INTERNATIONALE HOCHSCHULE

Johannes Walter

LONGEVITY BY DESIGN

AI, DATA AND HEALTHY AGEING

27.02.26

NEXA Center for Internet & Society - Polytecnico di Torino

Longevity, Healthspan, and Healthy Ageing

…are three terms that are often confused.

Longevity usually refers to lifespan…

the survival and mortality life expectancy at the population level.

How long do we live?

The World Health Organization concept Of Healthy Ageing…

shifts the goal from living longer to functional ability, intrinsic capacity, participation & independence.

How well do we function as we age?

The Healthspan is a widely used research shorthand…

for the years lived in good health. And is often explained as disease- and disability-free years, or through frailty and multimorbidity indicators

How many years are lived in good health?

“Longevity by Design” means using continuous data and AI to protect function earlier while keeping responsibility and final clinical decisions with humans.

HEALTHY AGEING IS NOT “LIVING LONGER”

The World Health Organization defines…

Healthy ageing is the process of developing and maintaining the functional ability that enables wellbeing in older age.

Our Intrinsic capacity

like Physical and mental capacities

Our Environment

Supportive housing, services, communities

Our Functional ability

What people can be and do

So why now?

…because health system pressure is rising at the same time as technology readiness.

On the systemic side…

- Chronic multimorbidity is rising and many disease processes have long trajectories
- Resource constraints and prioritisation becomes central
- Episodic care struggles to learn due to a lack of feedback loops.

On the technology side…

- We now have broader measurement (standard labs, wearables, imaging and genetics)
- AI can help structure heterogeneous signals and translate signals into decisions
- But the Impact depends on integration into workflows and on governance.

Systems biology

…focuses on interactions, feedback loops and emergent behaviours.

You can't measure health using just one metric…

- Health is a emergent behaviour of coupled processes like metabolism, hormones, inflammation and behaviour
- But Chronic disease is dynamic
- Often we see compensation for a long time, then gradual drift and finally symptoms become visible
- Prevention requires monitoring systems, not only isolated markers

Operationally that means…

- **Measuring functions,** like cardiorespiratory fitness, strength, mobility, cognition
- **Measuring stability:** metabolic control, inflammation, sleep and recovery capacity
- **Trajectories:** trends over time (not snapshots)
- **Multidimensional:** no single metric describes ageing end-to-end

AI can integrate multiple weak signals into an interpretable picture

Healthcare is being forced

…to redesign its operating model.

Today we have episodic models…

- Care starts when symptoms appear
- We use fragmented data across providers
- We have reactive decisions under time pressure
- Prevention is optional or underfunded

The consequence is that learning is hard because outcomes and upstream signals are not routinely connected.

Design challenge

A Continuous model flips this logic…

- Care starts with risk signals, not only with symptoms.
- Data flows are interoperable across electronic health record and devices.
- Decision support is embedded in the workflow
- Prevention becomes continuous and personalized
- The system becomes a learning system: evaluate, improve and iterate.

INTERNATIONALE HOCHSCHULE

ARTIFICIAL INTELLIGENCE SUPPORTS HEALTHY AGEING BUT ONLY WHEN IT IS DESIGNED AS PART OF A SOCIO-TECNICAL SYSTEM.

There are three high-value roles for AI in healthy ageing

…with responsibility and final decisions staying with humans.

Early risk detection

AI can identify frailty risk or detect silent disease earlier than traditional episodic care with multiple sources over time

Decision support and Human-in-the-loop

Better prevention

AI can help personalize interventions, identify who could benefit and support adherence through coaching.

Decision support and Human-in-the-loop

Clinical decision support

AI can support triage and prioritization, act as a second reader for imaging and reduce medication safety

Decision support and Human-in-the-loop

Healthy ageing needs multi-source data

…Electronic Health Record alone is rarely enough.

When we add sources…

Wearables contribute
activity, sleep, Heart Rate Variability (HRV)

Labs contribute
trends and reference ranges interpretation.

Imaging can
reveal early patterns

Social context
shapes exposure care access, and feasibility of interventions.

EHR / clinical workflow

Every additional source increases the need for consent management, data quality controls, provenance and accountability

The data pyramid

…is a pragmatic approach that connects scientific ambition with real-world scalability.

At the top we have…
deep phenotyping like proteomics, metabolomics, advanced imaging.
These are powerful for discovering subgroups, but expensive.

In the middle we have…
core measurements like standard labs, polygenetic risk scores, continuous glucose monitoring, in some settings also microbiome and genetics profiles

At the bottom we have…
scalable, broad signals: wearables, smartphone proxies, questionnaires.
They are imperfect, but can reach many people, continuously at low costs

The design principle is…

- Use deep data to learn which mechanisms matter and which subgroups exists
- Then translate the insights into scalable signals to screen and trigger targeted follow-up.

Multiomics is attractive

…because it measures multiple orthogonal biological layers.

The value proposition is…

higher sensitivity to pathway-level dysregulation and to stratify responders versus non-responder.

This matters because in prevention and treatment averages often hide meaningful heterogeneity.

Multiomics only helps if methods are rigorous…

We have to control multiple testing , define prospective endpoints and interpret results in context like age, medications or lifestyle

If multiomic signals are used to guide interventions we need replication and intervention studies to support causality

Genetics & polygenic risk scores (PRS)

…provide a risk lens but not determinism

Practically polygenic risk scores can help…

- Prioritize monitoring and prevention
- Identify who is likely to respond to which interventions

The key limitations are…

- Transferability across populations can be limited
- Explained variance is trait-dependent but not a diagnosis
- Always interpret with phenotype, environment and trajectories

Wearables can turn “annual snapshots” into “daily signals”

That is a major shift for prevention, but only if we define the action chain.

A practical “signal to action” ladder could be...

1	**A drop in steps for 7 days**	→	trigger check-in message or a call
2	**Sleep disruption and HRV change**	→	might trigger a medication, stressors review
3	**An Arrhythmia alert**	→	needs confirmation and clinical triage
4	**Repeated falls or near-falls**	→	point to home safety intverventions and physiotherapy

Passive monitoring: activity, sleep, heart rhythm

Remote monitoring in real-world settings

… the research project ALFREDO as a practical example of what is feasible.

Research Project: Alfredo

- The Goal was continuous, preventive monitoring in real-world ageing care
- Smart watches and home devices captured relevant physiological signals like sleep, Heart Rate, ECG, steps or weight.
- ALFREDO combined monitoring with online one-to-one coaching and online group coaching sessions to increase praticipation and medical verification (human-in-the-loop)
- The implementation involved partners including health insurer or the the alzheimer society

The Value comes from the closed loop:

Continous data produces insights, coaching and medical consultation worklflows turn insights into action and outcones can then be evaluated.

For example, we had prevented a stroke in a participant and identified sleep apnoea.

Outcomes: earlier risk detection and targeted follow-up instead of blanket screening / impact comes from the closed loop

Decision support works when it saves attention

…when it reduces cognitive load and administrative work.

Imaging triage

Design constraints are:

1. Decision support must be embedded In-the-moment of work: inside EHR, not separate systems
2. Must provide calibrated confidence
3. Explainability should match the task
4. Clear escalation paths and documentation must be defined

Reality check

Decision support fails when it demands attention by adding dashboards or unmanageable alerts.

The most common AI deployments are often narrow: imaging triage, measurement tools and specific screening tasks.

Feasibility

...depends on evidence and workflow fit

Area	Now	Next Steps are	Future Steps are
Detection	Imaging triage, measurement tools	Multimodal risk prediction that combines several sources	General-purpose clinical copilots, but only if they are verified, governed and integrated
Prevention	Rule-based and simple personalization	Adaptive programs that are evaluated in real settings	Future Vision could be the closed-loop prevention at scale (continuous signals feeding into interventions)
Operations	Administrative automation is already feasible (scheduling, documentation support)	Optimizing care coordination	Future Vision could be System-level resource allocation, but fair, transparent and accountable

Without Interoperability

...every integration becomes a one-off project. That means high costs and poor scalability.

A pragmatic interoperability stack has several layers:

Clinical Terminologies Standards	such as SNOMED CT define shared meaning
Common Data models	such as OMOP supports research and analytics across institutions
HL7 FHIR	supports exchange through APIs for clinical data
Workflow	Integration connects data to action inside EHR apps and clinical pathways

If you want to standardize something first:

Focus on…

- patient identity and consent metadata,
- core clinical concepts like (problems, medication, labs),
- event timestamp, provenance and
- clear outcome definitions for evaluation.

Interoperability means Scalability

Trust and Health data Protection

...are infrastructure requirements, not optional add-ons.

Under GDPR...

health, genetic and biometric data are special category data. Processing is prohibited by default, with defined exceptions under Art.9

That means every deployment needs a lawful basis under Art. 9:

- Purpose limitation, data minimization, strong security and access controls.
- Patients need transparency about what data is used, why and with which safeguards

On the AI regulation side, the EU AI Act...

introduces Risk-based obligations, especially for high risk and regulated systems in health care.

It requires....

- documentation, transparency, human oversight,
- governance structures and market surveillance.

Implementation

… is a socio-technical problem. AI projects fail because the surrounding system is not designed.

On the Data side…

we see missingness, bias, label leakage or poor provenance.

Must fixed by design…

through careful cohort definition, data contracts and audit trails.

On the Model side…

generalization gaps, drift and miscalibrated uncertainty are common.

Must fixed by design…

through external validation, monitoring and conservative deployment strategies.

On the Workflow side…

alert fatigue, no capacity to act and misaligned incentives can reduce the value.

Must fixed by design…

through embed AI in pathways that already exist, reduce work and ensure there is operational capacity.

On the Governance side…

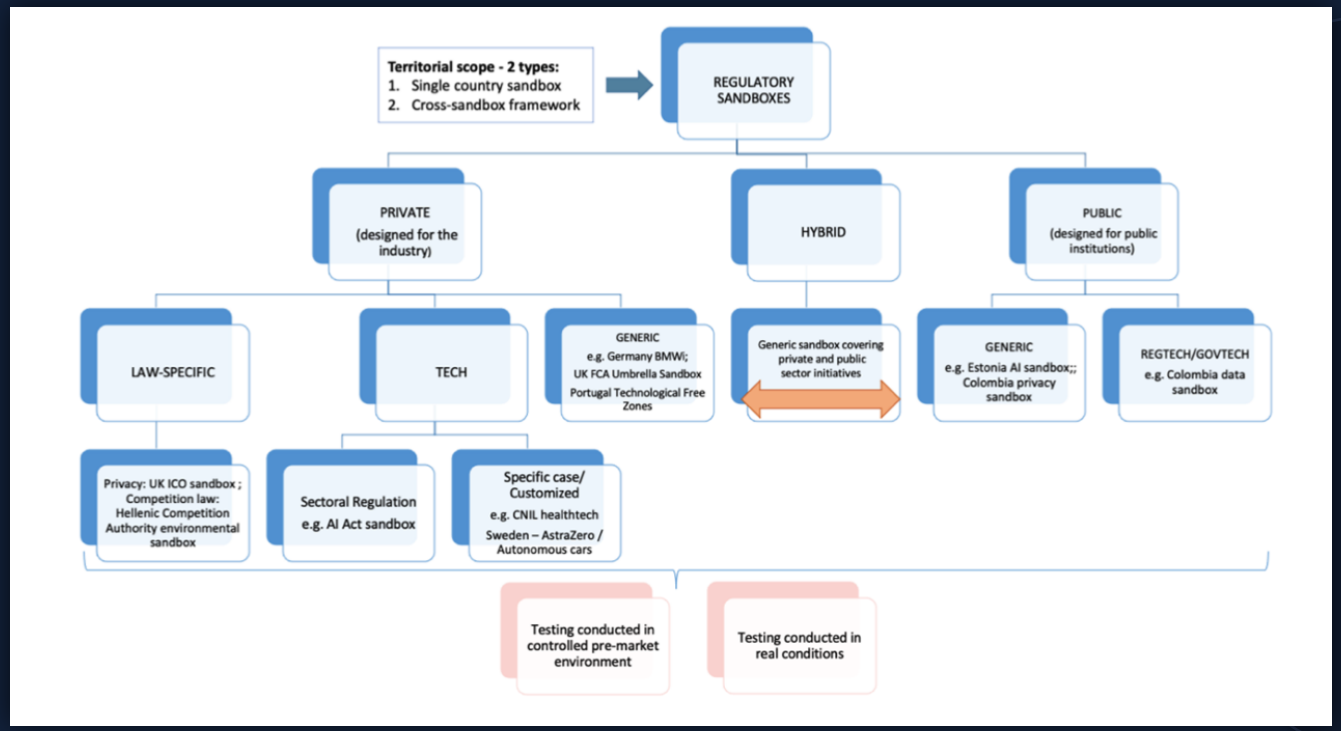
unclear accountability privacy, legal gaps and procurement friction can stop a project.

Must fixed by design…

through clear roles, incident handling and continuous oversight.

Regulated environments

… need controlled experimentation.



Regulatory Sandboxes could enable:

For Regulators…

- Sandboxes support learning-by-testing
- They inform long-term policy though experimentation
- Improve communication with market participants

For Firms…

- Can reduce time to market by streamlining authorization
- Reduce uncertainty about new technologies or business models
- Provide feedback on requirements and risks

For Consumers…

- Sandboxes can accelerate access to new and potentially safer products and services

Source: Adapted from OECD, REGULATORY SANDBOXES IN ARTIFICIAL INTELLIGENCE (2023)

Takeaways

1	**Start with outcomes**	Define the healthspan outcomes you care about and the decision you intend to change.
2	**Design the data supply chain**	Be sure about purpose, ownership, interoperability, retention. Data without governance becomes a liability.
3	**Make evaluation non-negotiable**	Use standards and measure utility, safety and equity. If you cannot evaluate, you cannot scale responsibly.
4	**Embed in workflows**	The design goal is to remove work, don’t add dashboards. Adoptions follows convenience.
5	**Govern with clarity**	Define Roles, accountability, monitoring, incident handling. Governance is how you maintain trust over time.

THANK YOU

Contact:
Johannes Walter
IU University of Applied Sciences
johannes.walter@iu.org
+491723759574

Questions, Suggestions, Wishes?

SELECTED REFERENCES

World Health Organization. (2015). World report on ageing and health. WHO.

European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union.

European Union. (2016). Regulation (EU) 2016/679 (General Data Protection Regulation). Official Journal of the European Union.

European Commission. (2025, February 6). Guidelines on the definition of an AI system established by Regulation (EU) 2024/1689 (AI Act).

Organisation for Economic Co-operation and Development. (2023). Regulatory sandboxes in artificial intelligence (OECD Digital Economy Papers No. 356).

Kordowitzki, P., & Ying, K. (2026). The pursuit of understanding human longevity. npj Aging, 12, 25 (Published 05 Feb 2026).

Edouard, P., Campo, D., & Escourrou, P. (2021). Validation of the Withings Sleep Analyzer, an under-the-mattress device for the detection of moderate-severe sleep apnea syndrome. Journal of Clinical Sleep Medicine

Badertscher, P., et al. (2022). Clinical validation of a novel smartwatch for automated detection of atrial fibrillation. Heart Rhythm O2, 3(3)

Mannhart, D., et al. (2023). Clinical validation of 5 direct-to-consumer wearable devices for atrial fibrillation screening. JACC: Clinical Electrophysiology, 9(2)

ALFREDO project. (2022). Preventive monitoring and AI-supported care pathways using wearables (project materials and pilot reports).

ACRONYMS GLOSSARY AND MEANING

- **AI in Healthcare** — *Artificial Intelligence*: Methods that learn patterns from data to support predictions, classification, and decision support.
- **ML** — *Machine Learning*: Subfield of AI focused on models that improve performance by learning from examples rather than hard-coded rules.
- **LLM** — *Large Language Model*: AI model trained on large text corpora to generate and interpret language; useful for summarisation, drafting, and "knowledge navigation," but needs governance to avoid errors.
- **CDSS** — *Clinical Decision Support System*: Tools that assist clinicians with recommendations/alerts; final responsibility remains with human decision-makers.
- **EHR/EMR** — *Electronic Health Record / Electronic Medical Record*: Digital patient records; core data source but often fragmented across providers/systems.
- **GDPR** — *General Data Protection Regulation (EU)*: Legal framework for personal data processing; defines lawful basis, rights, safeguards, and compliance duties.
- **AI Act** — *EU Artificial Intelligence Act*: EU regulation classifying AI systems by risk level and imposing obligations (e.g., documentation, transparency, oversight) for high-risk use cases.
- **Interoperability**: Ability of systems to exchange and correctly use data; essential for "data-based care" beyond silos.

Data standards / terminologies

- **HL7** — *Health Level Seven*: Organisation behind major healthcare messaging standards; foundational for exchanging clinical data.
- **FHIR** — *Fast Healthcare Interoperability Resources*: Modern HL7 standard using "resources" + APIs for health data exchange; enables scalable integration across systems.
- **OMOP** — *Observational Medical Outcomes Partnership (Common Data Model)*: Standard data model used to harmonise observational health data for analysis across institutions.
- **SNOMED CT** — *Systematized Nomenclature of Medicine—Clinical Terms*: Clinical terminology for consistent coding of diagnoses/clinical concepts.

Wearables / clinical signals

- **ECG (or EKG)** — *Electrocardiogram*: Measures the heart's electrical activity; helps detect arrhythmias (e.g., atrial fibrillation).
- **HR** — *Heart Rate*: Basic cardiovascular signal; useful for fitness and acute stress/illness signals.
- **HRV** — *Heart Rate Variability*: Variation in time between heartbeats; proxy for autonomic balance, recovery, stress, and illness signals.
- **BP** — *Blood Pressure*: Key cardiovascular risk factor; continuous or frequent monitoring can enable earlier intervention.
- **SpO_2** — *Peripheral Oxygen Saturation*: Proxy for blood oxygenation; useful for respiratory issues and sleep-related breathing disorders.
- **AF** — *Atrial Fibrillation*: Common arrhythmia; detection via wearables can trigger confirmatory diagnostics and stroke-risk management.
- **OSA** — *Obstructive Sleep Apnea*: Sleep breathing disorder; wearables/home sensors can flag risk and trigger formal diagnostic follow-up.

Trials / evaluation

- **RCT** — *Randomised Controlled Trial*: Gold-standard design for causal evidence; often slow/expensive but critical for clinical claims.
- **ROC** — *Receiver Operating Characteristic (curve)*: Plots sensitivity vs. false-positive rate to evaluate classifiers.
- **PPV / NPV** — *Positive/Negative Predictive Value*: Probability that alerts are true (PPV) or negatives are truly negative (NPV); depends on prevalence and matters for real-world deployment.
- **Sensitivity / Specificity**: Sensitivity = true positive rate; specificity = true negative rate; both shape clinical usefulness and workload.

Genetics / biomarkers (if you mention them)

- **PRS** — *Polygenic Risk Score*: Aggregate genetic risk estimate from many variants; helps stratify risk but varies by ancestry and dataset.
- **LDL / HDL** — *Low-/High-Density Lipoprotein Cholesterol*: Lipid markers used in cardiovascular risk assessment.
- **CGM** — *Continuous Glucose Monitor*: Tracks glucose continuously; supports "N-of-1" lifestyle experiments and personalised feedback loops.