Speakers

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Horizon 1
Digital health foundations

Horizon 2
Data & analytics

Horizon 3
New models of care

Disclosure

We have no conflicts of interest to declare.

Dr Oliver Canfell

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Horizon 1
Digital health foundations

slido

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Where are you joining from today?

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Principles

Technology is changing how we **understand** and **practice** nutrition.

Digital health technologies (and their data) are **rapidly disrupting** traditional, well-rehearsed multidisciplinary clinical and public health workflows

Digital health **can** positively transform nutrition and dietetics research and practice. Impact must be **measured to matter.**

Three horizons framework for digital health transformation

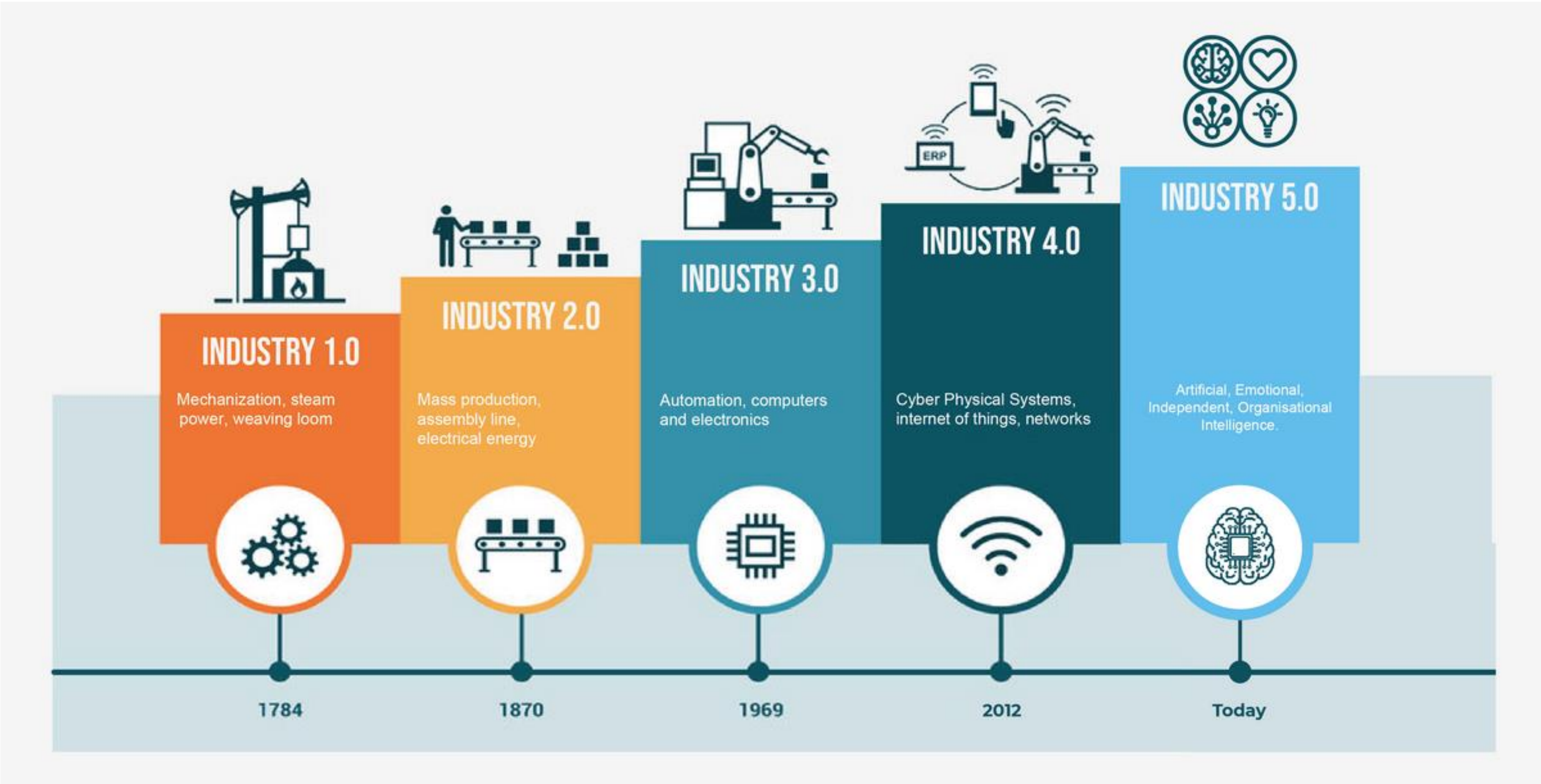
	HORIZON 1	HORIZON 2	HORIZON 3
	Building digital foundations: better care for individual patients	Transforming patient care: better care for groups of patients	Reimagining our future: new and innovative models of care
PEOPLE	Our workforce builds digital literacy	Intelligent use of data	Innovative workforce
PROCESS	Integrating information and technology	Transparency to increase efficiency	Digital innovation allows new models of care
INFORMATION	Collecting and collating	Live streaming analytics	Predictive and prescriptive analytics available
TECHNOLOGY	Broadens workflows to improve care	Establish links between data and analytics	Integrate innovative technology in the digital platform

1. Lim, HC, Austin, JA, van der Vegt, A., Rahimi, AK., Canfell, OJ., et al. (2022) *Appl Clin Inform*; 13(02): 339-354 DOI: 10.1055/s-0042-1743243
2. Canfell, O. J., Littlewood, R., Burton-Jones, A., & Sullivan, C. (2022). *Australian Health Review*, *46*(3), 279–283. https://doi.org/10.1071/AH21063

Learning Health System

All data entered during an episode of care is used to improve the care of subsequent patients in a continuous cycle of *learning*.

We are living in the fifth industrial revolution.

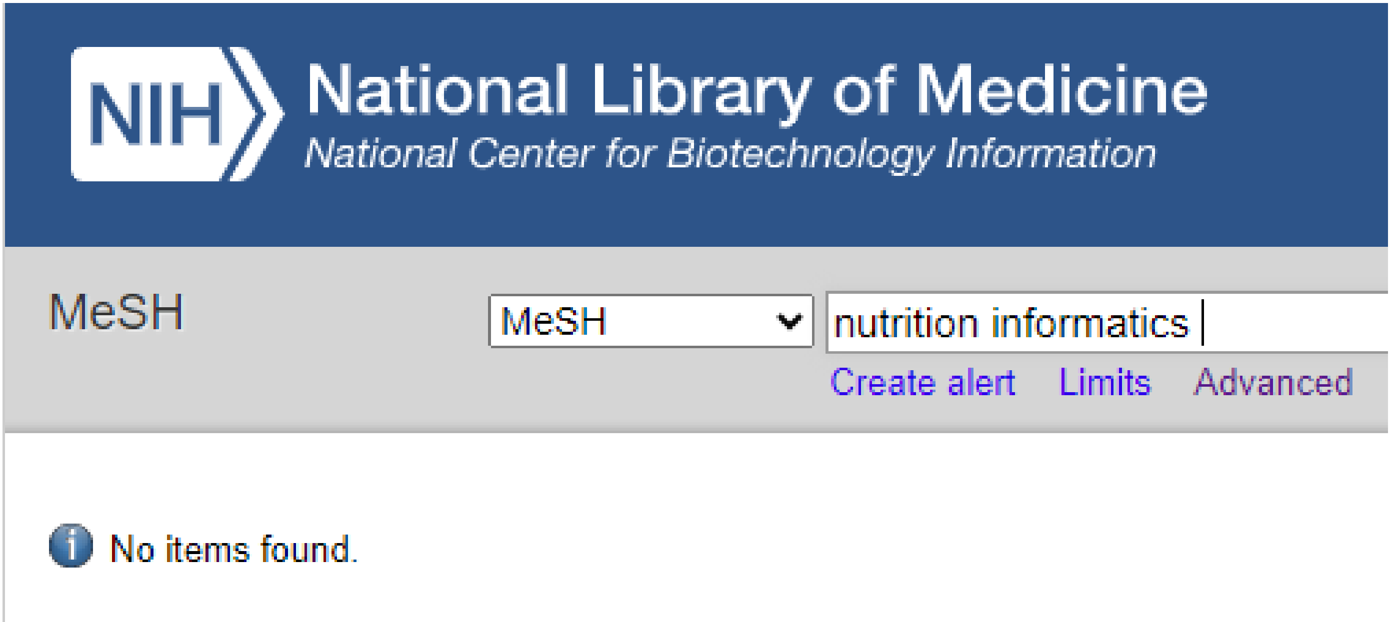


Sung, J. J., Stewart, C. L., & Freedman, B. (2020). *Medical Journal of Australia*, *213*(6), 253-255.e1. https://doi.org/10.5694/mja2.50755

A brief anthology

1982	**Information systems** Integrated set of files, procedures, and equipment for the storage, manipulation, and retrieval of information (PubMed)
1986	**Artificial intelligence** Theory and development of computer systems that perform tasks normally requiring human intelligence (PubMed)
1987	**Medical informatics** The field of information science concerned with analysis and dissemination of medical data via computers to health care and medicine (PubMed)
1993	**eHealth/Telemedicine** Delivery of health services via remote telecommunications (PubMed)
2024	**Digital health** The field of knowledge and practice associated with the development and use of digital technologies to improve health (WHO, 2020)

On the horizon?



2030?

Nutrition informatics
The intersection of information, nutrition, and technology

(Applied) Nutrition informatics
Manage nutrition data to improve knowledge and practice that improves quality and safety of health care.

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Nutrition informatics is an established sub-discipline.

Rusnak, S., & Charney, P. (2019). *Journal of the Academy of Nutrition and Dietetics*, *119*(8), 1375–1382. https://doi.org/10.1016/j.jand.2019.06.004

eat right.

FROM THE ACADEMY
Position Paper

Position of the Academy of Nutrition and Dietetics: Nutrition Informatics

Check for updates

- Rapidly evolving area of practice for registered dietitian-nutritionists
- Knowledge and skills transcend **all areas** of the dietetics profession
- Applications across the **Nutrition Care Process** in acute care public health, private practice, food service, industry

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Digital competencies exist for allied health professionals but are **lagging behind.**

18 global professional standards, 35 individual statements related to "digital health".

Lack reference to digital health, focus on **information management** statements, limited data translation, lower levels of learning

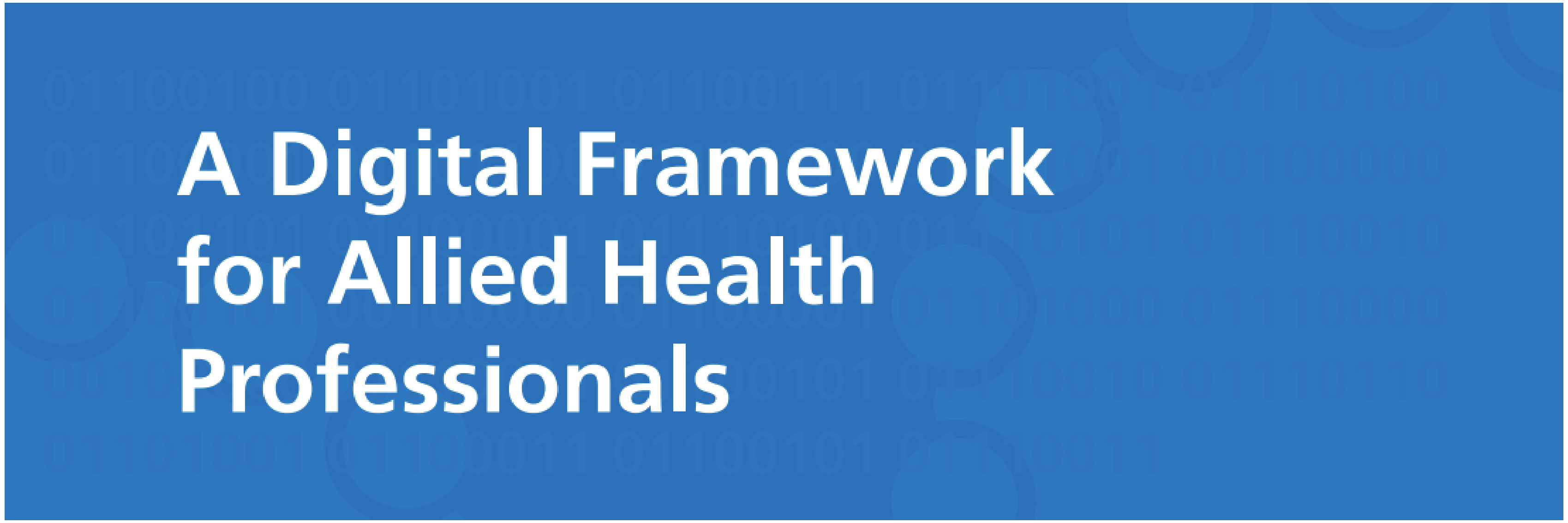
Major gap in competency statements for all allied health. Likely **limited integration** into tertiary curriculum.

Butler-Henderson, K., et al. (2020). *International Journal of Medical Informatics*, *144*, 104296–104296. https://doi.org/10.1016/j.ijmedinf.2020.104296

Digital competencies for dietitians are slowly evolving

Dietitian - Health & Care Professions Council (2023)

1. Principles of information and data governance
2. Use digital technologies appropriate to practice
3. Use digital record keeping tools
4. Gather and use data for quality improvement



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Which of the following best describes your current role?

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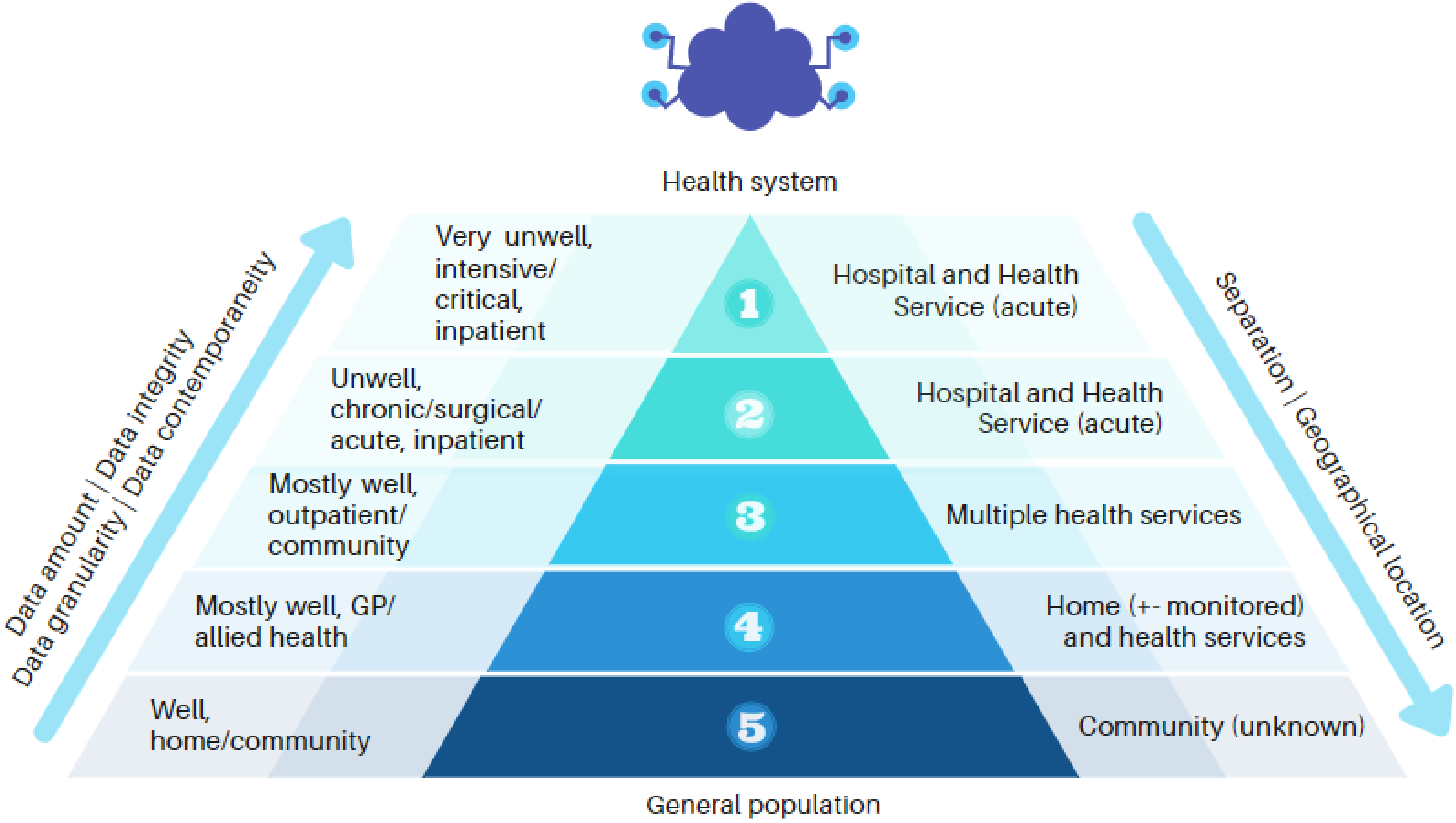
Health Data Pyramid

Health data paradox - everywhere and nowhere all at once.



1. Canfell Oliver J. et al. *Australian Health Review* **46**, 279-283. doi.org/10.1071/AH21063

Three horizons framework for digital health transformation[1]

	Foundation.	Transformation.	Innovation.
	Electronic medical/health records	Descriptive analytics	Predictive analytics
	New digital workflows	Data visualisation	Continuous learning
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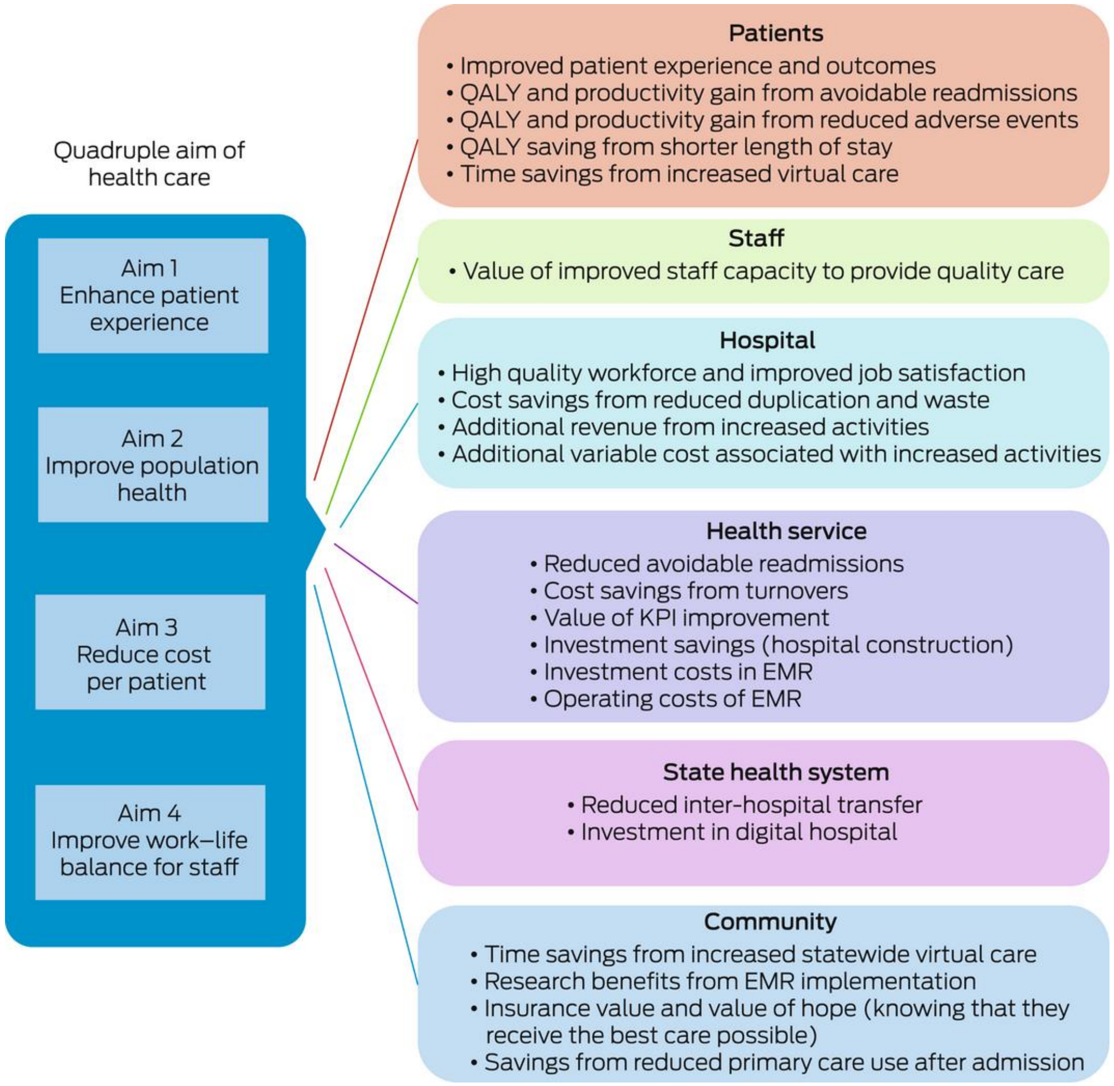
1. Lim, HC, Austin, JA, van der Vegt, A., Rahimi, AK., Canfell, OJ., et al. Appl Clin Inform 2022; 13(02): 339-354 DOI: 10.1055/s-0042-1743243

Aren't electronic medical records just 'digital paper'?

Measuring the impact of digital health is **complex** and **difficult**.

Investments (e.g., electronic health records) are significant (**£1.9B** to digitize all NHS Trusts with EHRs)

Evaluating **non-financial benefits** of digital health is critical to justifying further investment in digital health technologies.



1. Woods L, Eden R, Canfell OJ et al., Med J Aust. 2023 Feb 6;218(2):53-57. doi: 10.5694/mja2.51799.

Quintuple Aim of Healthcare[1]

How to measure the impact of digital health

- Improved population health
- Reduced costs
- Improved patient experience
- Improved practitioner experience
- Reduced health inequalities

1. Nundy S et al. JAMA. 2022 Feb 8;327(6):521-522. doi: 10.1001/jama.2021.25181. PMID: 35061006.
2. Woods L, Eden R, Canfell OJ et al., Med J Aust. 2023 Feb 6;218(2):53-57. doi: 10.5694/mja2.51799.

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Electronic health records can improve health system outcomes

Cross-sectional observational study
1,026 US hospitals
Digital maturity vs quality and safety

JOURNAL OF MEDICAL INTERNET RESEARCH — Snowdon et al

Original Paper

Digital Maturity as a Predictor of Quality and Safety Outcomes in US Hospitals: Cross-Sectional Observational Study

Anne Snowdon[1*], BSCN, MSc, PhD; Abdulkadir Hussein[1*], PhD; Melissa Danforth[2*], BA; Alexandra Wright[1*], BPR, MPA, PhD; Reid Oakes[3*], BSc

Improved surgical safety outcomes
Improved hospital safety grade

Reduced infection rates
Reduced adverse events
Reduced incidence of pressure ulcers

Retrospective observational study
13 digital hospitals in Queensland (Aus)
Pre-post EHR implementation (1-year)

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

ELSEVIER

Impact of digital health on the quadruple aims of healthcare: A correlational and longitudinal study (Digimat Study)

Leanna Woods[a,b,c,*], Rebekah Eden[d], Damian Green[e], Andrew Pearce[f], Raelene Donovan[e], Keith McNeil[b], Clair Sullivan[a,b,g]

Increased episodes of care
Increased staff leave

= Mortality, falls, length of stay

Reduced infection rates (-14.27%)
Reduced medication complications (-12.87%)

1. Snowdon, A., et al (2024). *Journal of Medical Internet Research*, *26*(2), e56316. https://doi.org/10.2196/56316
2. Woods L, et al. Int J Med Inform. 2024 Sep;189:105528. doi: 10.1016/j.ijmedinf.2024.105528. Epub 2024 Jun 21. PMID: 38935999.

Single-site retrospective cohort study
900-bed tertiary teaching hospital, Brisbane (Australia)
Pre-EMR vs Post-EMR implementation (1-year)

Electronic health records can improve efficiency in dietetics care

Table 1 Dietitian chart audit pre- and post-EMR (electronic medical record)

	Response	Pre-EMR (total n = 183) *n*	*n* (%)	Post-EMR (total n = 129) *n*	*n* (%)	Statistical significance P-value
Accessibility of chart	Yes	181	136 (76.4)	119	119 (100)	<0.001
	No		36 (20.2)		0	
	Partial		6 (3.4)		0	
Time until access (minutes)	<1	161	106 (65.8)	120	119 (99.2)	<0.001
	1–5		35 (21.7)		1 (0.8)	
	>5		20 (12.4)		0	
Referral clarity	Purpose	183	61 (33.3)	129	97 (75.2)	<0.001
Referral clarity	Referrer	183	55 (30.1)	129	58 (45.0)	<0.001
Referral clarity	Pertinent history	183	42 (23.0)	129	64 (49.6)	<0.001
Time looking for weight (minutes)	<1	114	97 (85.1)	117	112 (95.7)	<0.01
	1–5		11 (9.6)		5 (4.3)	
	>5		6 (5.3)		0	
Weight found	Yes	106	88 (83.0)	108	100 (92.6)	<0.01
	No		13 (12.3)		2 (1.9)	
	Partially		5 (4.7)		6 (5.6)	
Other relevant data	Yes	119	114 (95.8)	125	125 (100)	<0.05
	No		5 (4.2)		0	
	Partially		0		0	
Consult alerts	Unaware	103	85 (82.5)	110	38 (34.5)	<0.001
	Aware prior		13 (12.6)		72 (65.5)	
	Aware during or after consult		5 (4.9)		0	
Legibility	Very good	141	74 (52.5)	118	117 (99.2)	<0.001
	Good		38 (27.0)		1 (0.8)	
	Neutral		8 (5.7)		0	
	Poor		14 (9.9)		0	
	Very poor		7 (5.0)		0	

McCamley J, Vivanti A, Edirippulige S. Nutr Diet. 2019 Sep;76(4):480-485. doi: 10.1111/1747-0080.12552.

Electronic health records can improve efficiency in dietetics care

Single-site cross-sectional & longitudinal study
Paediatric hospital (USA)
Dietitian **productivity** in acute care

ORIGINAL ARTICLE

JHND BDA

Electronic health record time-tracking provides real-time data to measure and benchmark dietitian productivity

Jennifer Crouse[1] | Mary Beth Feuling[2] | Taylor Winter[1] | Praveen S. Goday[3] | Amber Smith[4]

Increased productivity in outpatient settings (75%)

Single-site quality improvement project
Tertiary hospital (USA)
Digitisation of nutritional supplements using EHR

Open Access BMJ Quality Improvement Programme

Submitted from BMJ Quality

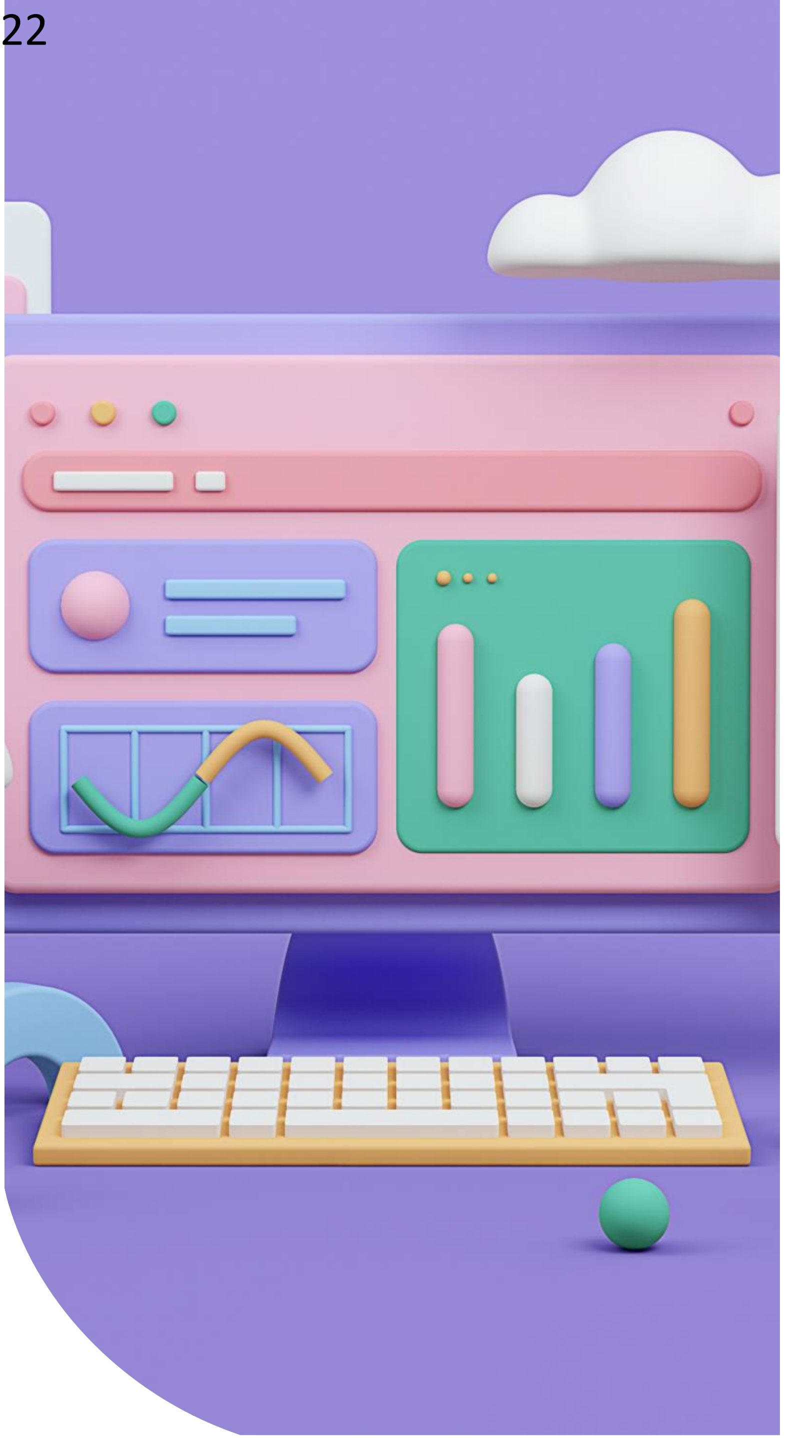
Optimizing the electronic health record to standardize administration and documentation of nutritional supplements

Sandra W. Citty, Amir Kamel, Cynthia Garvan, Lee Marlowe, Lynn Westhoff

Improved return of unused nutritional supplements (54% post vs 76% pre)

Improved offering and accuracy of nutritional supplements to patients

Crouse J et al. J Hum Nutr Diet. 2024 Feb;37(1):105-110. doi: 10.1111/jhn.13236.
Citty, S. W., et al (2017). *BMJ Open Quality*, 6(1), u212176.w4867. https://doi.org/10.1136/bmjquality.u212176.w4867



Key messages

Horizon 1

Digital health foundations

Horizon 1 focuses on **workforce capability** and digital **infrastructure** to create better care for **individual** patients

Nutrition informatics is an emerging sub-discipline that is **a core component** of nutrition and dietetics practice

Electronic medical/health records can **improve** process outcomes in dietetic practice. **Impact** is measured with the Quintuple Aim of Healthcare.

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Faculty of Life Sciences and Medicine

Horizon 2

Data & analytics

Clinical analytics – EHRs in the research landscape

The UK Pregnancy Better Eating and Activity Trial

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2009	2014	2015	2018	2020
UPBEAT trial funded	**1554** Pregnant women recruited	**Birth outcomes** Poston et al	**6- month Infant follow-up** Patel et al	**3-year childhood follow-up** Dalrymple et al.

Poston et al. (2015). Lancet Diabetes and Endocrinology , Patel et al. (2018) International Journal of Obesity & Dalrymple et al. (2020) International Journal of Pediatric Obesity

Randomised controlled trials & cohort studies

Pros	Cons
The foundation of our **research infrastructure**	High costs & logistical constraints
RCTs allows researchers to assess **causality**	Defined population (RCTs usually involve **smaller, more homogeneous samples)**
Carefully **designed**, defined population	Inclusion and exclusion criteria are strictly applied - limits **generalizability** but increases internal **validity**
Standardised protocols, predefined data collection (allowing for greater precision)	**significant time** to generate results
Designed to **minimise bias**	

Strict ethical approval – GDPR compliant

Why Data Matters in Dietetics

- **Digital health transformation** is rapidly reshaping healthcare.

- **Data & analytics** play a pivotal role in:

- Personalising care.
- Streamlining clinical workflows.
- Enhancing patient outcomes and efficiency.

- A key consideration of this is how we **collect**, **manage**, and **analyse** our data.
- We also need to understand the limitations of our data.

Why Data Matters in Dietetics

Data is the foundation of decision-making

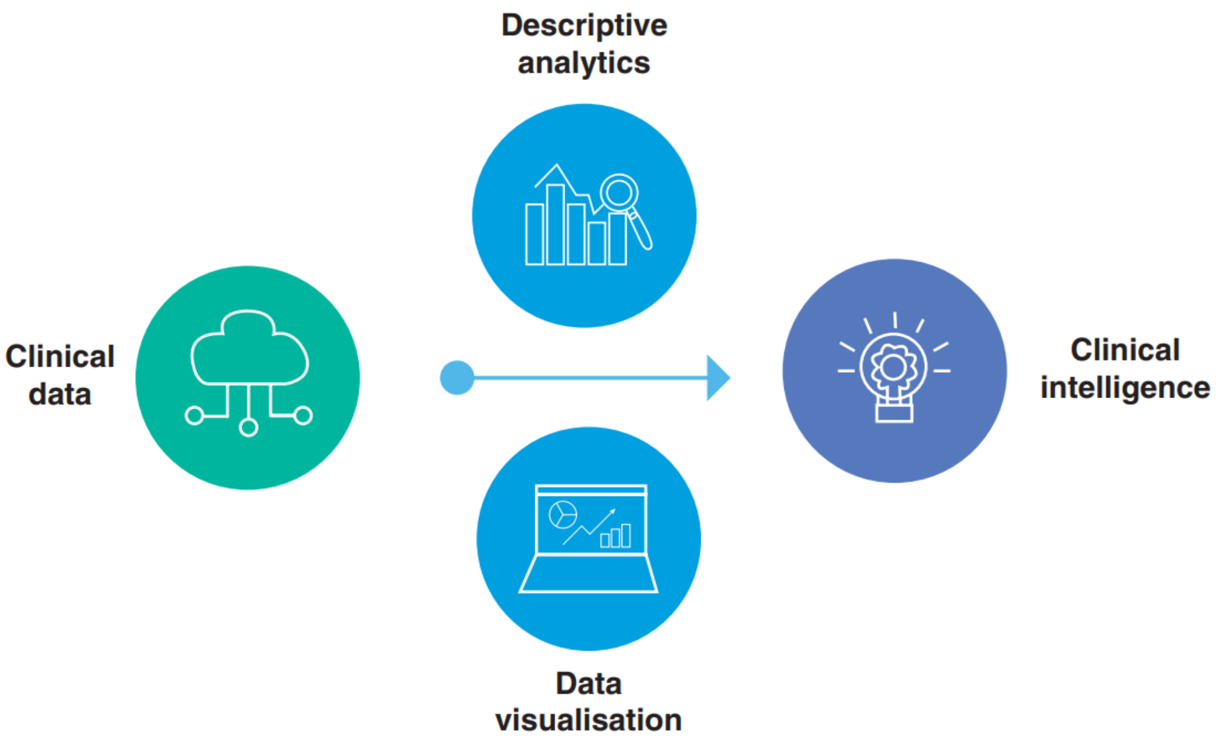

Fig 7.11 The relationship between clinical data and clinical intelligence

Woods, L., Canfell, O., & Sullivan, C. (2023). Applied Clinical Informatics. In H. Almond, & C. Mather (Eds.), *Digital Health: A transformative approach* Elsevier. https://evolve.elsevier.com/cs/product/9780729598392?role=studen

Types of data - EHRs

On the basis of...	Structured Data	Unstructured Data
Technology	Based on a relational database	Based on character and binary data
Flexibility	Less flexible and schema-dependent	Absence of schema so more flexible
Scalability	Hard to scale	More scalable
Robustness	Very robust	Less robust
Performance	Can perform a structured query that allows complex joining leading to higher performance	Textual queries possible but performance is lower
Nature	Hard numbers that can be counted	Qualitative so cannot be processed and analyzed using conventional tools
Format	Predefined format	Variety of formats
Analysis	Easy to search	Searching is more difficult

Data Schema

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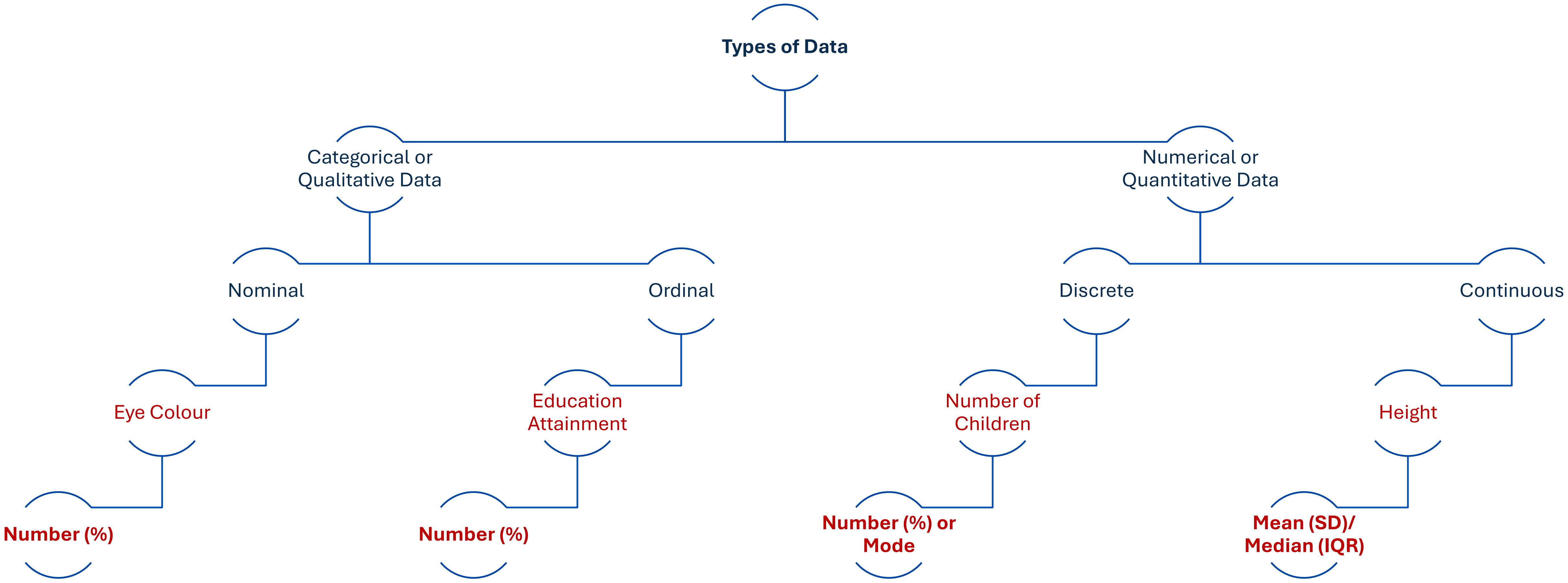
A database schema defines how data is **organised** within a **database**; this includes, table names, fields, data types and the relationships between these entities

B	D	E
Variable names	Variable explanation	Variable options
participant_id	Unique participant number on UPBEAT study, includes recruited and excluded	count
centre	Centre in which participant was aproached	1- St Thomas' 2-CAN 3-Newcastle 4-Glasgow 5-Manchester 6-Bradford 7-Sunderland 8-St Georges'
1_midwife_contact_date	Date participant was first aproached by the Midwife, includes recruited and excluded	date
1_age	Age of participant when aproached, includes recruited and excluded	count
1_main_ethn	Ethnicity of the participants aproached, includes recruited and excluded	1-Asian 2-Black 3-Other 4-White
1_lower_super_output_area	Lower super output area code, includes recruited and excluded	A1111111
1_wgt_kg_reported	Participant's weight in kilograms (kg), includes recruited and excluded (self reported)	continuous
1_wgt_st_reported	Participant's weight at booking in stones (st), includes recruited and excluded (self reported)	continuous
1_wgt_lb_reported	Participant's weight in pounds (lbs) added to stones, includes	continuous

Table 1: Measures of infant body composition and methodology for calculation

Infant body composition variable	Definition	Method of calculation
Sum of skin-folds (mm) *	Infant sum of biceps and subscapular skin-folds measured in triplicates.	The mean of each variable will be used for the calculation for the primary outcome.
Triceps skin-fold thickness (mm)	Infant triceps skin-fold thickness measured in triplicates	Continuous variable. A mean value will be generated.
Subscapular skin-fold thickness (mm)	Infant subscapular skin-fold thickness measured in triplicates	Continuous variable. A mean value will be generated.
Weight (grams)	Infant weight in grams	Continuous variable exported directly from the database.
Height/ length (cm)	Infant height/ length (cm)	Continuous variable exported directly from the database.
Weight for age Z-scores (WAZ)	The number of standard deviations of the actual infant weight from the median weight	The variable will be generated utilising the WHO Anthro (version 3.2.2, January 2011)

Understanding Data Types



EHR Data - the Pros

EHR data from clinical care

- **Large data:** an opportunity to examine rare conditions.
- **Linked dataset:** between primary care, prescriptions and hospital data
- **Representative of routine clinical care**: an opportunity to analyse in real time.
- **Accessible and quick**: Available at a lower cost and without long delays (after ethics approval).
- Since the introduction of EPIC, the data is not subject to rapid changes in format
- **Rich clinical information**: diagnoses, procedures, prescription, clinical notes, images, laboratory results, allergies & family history.

EHR Data - the Cons

EHR data is not necessarily harmonious with research studies

- **Data Privacy & Security:** Managing patient data responsibly with GDPR and healthcare standards.
- **Accuracy:** Ensuring both the healthcare professional and patients can effectively use the digital tool.
- **Missing data:** e.g. healthier patients may have less observations.
- **Data Integration:** Challenges of integrating data from several EHRs, and potentially apps to ensure the data is in a cohesive system.
- Information exchange and **data linkage** and sharing very difficult.
- **Sensitivity** of data can limit use and ability to share data (e.g. names can appear in datasets).
- There can be a lack of **standardization**

Missing Data in EHRs

Missing Data can impact on our interpretation of results and impact bias.

- Data not collection:
  - In GP records, a large proportion of patients have no blood pressure measurements
  - Is the patient younger? or the patient does not need routine appointments?
- Data not documented:
  - A patient with known diabetes visits a cardiologist for a routine heart exam.
  - A fragmented system of data collection

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Electronic health records can support predictive analytics in dietetics care

Hilbrands J et al.. J Hum Nutr Diet. 2023 Oct;36(5):1912-1921. doi: 10.1111/jhn.13177.

NUTRITIONAL SUPPORT AND ASSESSMENT

JHND BDA

Evaluation of an electronic medical record−based Paediatric Nutrition Screening Tool

Julia Hilbrands[1] | Mary Beth Feuling[1] | Aniko Szabo[2] | Bi Q. Teng[2] | Chandler Burgess[1] | Brittani Clark[1] | Jennifer Crouse[1] | Heather Fortin[1] | Becky Heisler[1] | Catherine Karls[1] | Olivia Lampone[1] | Lauren Matschull[1] | Marissa Seyfert[1] | Amber Smith[3] | Praveen S. Goday[4]

Single-site retrospective cohort study
Paediatric hospital (USA) (n=1,575)
Accuracy of digital prediction tool versus traditional paper tool (nutrition risk)

Predictors of malnutrition diagnosis using EHR data:
Food allergies, intubation, parenteral nutrition, RD-identified risk, BMI-for-age z score, intake <50% for 3 days

Increased sensitivity (93.9% versus 32%) for identifying paediatric nutrition risk

Population health informatics in action

Electronic health records

Measured clinical data

Cocoros, N. M., et al (2021). American Journal of Public Health (1971), 111(2), 269–276. https://doi.org/10.2105/AJPH.2020.305963

Canfell OJ, et al. Precision Public Health for Non-communicable Diseases: An Emerging Strategic Roadmap and Multinational Use Cases. Front Public Health. 2022 Apr 8;10:854525. doi: 10.3389/fpubh.2022.854525. PMID: 35462850; PMCID: PMC9024120.

Key messages

Horizon 2

Data & analytics

Horizon 2 focuses on **transforming** patient care and informing better care for groups of patients

Intelligent use of data allows us to live stream **analytics**

By understanding our **data**, and any potential limitations, we can **establish links** between data and analytics.

Sinead Burke RD

Allied Health Professional Information Officer (AHPIO)

Clinical Lead Dietitian (CKD)

Royal Free London NHS Foundation Trust

Horizon 3

New models of care

New Models of Care

Clinically Led

Operationally Driven

Digitally Enabled

"A wide range of technologies that reduce human intervention in processes"

Robotic Process Automation (RPA)/ Intelligent Automation (IA)

https://transform.england.nhs.uk/key-tools-and-info/guidance-for-designing-delivering-and-sustaining-rpa-within-the-nhs/understanding-rpa/

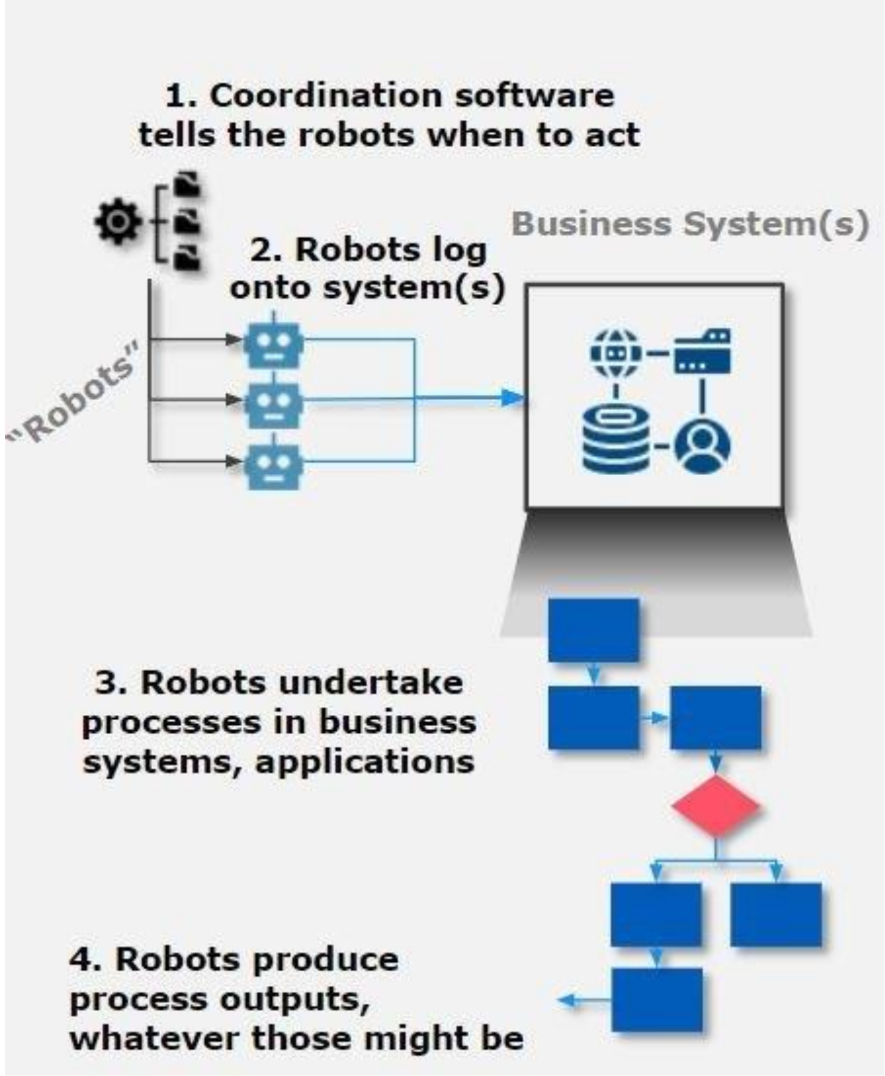
Ideal for:

- High volume, low complexity tasks
- Mature and stable processes
- Structured data and readable electronic inputs (N.B., IA can digitise some structured data for automation)
- Rule based processes (simple e.g., if/then)

Limitations:

- Interpreting unstructured data to make decisions (unless combined with AI)
- Working with systems (e.g., websites or apps) that continually change interface
- Robot requires access to multiple platforms – clinical safety case/DPIA

Robotic Process Automation – what should dietitians know?



Automation can be applied to both business and clinical functions.

Examples:

Move patients from national referral system into local EPR, populate triage comments into correspondence to GP

HR – starters and leavers, rostering

Appointment reminders

https://www.e-lfh.org.uk/programmes/robotic-process-automation/

Artificial Intelligence (AI)

https://transform.england.nhs.uk/key-tools-and-info/guidance-for-designing-delivering-and-sustaining-rpa-within-the-nhs/understanding-rpa/

"The use of digital technology to create systems capable of performing tasks commonly thought to require human intelligence"

Ideal for:

- Making predictions on a likely outcome, based on learning from a dataset
- Where decisions need more detailed algorithm than just rule based if/then
- Multimodal data sources
- Improving ability to provide remote care (clinical and research settings)

Limitations:

- Bias created by using non-representational data samples for learning
- Open-source AI unsafe for PID
- Data privacy on apps
- Medical devices (MHRA)

Artificial Intelligence: what should dietitians know?

NHS Royal Free London NHS Foundation Trust

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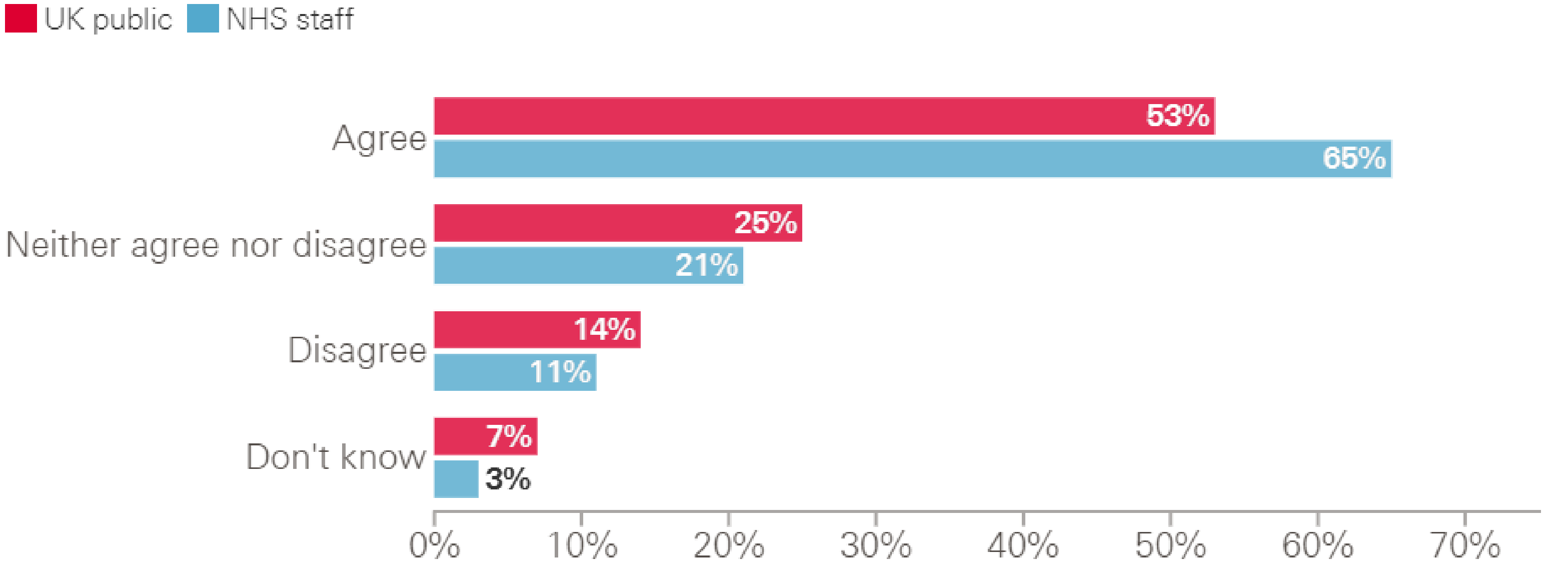
The UK public and NHS staff think AI systems will impact the human dimension of care

To what extent do you agree with the statement: 'AI systems will make me feel more distant from (health care staff/patients)'?



The Health Foundation

Source: UK NHS staff survey fieldwork carried out online by Censuswide, 7 June to 8 July 2024; total sample size 1,292 NHS staff aged 16 years and older. UK public survey fieldwork carried out online and by phone by Censuswide, 7 June to 8 July 2024; total sample size 7,201 adults (85% from England, 8% Scotland, 5% Wales and 3% Northern Ireland); figures have been weighted and are representative of all UK adults (aged 16 years and older).

https://www.health.org.uk/publications/long-reads/ai-in-health-care-what-do-the-public-and-nhs-staff-think

Artificial Intelligence: what should dietitians know?

Royal Free London NHS Foundation Trust

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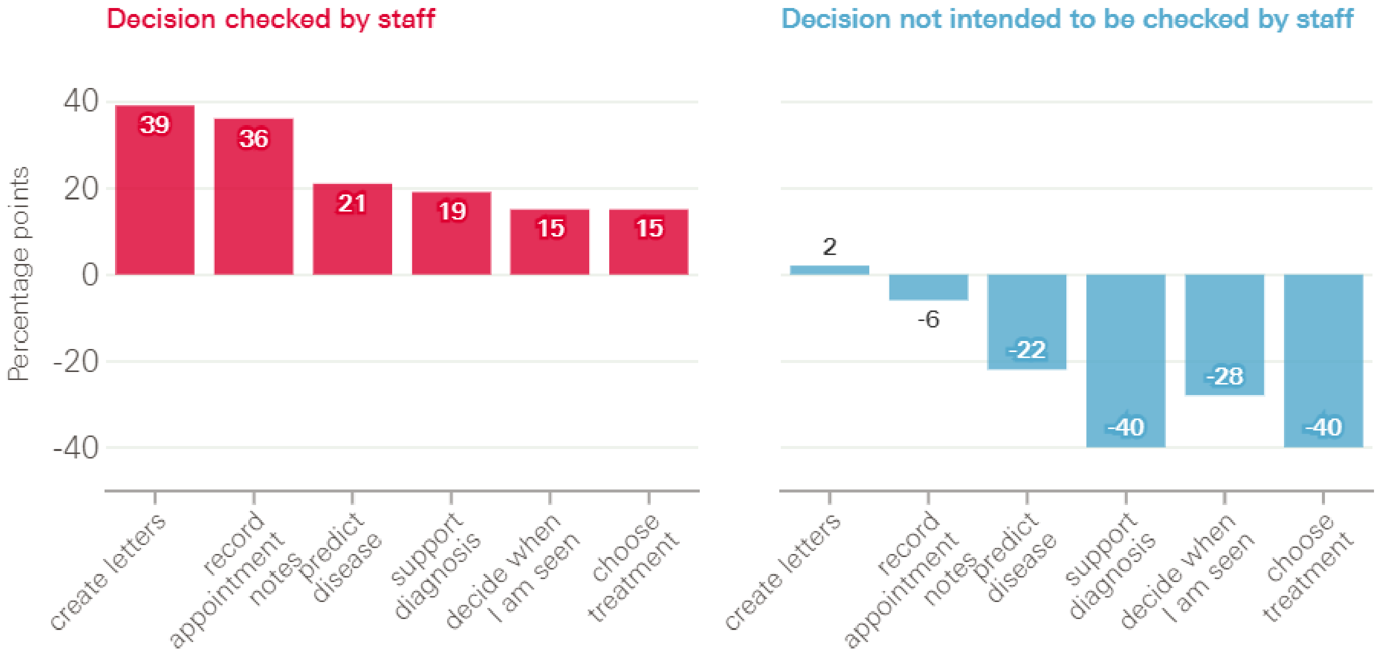
The public do not, on balance, support the use of AI in the NHS if the outputs are not checked by staff

'I would be happy for the NHS to use AI to...'



The Health Foundation

Source: UK public survey fieldwork carried out online and by phone by Censuswide, 7 June to 8 July 2024; total sample size 7,201 adults (85% from England, 8% Scotland, 5% Wales and 3% Northern Ireland); figures have been weighted and are representative of all UK adults (aged 16 years and older). • Scores are calculated as the percentage point (pp) difference between the proportion who would be happy and the proportion who would not be happy with each scenario. X-axis labels have been paraphrased for ease of reading.

https://www.health.org.uk/publications/long-reads/ai-in-health-care-what-do-the-public-and-nhs-staff-think

Artificial Intelligence: what should dietitians know?

NHS
Royal Free London
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The Industrial Strategy AI Mission sets the UK the target of "using data, Artificial Intelligence and innovation to transform the prevention, early diagnosis and treatment of chronic diseases by 2030." (Gov.uk, 2017)

Important:
People have the right under **GDPR Article 22(1)** not to be subject to solely automated decision making, where the outcome has a legal or similarly significant effect on them.

https://ico.org.uk/for-organisations/uk-gdpr-guidance-and-resources/individual-rights/automated-decision-making-and-profiling/what-does-the-uk-gdpr-say-about-automated-decision-making-and-profiling/

If you have an AI assisted process, you must be **transparent** in how AI is being used.

You must **always** offer an alternative for people who do not wish to have decisions generated by AI.

Artificial Intelligence: what should dietitians know?

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Digital Epidemiology

(BMC, September 2024)

Integrating machine learning and artificial intelligence in life-course epidemiology: pathways to innovative public health solutions

Shanquan Chen, Jiazhou Yu, Sarah Chamouni, Yuqi Wang & Yunfei Li

BMC Medicine 22, Article number: 354 (2024) | Cite this article

UK NSC sponsors new research into use of AI in breast screening

Rosalind Given-Wilson, 17 May 2023 - General

National Screening Programmes

https://nationalscreening.blog.gov.uk

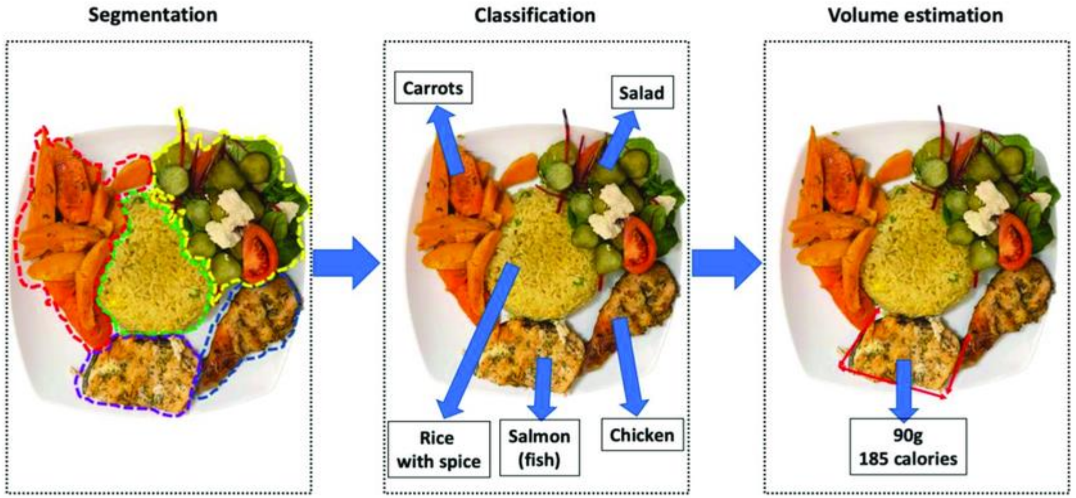
Wearables

Curr Surg Rep. 2021; 9(7): 20.
Published online 2021 Jun 8. doi: 10.1007/s40137-021-00297-3
PMCID: PMC8186363
PMID: 34123579

The Age of Artificial Intelligence: Use of Digital Technology in Clinical Nutrition

Berkeley N. Limketkai,[1] Kasuen Mauldin,[2] Natalie Manitius,[1] Laleh Jalilian,[3] and Bradley R. Salonen[4]

Artificial Intelligence: what should dietitians know?



Computer Vision

Mobile Computer Vision-Based Applications for Food Recognition and Volume and Calorific Estimation: A Systematic Review

December 2022 · 11(1):59
DOI: 10.3390/healthcare11010059

Lameck Mbangula Amugongo · Alexander Kriebitz · Auxane Boch · Christoph Lütge

Observational Study > Fam Pract. 2024 Apr 15;41(2):86-91. doi: 10.1093/fampra/cmad092.

The association between use of ambient voice technology documentation during primary care patient encounters, documentation burden, and provider burnout

Lance M Owens [1], Joshua J Wilda [2], Peter Y Hahn [3], Tracy Koehler [3], Jeffrey J Fletcher [3]

Affiliations + expand

PMID: 37672297 DOI: 10.1093/fampra/cmad092

Ambient Listening (Ambient Voice Technologies – AVT)

"P4" or "Precision" Medicine: Predictive, Preventative, Personalised and Participatory

King's College London

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"Uses agrees standards of high-quality care to report on a population e.g., with a shared condition"

Dashboards and Registries

https://www.healthknowledge.org.uk/e-learning/health-information/sickness-health-practitioners/registries-condition-specific-data

Ideal for:

- Long term condition management, with national guidelines for screening, monitoring and interventions
- Identifying gaps in care or poorer clinical outcomes in specific sub-populations
- Informing service strategy
- Can prompt interventions/ reviews for individuals

Limitations:

- Can only report structured inputs against pre-determined standards
- Need to be vendor agnostic to take feeds from all EPR's
- Can be expensive and laborious to maintain
- Challenge to evaluate completeness of data

Dashboards and Registries: what should dietitians know?

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https://digital.nhs.uk/dashboards

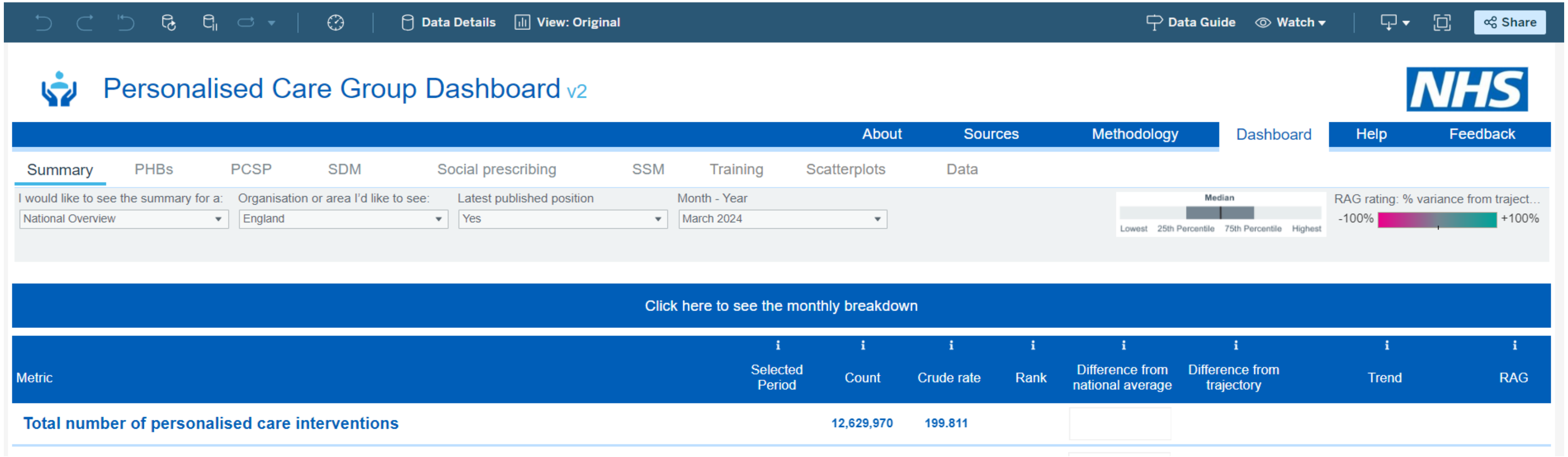
National Obesity Audit (NOA) dashboards

The National Obesity Audit (NOA) dashboard hub provides links to the interactive data visualisation tools containing data relating to access of services and health outcomes for people living with overweight and obesity

→

National Clinical Audit and Patient Outcomes Program (NCAPOP)

National Diabetes Audit, CVDPrevent, Eating Disorders, National Obesity Audit, Paediatric Diabetes etc.



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Camden

https://fingertips.phe.org.uk/topic/public-health-dashboard

Compare:

- Similar local authorities
- Deprivation group
- All local authorities

Show data for:

- Summary rank
- Child obesity
- NHS Health Checks
- Tobacco control
- Alcohol treatment
- Drug treatment
- Best start in life
- Sexual and reproductive health
- Air Quality

Camden is in
Socioeconomic decile 6

Socioeconomic deprivation
Average

Deprivation group

Similar view: Camden's rank within its IMD(2019) decile group

Key for summary rank indicators

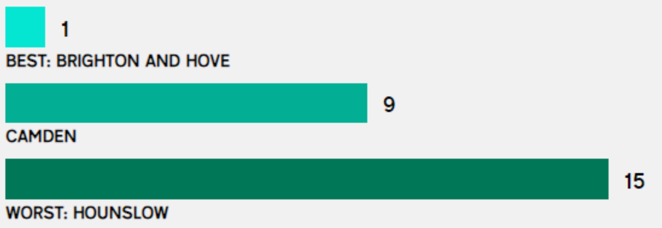
Group	Definition	Label
1st quartile	Lowest 25% of LAs (low rank is good)	Best
2nd quartile	LAs with values that lie between 25% and 50% in the rankings	Better than average rank
3rd quartile	LAs with values that lie between 50% and 75% in the rankings	Worse than average rank
4th quartile	Highest 25% of LAs	Worst

Rank	Indicator data

9th
OUT OF 15 SIMILAR LOCAL AUTHORITIES

WORSE THAN AVERAGE RANK

Child obesity summary rank (2018/19)



New Models of Care

Scenario: Your service delivers a high volume of training sessions to staff, and you want to reduce the administrative burden.

RPA

- schedule into next available session, appropriate for the education type
- sending of certificates to evidence attendance
- collection of session feedback from delegates
- offer a subsequent training session if relevant (if there is a defined order of sessions)

AI

- Generate suggested improvements to your session based on collated participant feedback

New Models of Care

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Scenario: You would like to use population health data to inform a program strategy/ campaign

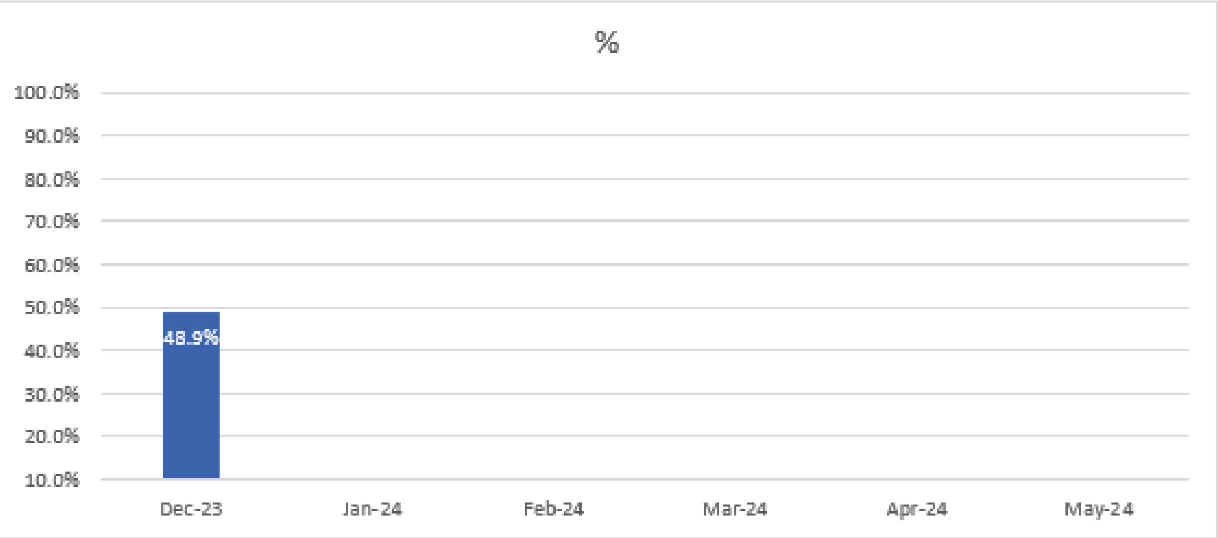
EPR Optimisation

- Coded data (capturing the "knowns")

Dashboard

- Does it already exist locally or nationally?
- Who owns the data for the population? Ensure observation of the GDPR at all times.
- Who is your audience?
- How will it be used? Benchmarking, compliance, education.

7. Proportion on CKD register with an uACR in the past 12 months (NCL)



North Central London Health and Care
Integrated Care System

Are people living with CKD in NCL/ your Borough being monitored appropriately?

Full description of metric: What proportion of people on the CKD register (i.e., with CKD Stage 3-5) in NCL have a recorded uACR in the past 12 months?

What does this result mean?

All people (100%) living with CKD should have their uACR checked *at least annually alongside eGFR*. This result indicates that **fewer than half (48.9%)** of the people on the CKD register (CKD stages 3-5) have had this test completed/ documented.

Why is this significant?

- ✓ Elevated uACR (>3mg/mmol) indicates protein leak into the urine (albuminuria/ proteinuria) and is an important prognostic test for CKD.
- ✓ The amount of proteinuria must be known to accurately code CKD in the patient's record e.g. G2**A3**
- ✓ uACR must be measured to guide BP targets for people living with CKD.
- ✓ Quantifying proteinuria is important to ensure they are on optimal protective therapies such as SGLT-2 inhibitors.

How can we improve this measure?

The NCL CKD Pathway https://gps.northcentrallondon.icb.nhs.uk/pathways/chronic-kidney-disease-ckd provides guidance on the frequency of monitoring uACR and eGFR based on the severity of CKD.

CKD Classification by eGFR & Albuminuria

eGFR ml/min/1.73m²	Albuminuria categories Albumin:Creatinine Ratio (ACR) spot urine		
	A 1 <3 mg/mmol	A 2 3-30 mg/mmol	A 3 >30 mg/mmol
G1 ≥ 90		G1 A2	G1 A3
G2 60-89		G2 A2	G2 A3
G3a 45-59	G3a A1	G3a A2	G3a A3
G3b 30-44	G3b A1	G3b A2	G3b A3
G4 15-29	G4 A1	G4 A2	G4 A3
G5 <15	G5 A1	G5 A2	G5 A3

- Deep red (DR): Extremely high risk - Test 4+ times/year
- Red: Very high risk - Test 3 times/year
- Orange: High risk - Test 2 times/year
- Yellow (Y): Moderately increased risk - Test once/year
- Green: Low or no risk – test once/year **IF CKD**

New Models of Care

Scenario: You wish to efficiently populate nutrition transfers of care between acute, secondary and primary care.

EPR Optimisation

Professional Record Standards Body

Pan London publication: Nutrition Transfers of Care: Improving Quality, Efficacy and Safety – due this month.

Came from a desire to improve a mostly negative experience of transcribing or pasting data into a document external to the patient's electronic record.

Standard principles:

Goal to eliminate the population of documents out with the EPR.

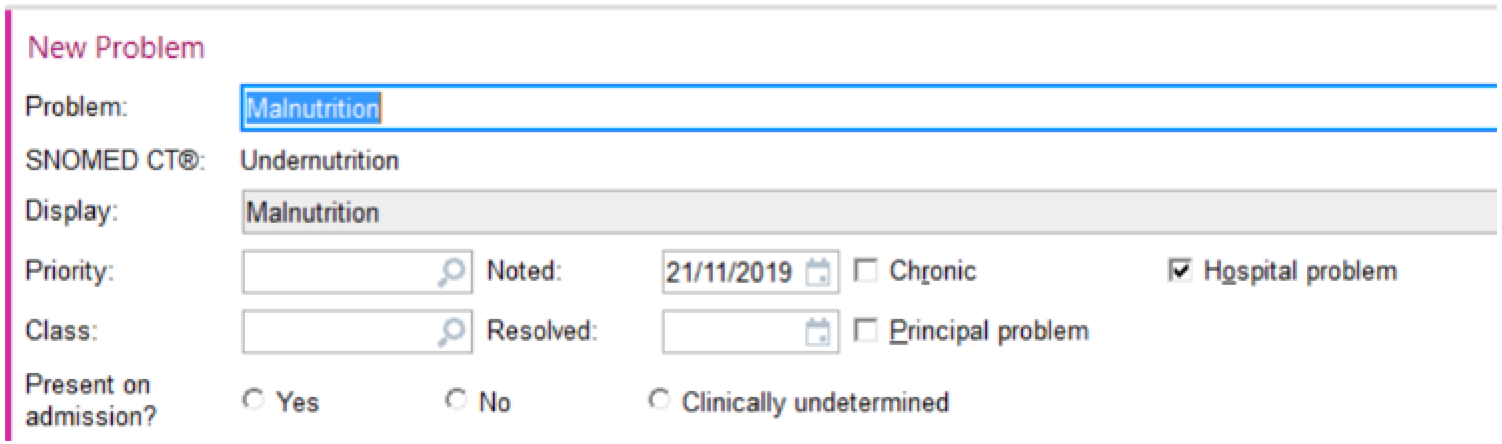
Adopt SNOMED CT coded diagnoses, dietitians must take responsibility for documenting nutrition diagnoses they have made.

Adopt the National Professional Records Standards Body (PRSB) standards in line with a National Transfer of Care Initiative.

New Models of Care

Scenario: You wish to efficiently populate nutrition transfers of care between acute, secondary and primary care.

EPR Optimisation



New Problem

Problem: Malnutrition

SNOMED CT®: Undernutrition

Display: Malnutrition

Priority: | Noted: 21/11/2019 | ☐ Chronic | ☑ Hospital problem

Class: | Resolved: | ☐ Principal problem

Present on admission? ○ Yes ○ No ○ Clinically undetermined

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Scenario: You wish to efficiently populate nutrition transfers of care between acute, secondary and primary care.

EPR Optimisation

Nutrition Transfer of Care: A recommended digital dataset for London

The recommended digital dataset has been defined below, with the data fields defined by the standards outlined in the National Transfer of Care Initiative noted in **blue text** for ease of identification. You can read more about the initiative, and the mandatory information standards notice (ISN) in the supporting documentation, Nutrition Transfers of Care: improving quality, safety and efficiency across London.

Data	Definition	Source	Include for GP only correspondence (e.g. not for dietetic f/u)?
Demographics			
NHS Number	The unique identifier for a person within the NHS in England and Wales.	**PDS/PAS**	Yes
Title	Person title.	**PDS/PAS**	Yes
Patient Surname	The family name or surname of the person.	**PDS/PAS**	Yes

New Models of Care

Scenario: You wish to improve the appropriateness of ONS use in primary care

EPR Optimisation

- ONS automatically cancelled on discharge
- Simple ONS review post discharge via a "patient portal"

AI Voicebot

- Patients who are on ONS in the community, with no planned review with community or secondary dietetic team
- Series of questions e.g., Change in appetite, weight stability, clothes fitting, enjoy/ taking supplements, concern of self or family
- Consider accessibility challenges – neurodiverse, non-English speakers, hard of hearing
- Use for the "low hanging fruit"

New Models of Care

Scenario: You wish to improve the appropriateness of ONS use in primary care

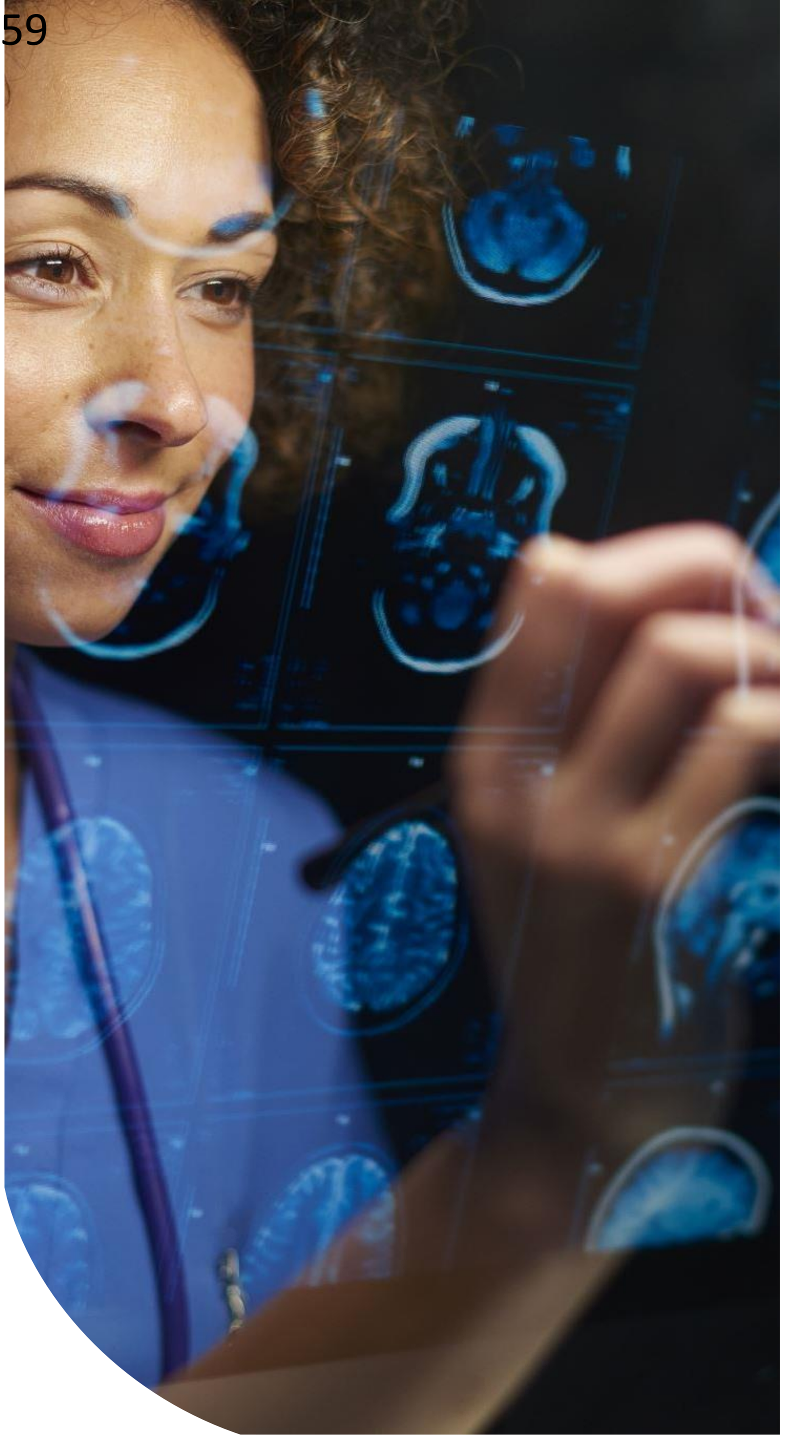
- Supervised language learning model (LLM)

Accuracy and safety of an autonomous artificial intelligence clinical assistant conducting telemedicine follow-up assessment for cataract surgery

Edward Meinert,[a,b,c,d,] Madison Milne-Ives,[a,b] Ernest Lim,[e,f,g] Aisling Higham,[e,h] Selina Boege,[a,b] Nick de Pennington,[e] Mamta Bajre,[i] Guy Mole,[e,h,j] Eduardo Normando,[c,**] and Kanmin Xue[h,j,***]*

EClinicalMedicine. 2024 Jul 3:73:102692. doi: 10.1016/j.eclinm.2024.102692.

- Voice AI Model (Dora, Ufonia) successful in 9 hospital trusts in England, reviewing people post routine surgery.
- 5 symptom questions, LLM trained to identify who should be flagged for human follow up
- 89% agreement in trials, acceptability in patient interviews high – though raised concern with lack of human touch in cases of complications



Key messages

Horizon 3

New models of care

Clinically led, operationally driven, digitally enabled transformation.

Emerging technologies such as Robotic Process Automation and Artificial Intelligence have a key role to play in business and clinical aspects of dietetics.

Using digital models of care to deliver the quintuple aims alongside "human" care is the way forward.

What is on the horizon?
Priorities for digital health in nutrition and dietetics

High-quality evidence generation across the Nutrition Care Process

Horizon 1 (digital competency, infrastructure, governance, maturity) must come before AI

Meaningful patient and public engagement will guide digital ethics and research priorities

Integrating data - a 'digital front door' for nutrition and dietetics

Education and training (tertiary curriculum, standardized competencies, digital clinical pathways)

Patient and public trust depends on strict privacy, confidentiality, and respect

What might the future look like?

Clinical decision-support tools based on **causal artificial intelligence** will **predict individual patient responses** to numerous potential dietary interventions (e.g., oral nutritional supplements, low-energy diets, ketogenic intervention)

Natural language processing will analyse free-text nutrition data in electronic health records to derive dietary patterns and nutrient intake across multiple care episodes

Routinely collected public health data (from consumer purchasing behaviours, health records, geospatial infrastructure) will guide **just-in-time-adaptive interventions** (JITAI) to promote healthier food decisions or information about food access

1. Feuerriegel, S., Frauen, D., Melnychuk, V. *et al.* Causal machine learning for predicting treatment outcomes. *Nat Med* **30**, 958–968 (2024). https://doi.org/10.1038/s41591-024-02902-1
2. Shoenbill K, Song Y, Gress L, Johnson H, Smith M, Mendonca EA. Natural language processing of lifestyle modification documentation. Health Informatics J. 2020 Mar;26(1):388-405. doi: 10.1177/1460458218824742. Epub 2019 Feb 22. PMID: 30791802; PMCID: PMC6722039.
3. Canfell OJ, Davidson K, Woods L, Sullivan C, Cocoros NM, Klompas M, Zambarano B, Eakin E, Littlewood R, Burton-Jones A. Precision Public Health for Non-communicable Diseases: An Emerging Strategic Roadmap and Multinational Use Cases. Front Public Health. 2022 Apr 8;10:854525. doi: 10.3389/fpubh.2022.854525. PMID: 35462850; PMCID: PMC9024120.

The potential of digital health across the Nutrition Care Process

Kelly J.T., Collins P.F., McCamley J., Ball L., Roberts S. & Campbell K.L. (2021) *J Hum Nutr Diet*. 34, 134–146. https://doi.org/10.1111/jhn.12827 slido

Please download and install the Slido app on all computers you use

How would you like to engage further in digital health for nutrition and dietetics? Rank each option in your order of preference from highest to lowest.

ⓘ Start presenting to display the poll results on this slide.

Thank you!

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