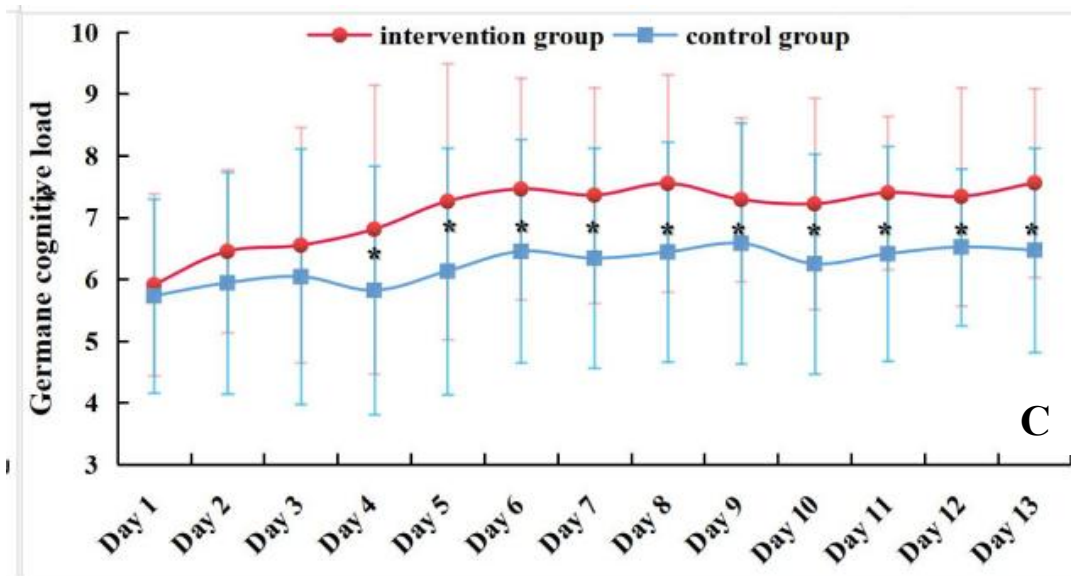
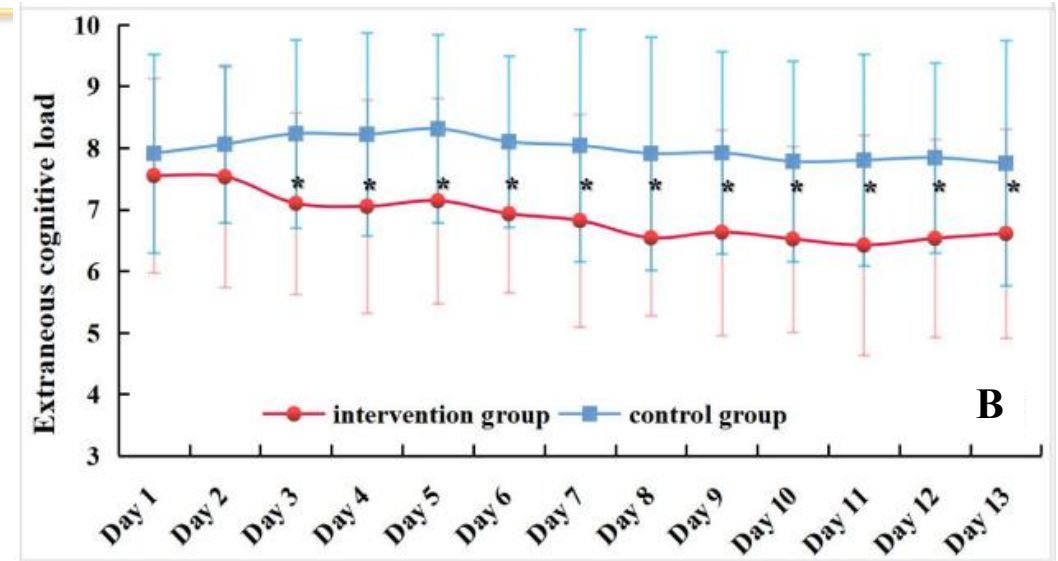
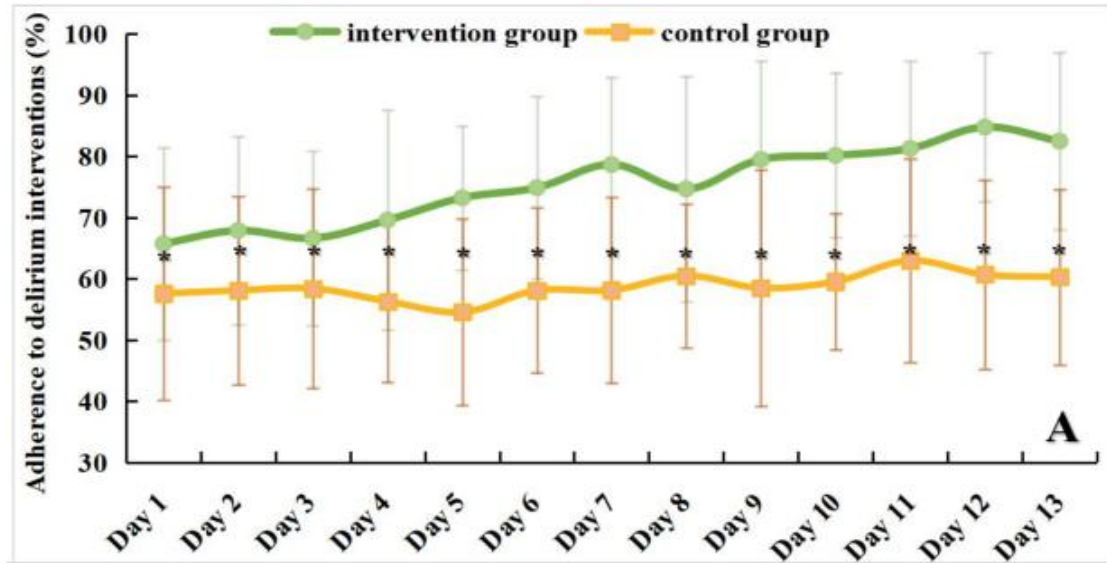


Mechanism in Reducing Incidence





Mechanism in Reducing Incidence





LLM Applications in Nursing

Outpatient reception via collaboration between nurses and a large language model: a randomized controlled trial

Received: 17 December 2023

Accepted: 20 June 2024

Published online: 15 July 2024



Check for updates

Peixing Wan^{1,2,6}, Zigeng Huang^{1,6}, Wenjun Tang¹, Yulan Nie³, Dajun Pei⁴,
Shaofen Deng³, Jing Chen⁴, Yizhi Zhou³, Hongru Duan³, Qingyu Chen ^{5,7} &
Erping Long ^{1,7}

Reception is an essential process for patients seeking medical care and a critical component influencing the healthcare experience. However, current communication systems rely mainly on human efforts, which are both



Objectives



**To collect a large-scale corpus
of real-world Nurse-Patient
conversations**

01

02

**To develop a Site-Specific
Prompt Engineering Chatbot
(SSPEC)**

03

04





Objectives



To collect a large-scale corpus of real-world Nurse-Patient conversations



To develop a Site-Specific Prompt Engineering Chatbot (SSPEC)



To compare the performance of SSPEC and nurses in answering patient queries in a simulated environment

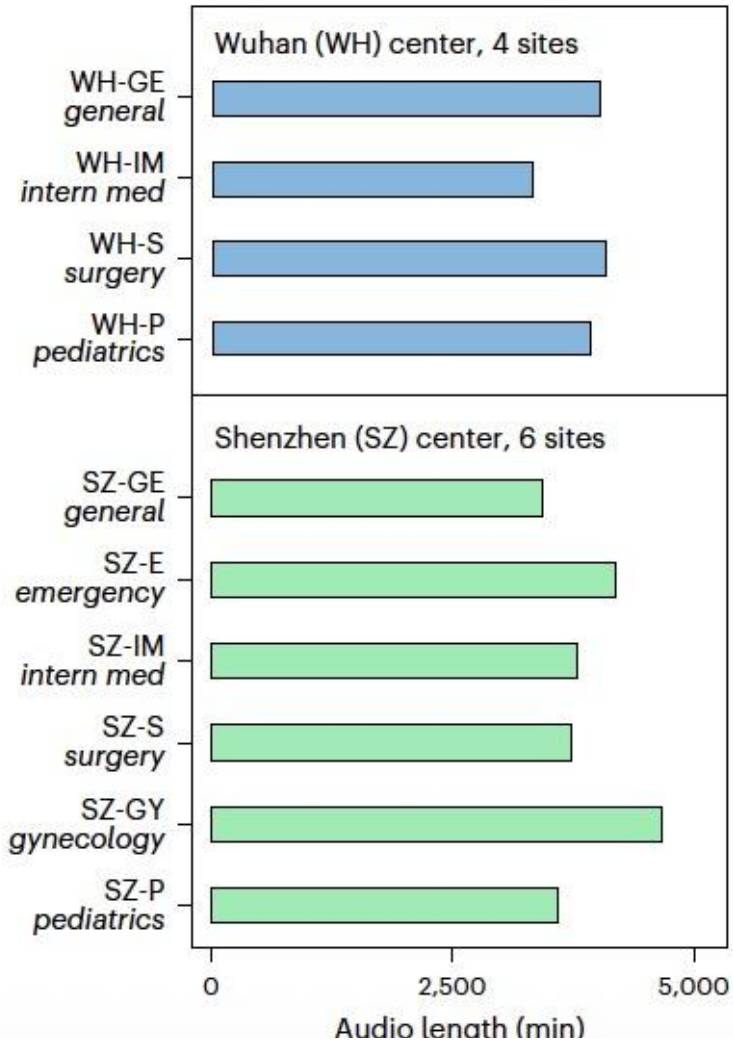


To establish a nurse–SSPEC collaboration model and evaluate its effectiveness through RCT

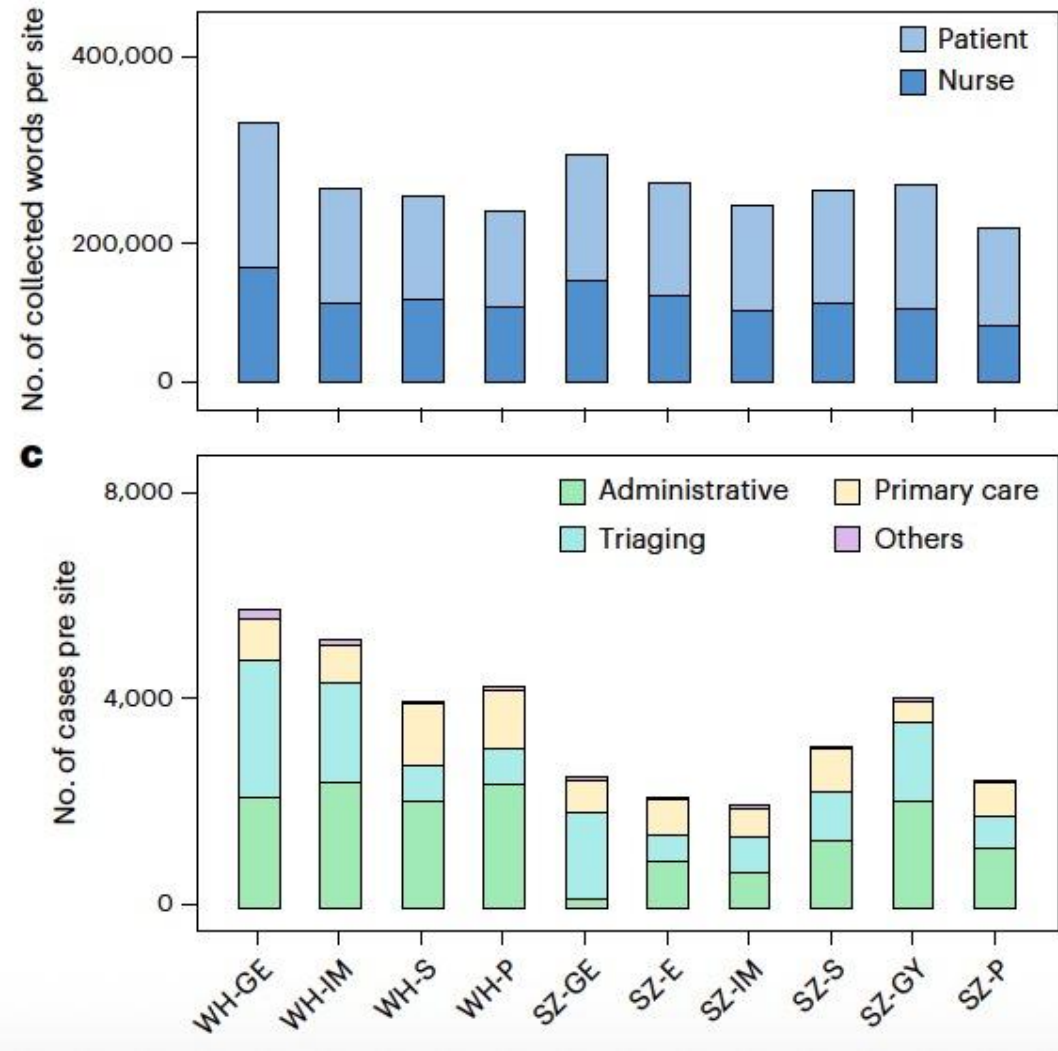




Dataset Collection Overview



Duration of voice data collection (min)

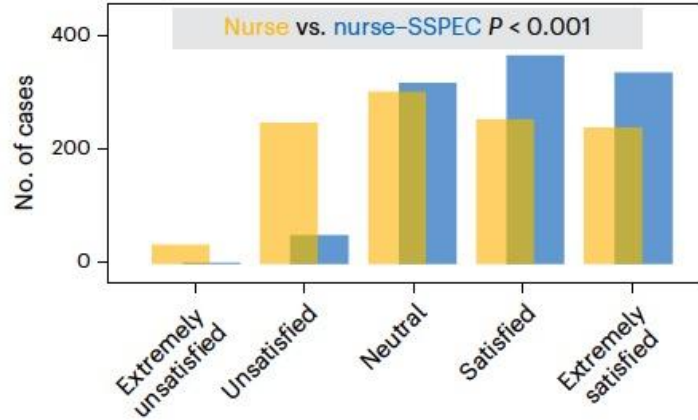


Total: 35,418 recorded nurse–patient dialogues



Performance of Nurses VS Nurse-SSPEC

a



b

Has the use of SSPEC reduced your workload?

- 19 of 20 (95%) nurses think YES

Has the use of SSPEC alleviated your stress?

- 18 of 20 (90%) nurses think YES

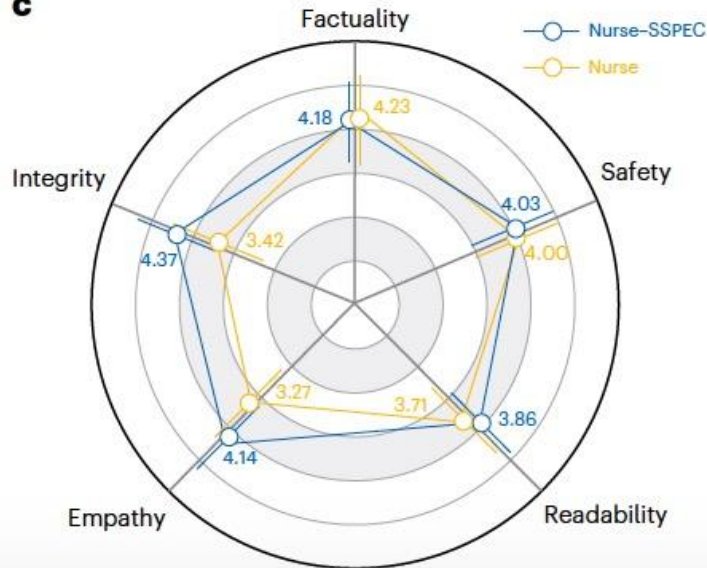
Which working mode do you prefer?

- 19 of 20 (95%) nurses select SSPEC

Primary Outcome

Patients satisfaction is higher with nurse-SSPEC (3.91 ± 0.90) than nurses (3.39 ± 1.15 , $P < 0.001$)

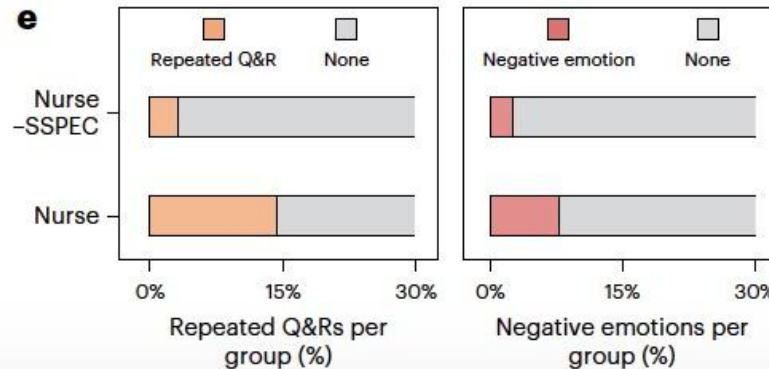
c



d

		Alert system	
		Uncertain	Certain
Actual	Uncertain	TP = 34	FP = 2
	Certain	FN = 6	TN = 1,038

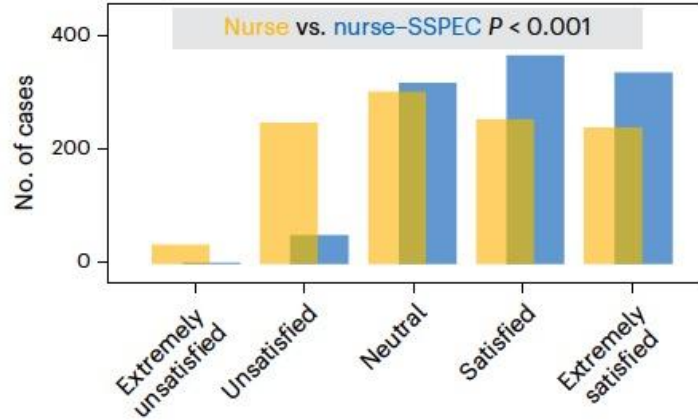
e





Performance of Nurses VS Nurse-SSPEC

a



b

Has the use of SSPEC reduced your workload?

- 19 of 20 (95%) nurses think YES

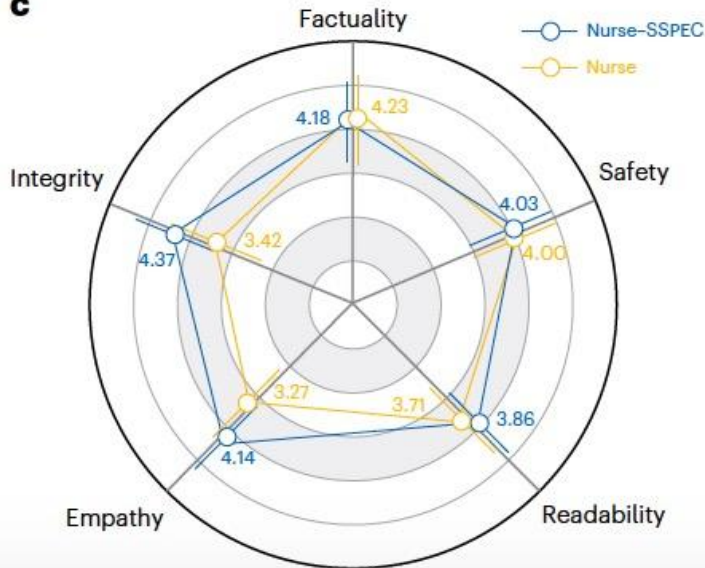
Has the use of SSPEC alleviated your stress?

- 18 of 20 (90%) nurses think YES

Which working mode do you prefer?

- 19 of 20 (95%) nurses select SSPEC

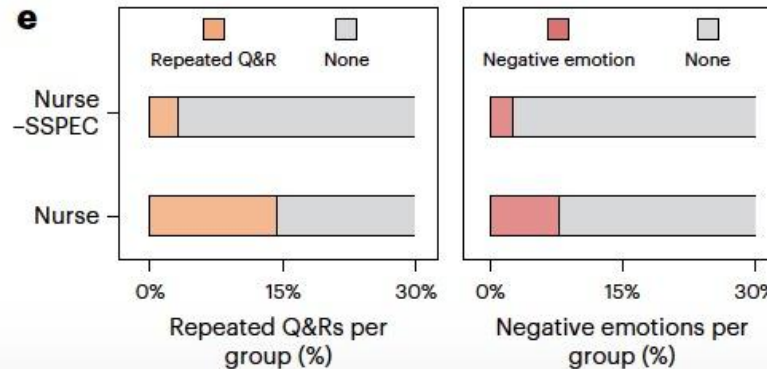
c



d

		Alert system	
		Uncertain	Certain
Actual	Uncertain	TP = 34	FP = 2
	Certain	FN = 6	TN = 1,038

e



Primary Outcome

Patients satisfaction is higher with nurse-SSPEC (3.91 ± 0.90) than nurses (3.39 ± 1.15 , $P < 0.001$)

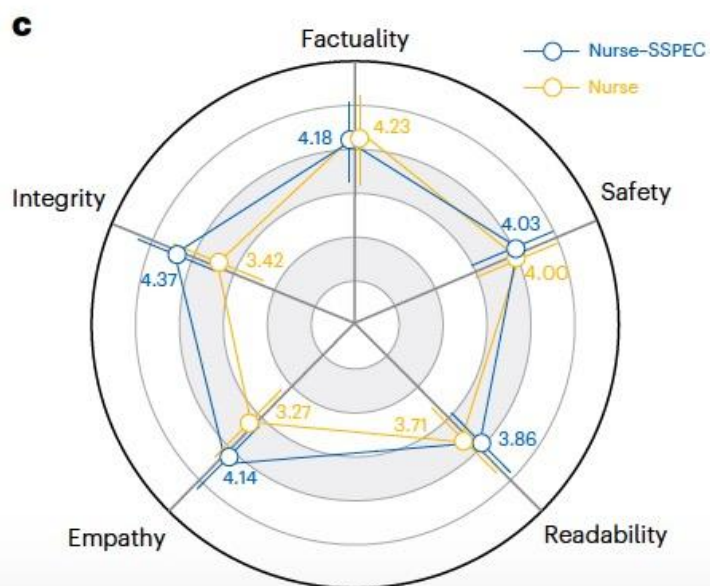
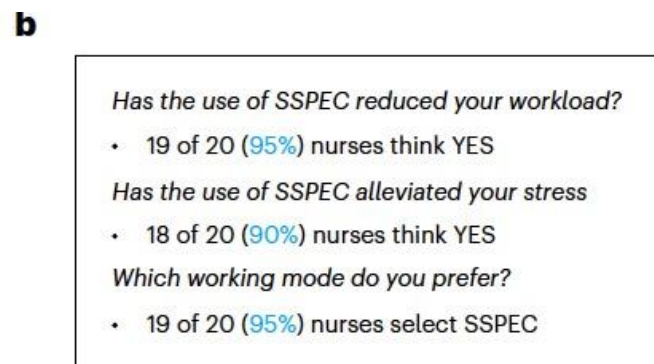
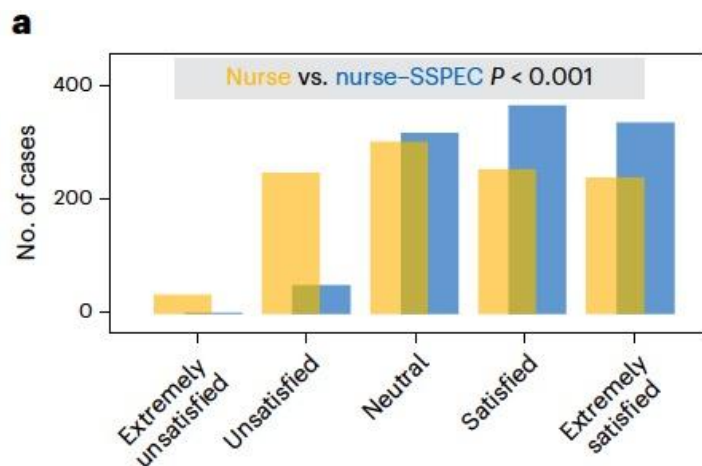
Secondary Outcomes

Redundant Q&A rate ↓: 3.2% vs. 14.4% ($P < 0.001$)

Proportion of negative emotions ↓: 2.4% vs. 7.8% ($P < 0.001$)

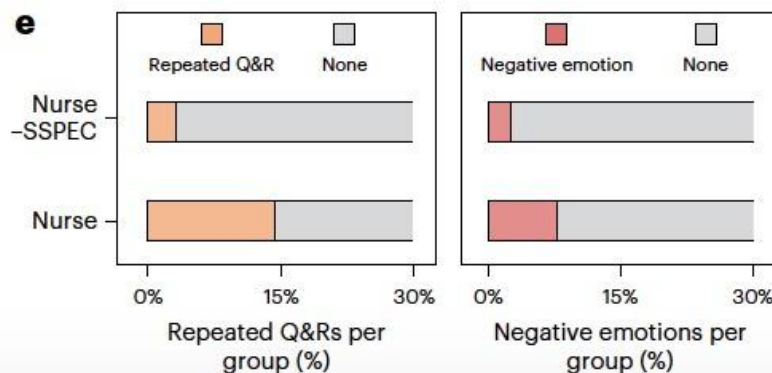


Performance of Nurses VS Nurse-SSPEC



d

		Alert system	
		Uncertain	Certain
Actual	Uncertain	TP = 34	FP = 2
	Certain	FN = 6	TN = 1,038



Primary Outcome

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Secondary Outcomes

Redundant Q&A rate ↓: 3.2% vs. 14.4% ($P < 0.001$)

Proportion of negative emotions ↓: 2.4% vs. 7.8% ($P < 0.001$)

Overall answer quality improved

Completeness

Consistency

Comprehensibility

(2) LLM-Powered Dysphagia Screening With Multimodal Physiological Signal Analysis and Medically Informed Prompts

Yanxia Liu^{ID}, Le Wang^{ID}, Lian Wang^{ID}, and Xiaomei Wei

Abstract—Dysphagia is a common complication among stroke patients, significantly increasing the risk of aspiration pneumonia, malnutrition, and mortality. Traditional diagnostic techniques, such as bedside screening and videofluoroscopic swallowing studies, are limited by accessibility, reliability, and invasiveness. To address the challenges of limited data and complex multimodal signals, we propose a large language model (LLM)-based framework for dysphagia screening. This framework integrates multimodal physiological signals—including laryngeal vibration, nasal airflow, and swallowing sound—and leverages the

Index Terms—Dysphagia screening, large language models, time-series analysis, prompt learning.

I. INTRODUCTION

DYSPHAGIA, one of the most common complications among stroke patients, is defined as a symptom characterized by difficulty in forming or moving the alimentary bolus safely from the mouth to the stomach [1]. Studies have shown that approximately 37%–78% of stroke patients



The Clinical Gap in Dysphagia Screening

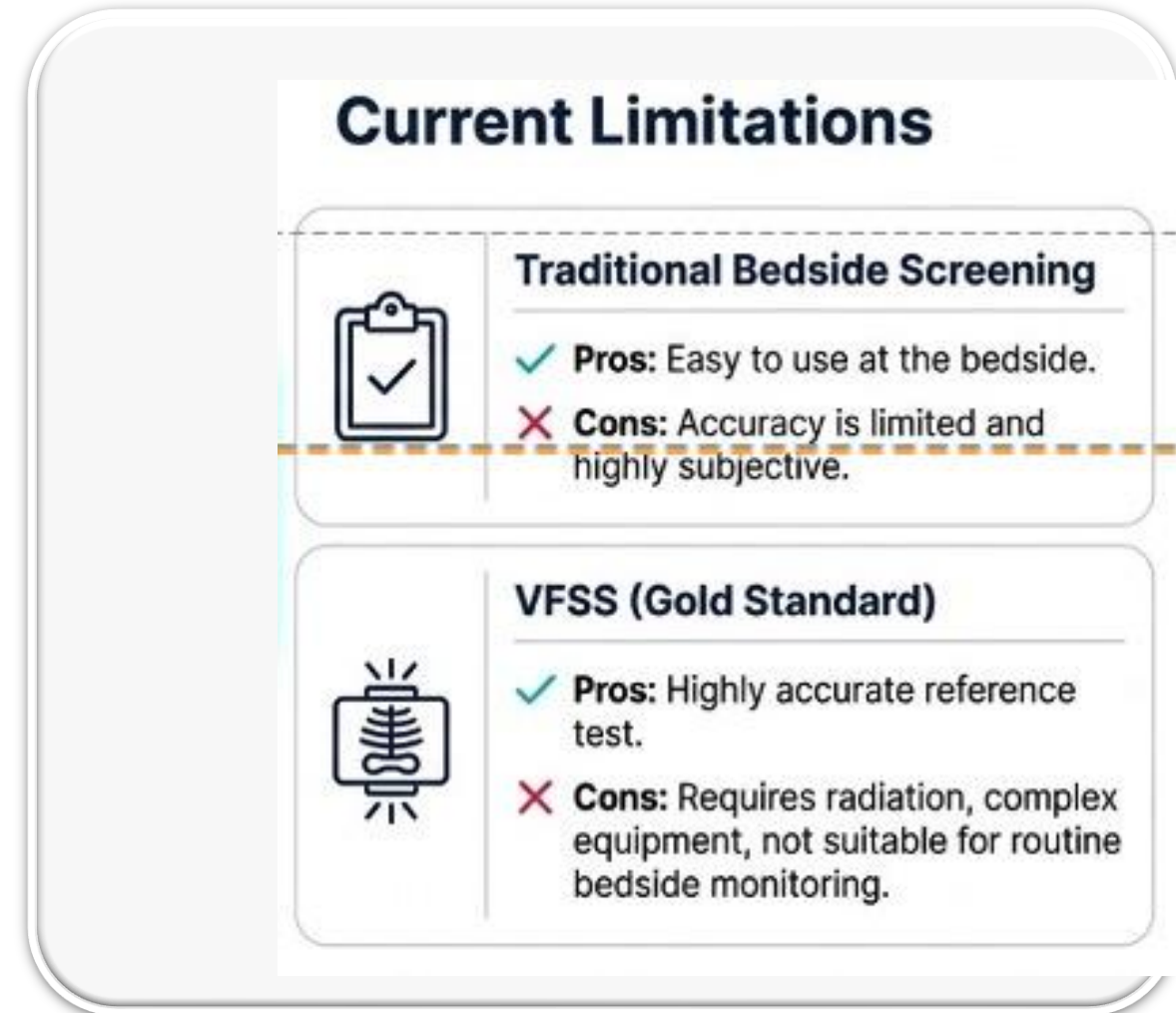
Major Safety Issue for Post-Stroke Care





The Clinical Gap in Dysphagia Screening

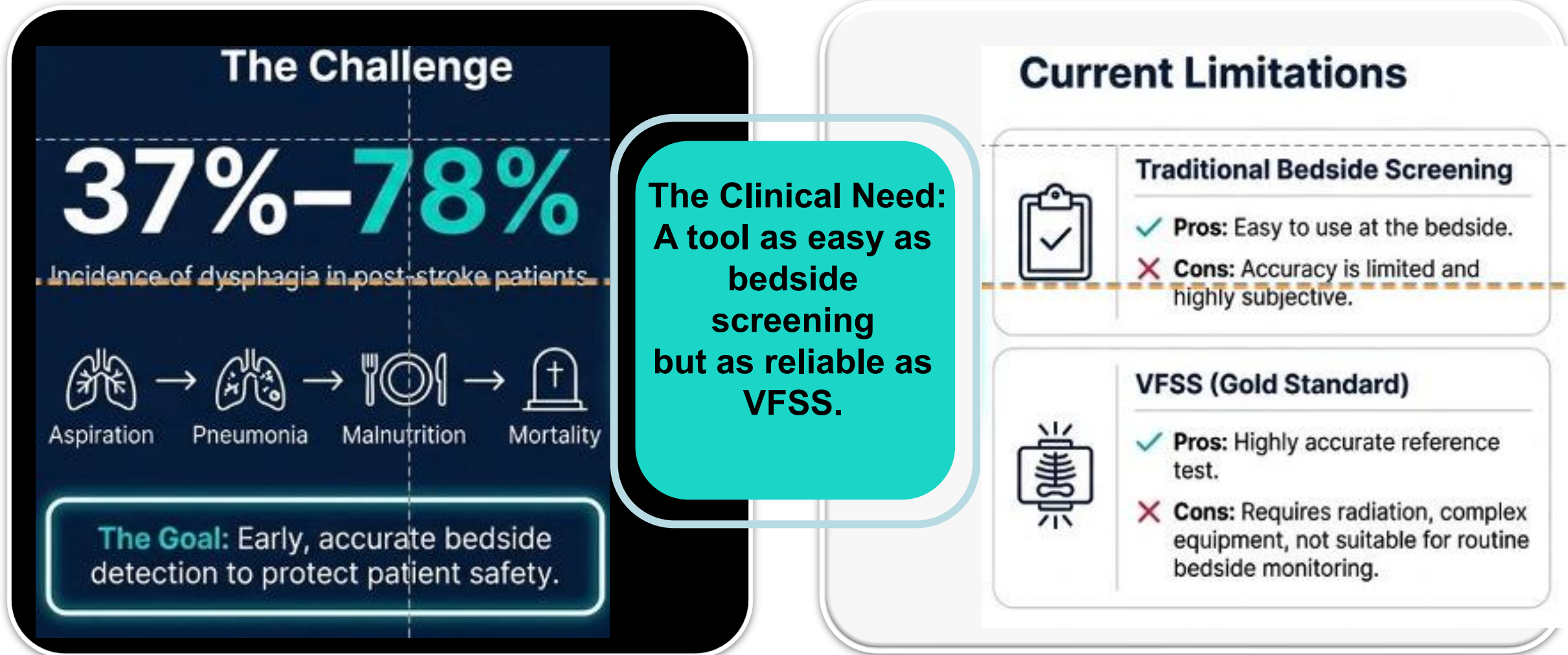
Major Safety Issue for Post-Stroke Care





The Clinical Gap in Dysphagia Screening

Major Safety Issue for Post-Stroke Care





Letting AI “Hear & Sense” Swallow at the Bedside

1. Non-Invasive Data Collection



Nasal Airflow
(Breathing patterns)



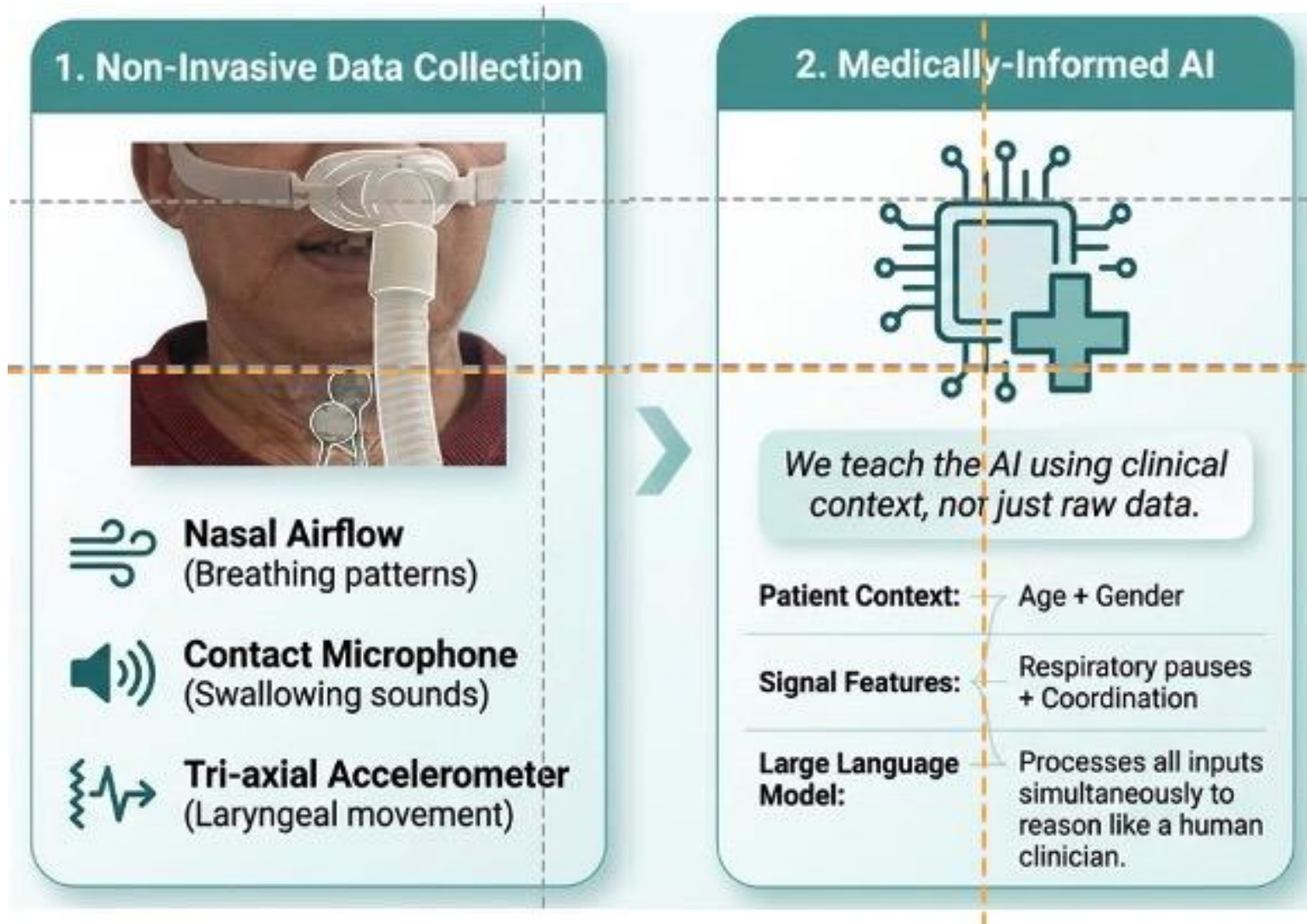
Contact Microphone
(Swallowing sounds)



Tri-axial Accelerometer
(Laryngeal movement)

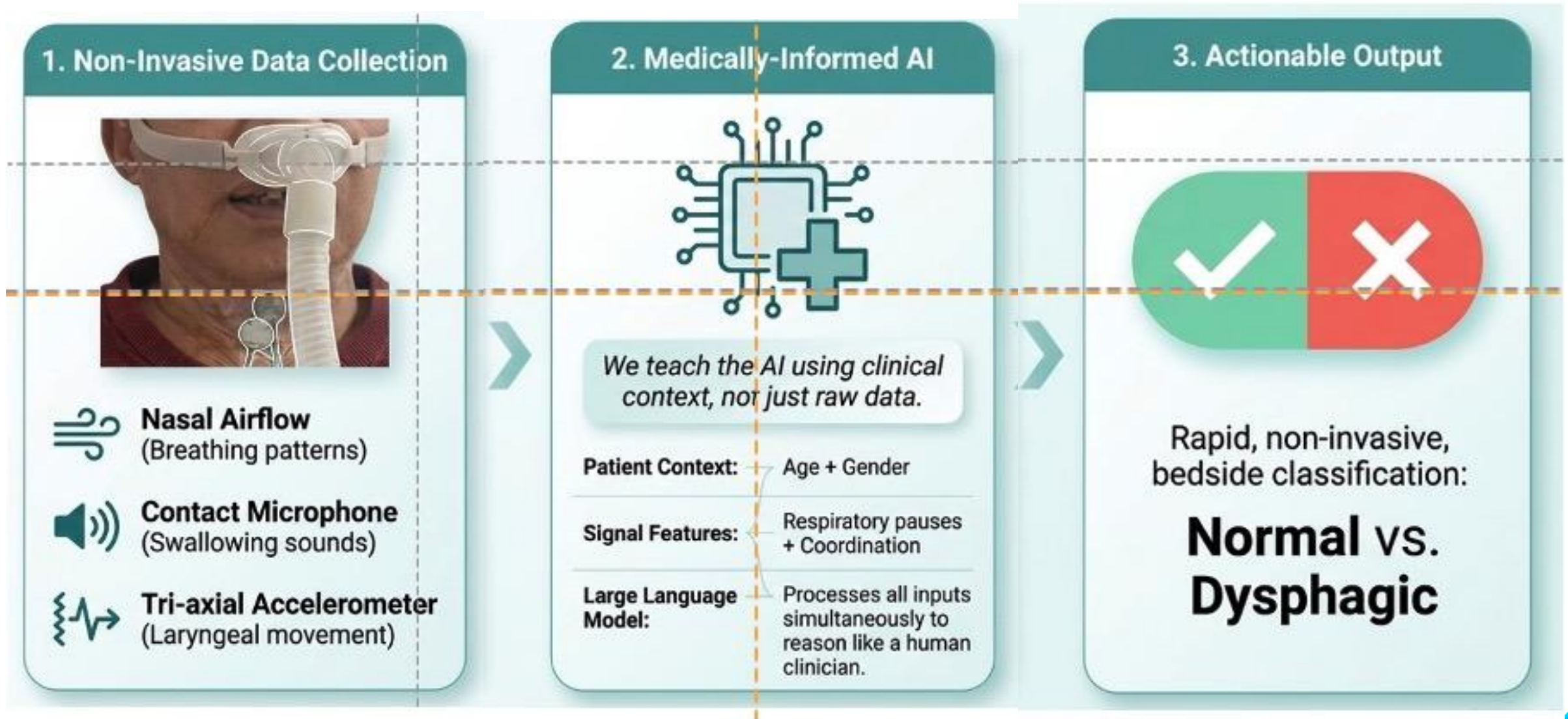


Letting AI “Hear & Sense” Swallow at the Bedside





Letting AI “Hear & Sense” Swallow at the Bedside

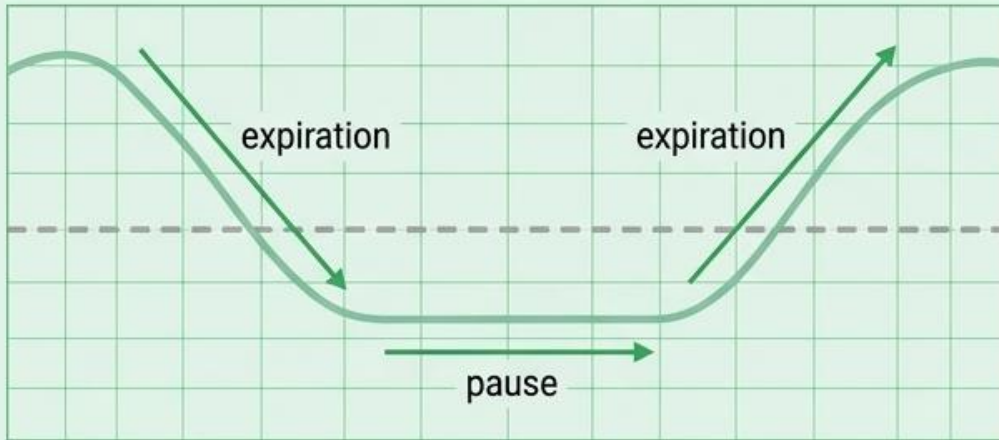




Unlocking Insights: Breathing-Swallow Coordination

The Typical Safe Pattern

EE Pattern (Exhale → Swallow → Exhale)



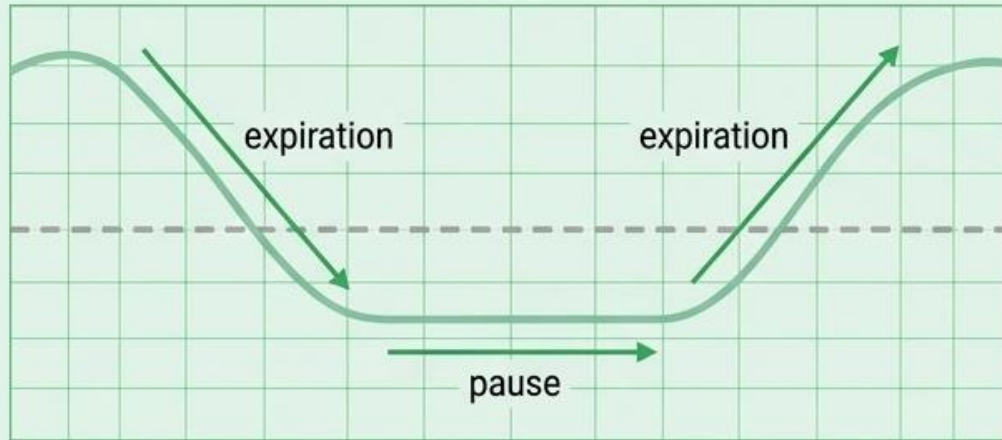
Clinical Meaning: The safest and most common pattern in healthy individuals. The airway is effectively protected during the swallow.



Unlocking Insights: Breathing-Swallow Coordination

The Typical Safe Pattern

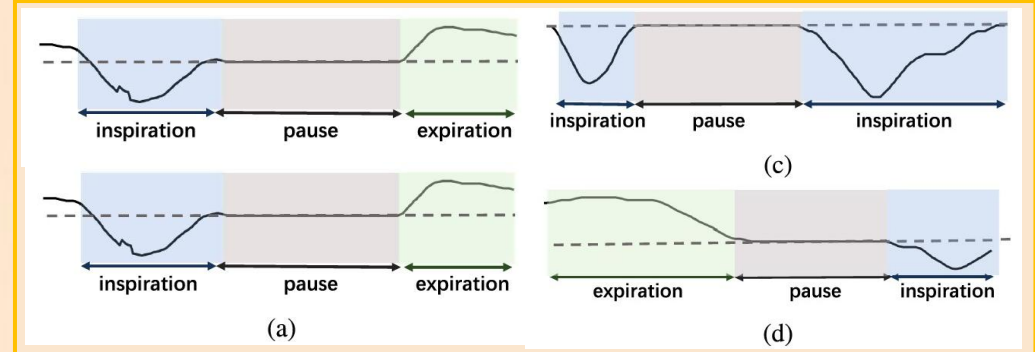
EE Pattern (Exhale → Swallow → Exhale)



Clinical Meaning: The safest and most common pattern in healthy individuals. The airway is effectively protected during the swallow.

Warning Signs

IE, II, EI Patterns (Inhale-involved patterns)



- **Clinical Meaning:** Indicates poor muscle coordination.
- **The Risk:** Significantly higher risk of aspiration.



Critical Warning: The AI also flags a prolonged respiratory pause as a major indicator of swallowing difficulty.

Analyzes the micro-pauses between breathing and swallowing
Detects subtle risks that human ears might miss



Clinical Validation

Cohort: 217 Participants (109 post-stroke patients + 108 healthy controls)



Clinical Validation

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Dataset: 2,664 swallowing samples analyzed (7:3)



Clinical Validation

Cohort: 217 Participants (109 post-stroke patients + 108 healthy controls)

Dataset: 2,664 swallowing samples analyzed (7:3)



96.3%

Accuracy
(Overall correct judgments)



95.2%

Sensitivity
(Effectively catching dysphagia cases)



97.4%

Specificity
(Accurately identifying healthy swallowing)

Model remains highly robust

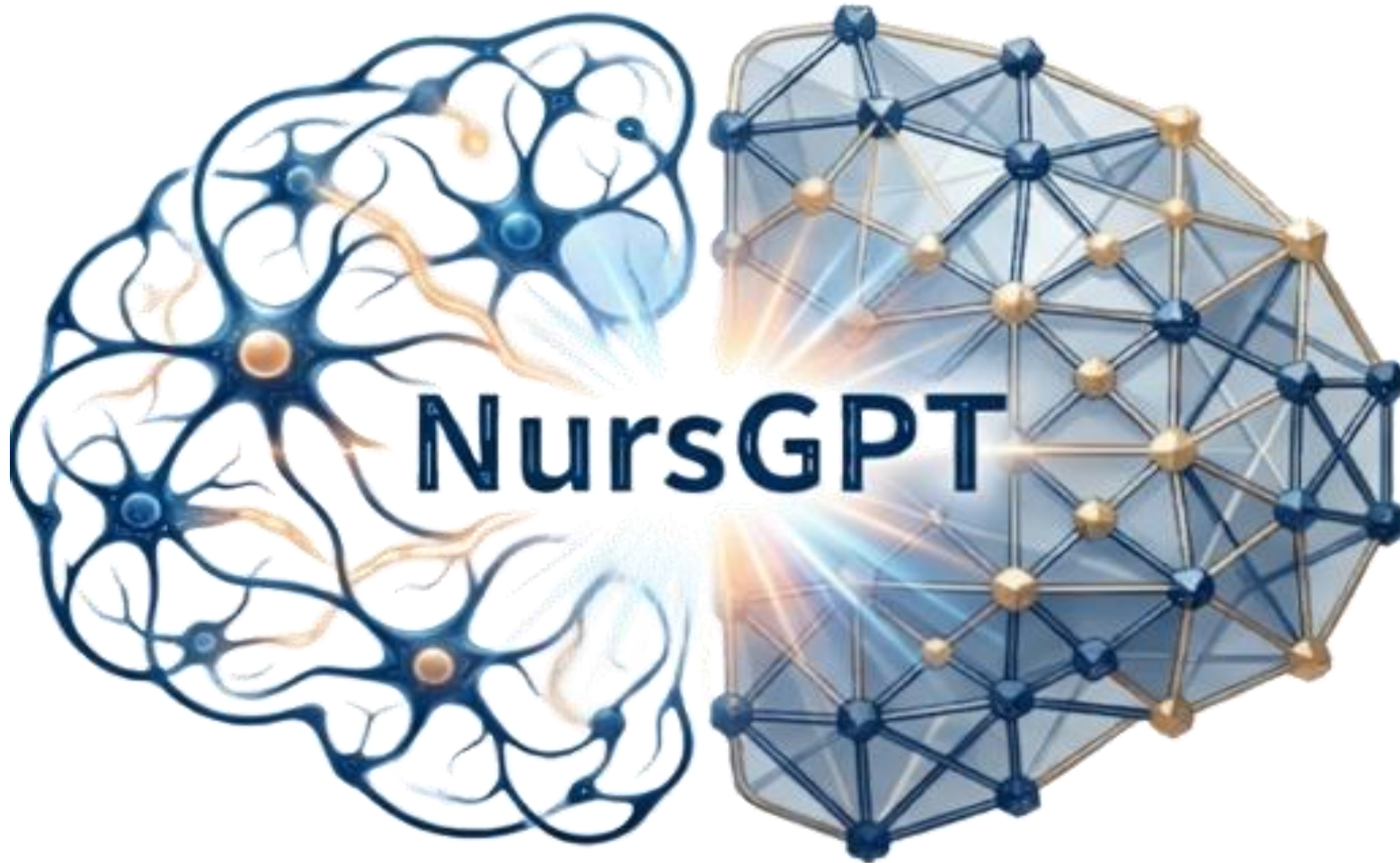
Achieving 91.9% accuracy even only use 10% of the dataset



Toward General Nursing AI: NursGPT



NursGPT: Toward General Nursing AI





NursGPT: A Multidisciplinary Research Team

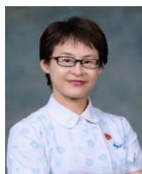
Clinical nurses & nursing scientists



Xiwei Zhang
Director of Nursing



Lixin Zhang
Head Nurse



Jun Wang
Deputy Director
of Nursing



Shu Ding
Deputy Director
of Nursing



PI & Overall Design Prof. Ying Wu Research Team Capital Medical University



Prof. Ying Wu



Faculty
Member



Faculty
Member



Faculty
Member



Faculty
Member



PhD
Student



PhD
Student



PhD
Student



PhD
Student



PhD
Student



PhD
Student



PhD
Student



PhD
Student



PhD
Student



Master
Student



Data scientists & model evaluators



Prof. Ning An

Department of Computer Science
and Technology

Hefei University of Technology



Nursing system developers



和顺慧康

Beijing Heshun Huikang
Technology Co., Ltd.

LLM research enterprise partners



Nanjing KGT Data Technology Co., Ltd.





Take-Home Message



 **Digital innovation in nursing is no longer optional — it's essential**





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 **When nurses lead innovation, technology works better**





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 **AI and LLMs open the door to general nursing AI**

01

02

03

04

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 **NursGPT connects assessment, decisions, action & follow-up**





Take-Home Message



 **Digital innovation in nursing is no longer optional — it's essential**



 **AI and LLMs open the door to general nursing AI**

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02

 **When nurses lead innovation, technology works better**



03

04

 **NursGPT connects assessment, decisions, action & follow-up**



The future of nursing innovation is human-centered, nurse-led, and AI-empowered



Thank You

October 21
Ying Wu