

Generative AI in Personalized Digital Health and Prevention

*Exploring Potentials from Patient-Generated Health Data
Sensemaking to Context-Aware Behavior Change Support*

*Keynote presentation for the Center for Digital Health Interventions
CDHI Lecture Series Digital Health Forum*

Location: Online (Zoom)

Date: 2025-04-01

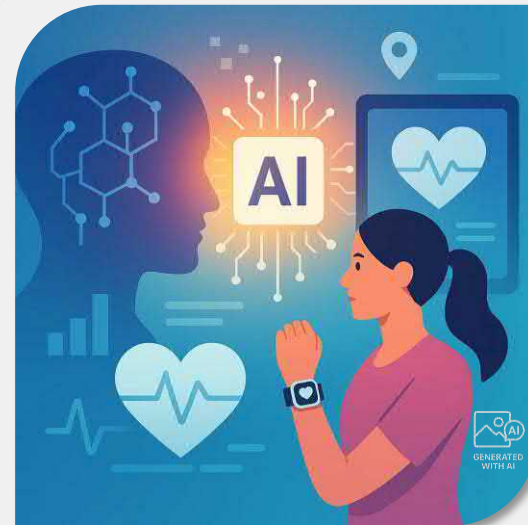
Speaker: Dr.-Ing. Jan David Smeddinck

[@smeddinck.bsky.social](https://bsky.app/profile/smeddinck.bsky.social)

<https://dhp.lbg.ac.at/>



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Key Talking Points

1. The growing importance of digital health solutions in addressing challenges of aging populations and chronic diseases ... prevention > treatment
2. Why personalized health (esp. in long-term health considerations)?
3. How AI enables personalized healthcare interventions that adapt to individual needs and contexts?
4. Scoping Digital Health Interventions with the MAGnify Framework of Lenses
 - a) Use-Cases / Worked Examples on GenAI in Digital Health Interventions for Beh. Ch.
5. Key concerns including privacy, biases, accountability, responsibility, explainability, etc.
6. Human-AI interaction design and development considerations
7. Need for long-term and integrated / holistic perspectives ...
Human-AI Relations in digital health and real-world implementations



Jan (David) Smeddinck

- PhD (Dr.-Ing.) in Computer Science / HCI, University of Bremen, Germany
 - *“Human-Computer Interaction with Adaptable and Adaptive Motion-based Games for Health”*
- 2017 – 2018: Visiting postdoc at the International Computer Science Institute (ICSI), Berkeley, USA (DAAD IFI funded)
- August '18 – '21: Lecturer in Digital Health at Open Lab, Newcastle University
 - Led Digital Health research group with 13 members
- *Co-Director & Principal Investigator for Digital Interventions and Data Analytics at the Ludwig Boltzmann Institute for Digital Health and Prevention (LBI-DHP)*

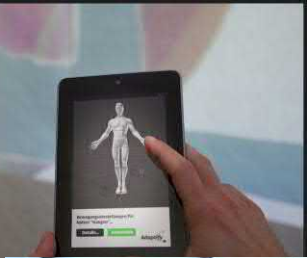
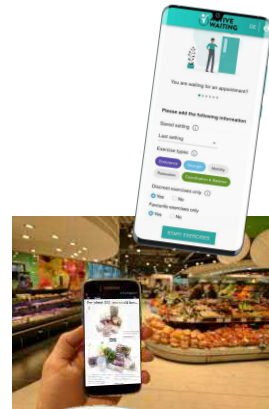
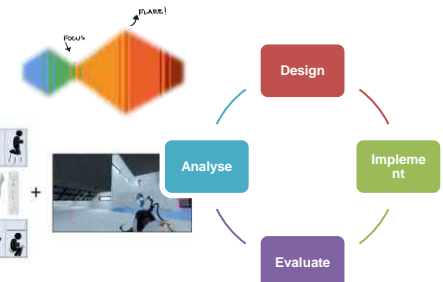
Klaus Tschira Stiftung
gemeinnützige GmbH



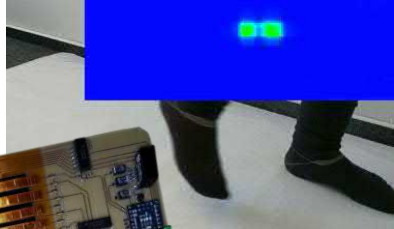
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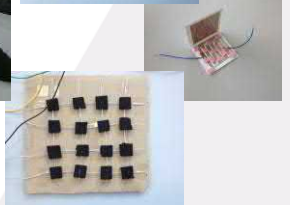
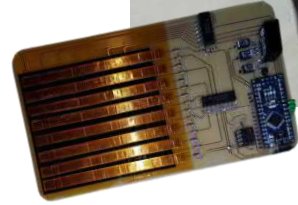
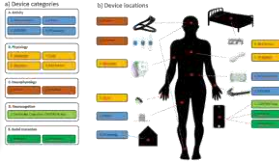
15 years of work in digital health but times have never been more exciting!



ADAPTIFY



IDEA FAST

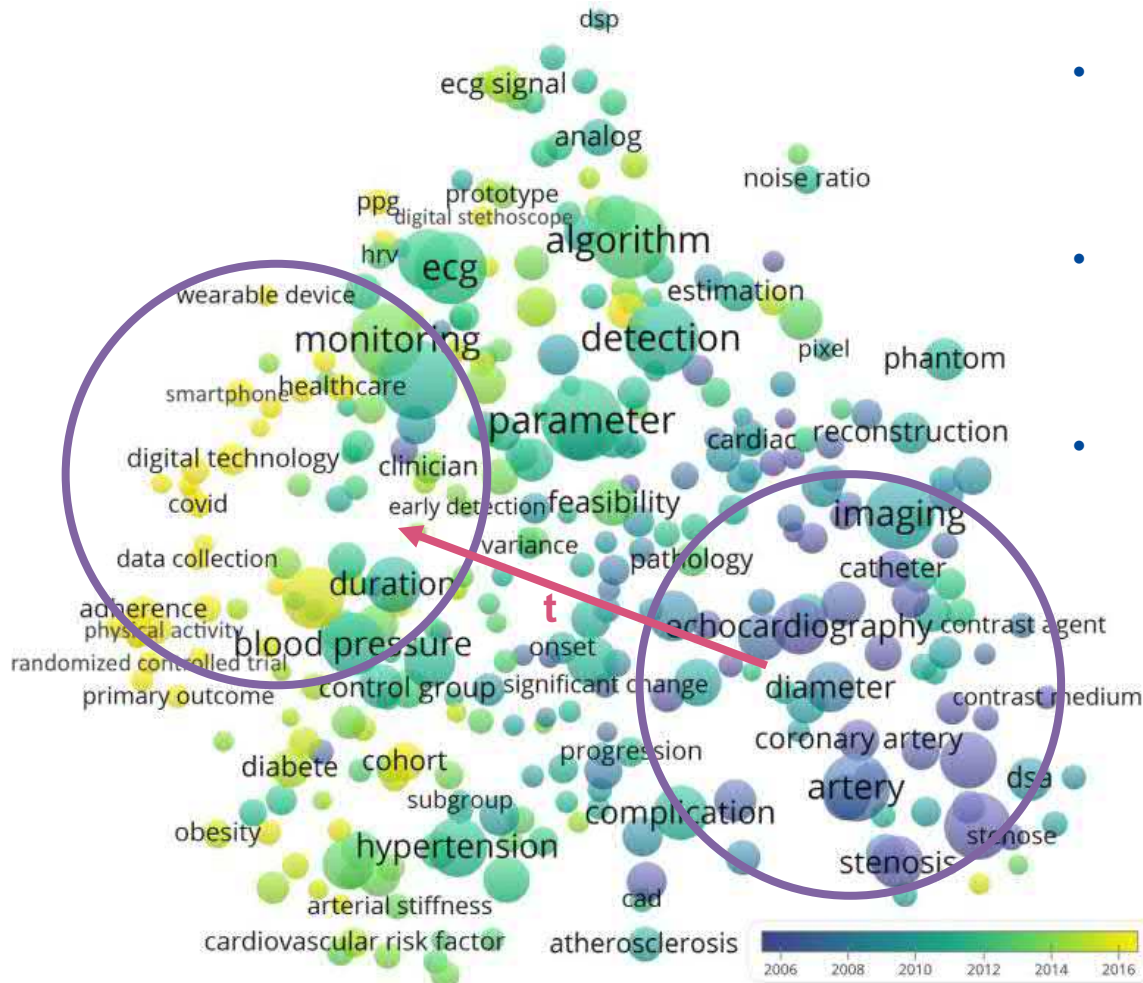


Modern Societal Health Challenges: Aging Society, Lifestyle Changes, CVD / Chronic Afflictions & Physical Activity

- People > 65 years in 2010: ~524 million; in 2019: ~703 million; in 2050: ~ 1.5 billion (WHO/ NIH, 2011)
- Regular physical activity: strong connection with well-being and healthy aging (Böhm et al., 2009)
- Austria: < 50% of 18-64-year-olds meet the WHO PA recommendation for 2.5 weekly hrs moderate aerobic exercise and < 25% meet the recommendations for aerobic + strength (Statistik Austria 2019)
- **healthy life years for persons aged 65+ in Austria decreased from 11.35 in 2014 to 9.75 in 2019. main drivers: obesity & mental health** (Rechnungshof Österreich 2023)



Digital Health Technology e.g. in Cardiology



- Frequency of terms in titles + abstracts in literature on digital technologies in cardiology
- Circle size indicates count- Circle color shows average year of publication
- Distance between circles indicates frequency of simultaneous occurrence

Yeung, A. W. K., Kulnik, S. T., Parvanov, E. D., Fassl, A., Völkl-Kernstock, S., Kletecka-Pulker, M., Crutzen, R., Gutenberg, J., Höppchen, I., Niebauer, J., Smeddinck, J. D., Willschke, H., & Atanasov, A. G. (2022). Digital technology cardiology applications: Analysis of the scientific literature. *JMIR*, 35.

Due to Challenges / Needs: Boom in Digital Health & DHAPPs

- Aka “eHealth, mHealth, telehealth”, etc.
- Global digital health market:
USD 143.9 billion (2021)
- Projection for 2028: 367.2 billion
(Zion Market Research, 2022)

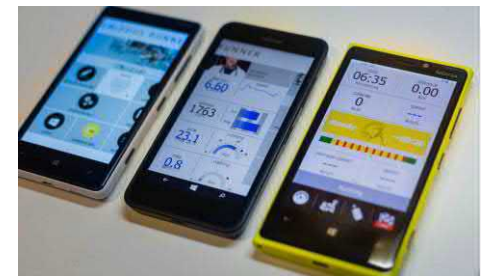
Digital Health Applications:

Potential for motivation, extension, improvement ...
... diagnoses, treatments, accessibility, cost efficiency ...
→ personalized health ("precision medicine"),
prevention > treatment

Zion Market Research. (2022, May 11). Digital Health Market—Global Industry Analysis.
<https://www.zionmarketresearch.com/report/digital-health-market>



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Located at the University Hospital Salzburg: Unique, Synergetic Environment



*Focus on applied research,
practical perspectives,
stakeholder involvement, ...*



*Highly interdisciplinary and international
team of ~33 members / staff...*



LBI Partners:



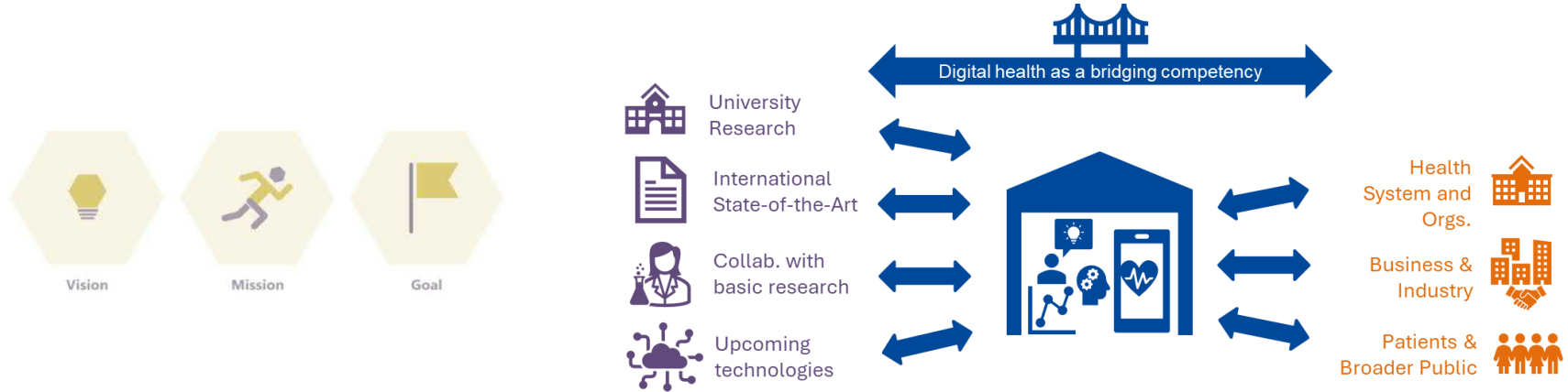
FH Salzburg





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LBI-DHP: Bridging Research & Innovation in Digital Health



Mission: foster lifelong, sustainable and heart-healthy physical activity...

... with research and innovation in digital health ...

Includes ML & AI work on: personalization, risk scores, predictive modeling, just-in-time adaptive interventions, supporting shared decision-making, ...

Working Principles & Process





Highlights from the LBI-DHP...

GaSaBe: All of Salzburg Moving

Ganz Salzburg Bewegten

Mit-Forschende
Unterstütze uns und führe Interviews
Mai/Juli 2023

Interaktive Ausstellung
Wir präsentieren die gemeinsamen Ergebnisse und du stimmst ab: Dezember 2023

IdeenWerkstatt
Wir geben deinen Ideen eine Form
23.06. - 24.06.2023

Bewegte Befragung
Sag uns was dich bewegt
12.04.-15.04.2023

ValOpti: HR Wearables Eval.

Day 1: Laboratory testing		
Lifestyle Activities	Treadmill Step Test	Cycle Ergometry Test
5min sit quietly	5min stand quietly	5min sit quietly
2min walking	5min walking	2min @VPA HR
2min seated typing	30 sec rest	2min Rest
2min full body daily living activities	5min @VPA HR	2min @VPA HR
5min sit quietly	5min @VPA running	30 sec rest
	5min @VPA running repeat until evaluation	2min @VPA HR
		2min Rest

Day 2: 24h Free-Living testing

Day 3: 24h Free-Living testing with same activities as on day 2

Health Data Interop. SaaS

Bundesministerium Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie

NEXUS DIGITAL HEALTH INNOVATION CHALLENGE

www.datanexus.at

22. Mai

DH-Convener

Dig. Health Interv. & MORE

Digital Health Intervention Prototypes

Shared Achievements: reach daily in-gestested step count goals as a team; make report; activate meaningful

Active Walking: custom workout; achieved by X minutes (filter by current context); „energetic spacer“; „walking not walking“

Active Audio Adventures: explore areas; experience exciting stories; GPS-enabled; dynamic audio-based augmented reality

APT

aktivplan

Phase II Reha
Phase III oder Phase IV Reha

Interventionsgruppe
Kontrollgruppe

Baseline 4 Wochen 8 Wochen 13 Wochen

ACTIVE-CaRe Pilot Study (MPG)

Large-Scale Research Collaborations

innovative health initiative

IDERHA
integrating health data

Precision Health: Highlighting Prevention over Treatment & Tackling Personalization along Patient / Health Journeys

Adaptive & Personalized Digital Health Interventions



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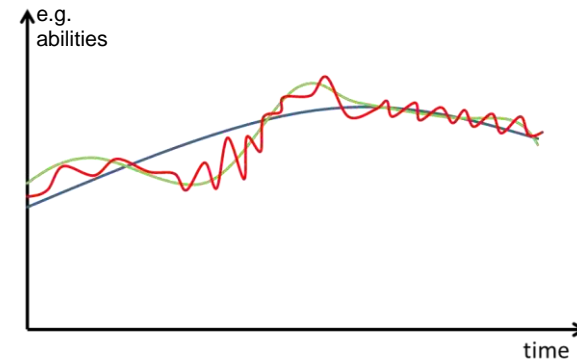
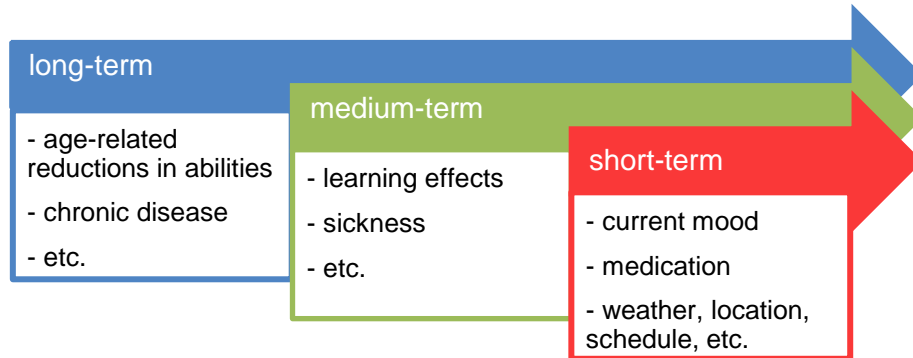
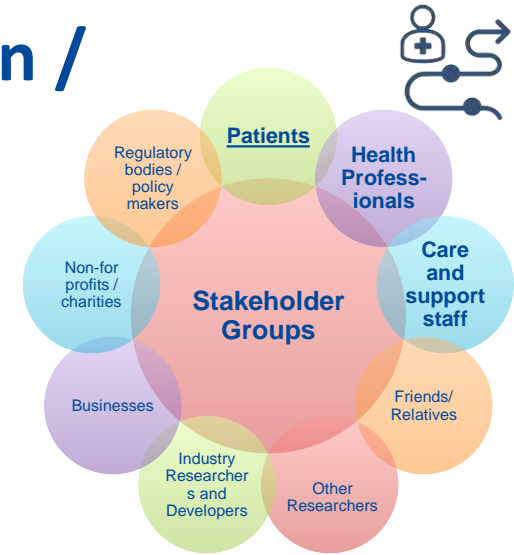
Prevention > Treatment: Potential of Life-Accompanying Digital Health Technologies

- DHT can enable “precision” rehabilitation / prevention interventions using wearable sensors and machine learning
(Adans-Dester et. al 2020)
- Health digital twins (HDT) are virtual models of patients that can offer predictive abilities and personalized treatments
(Venkatesh et al. 2022)



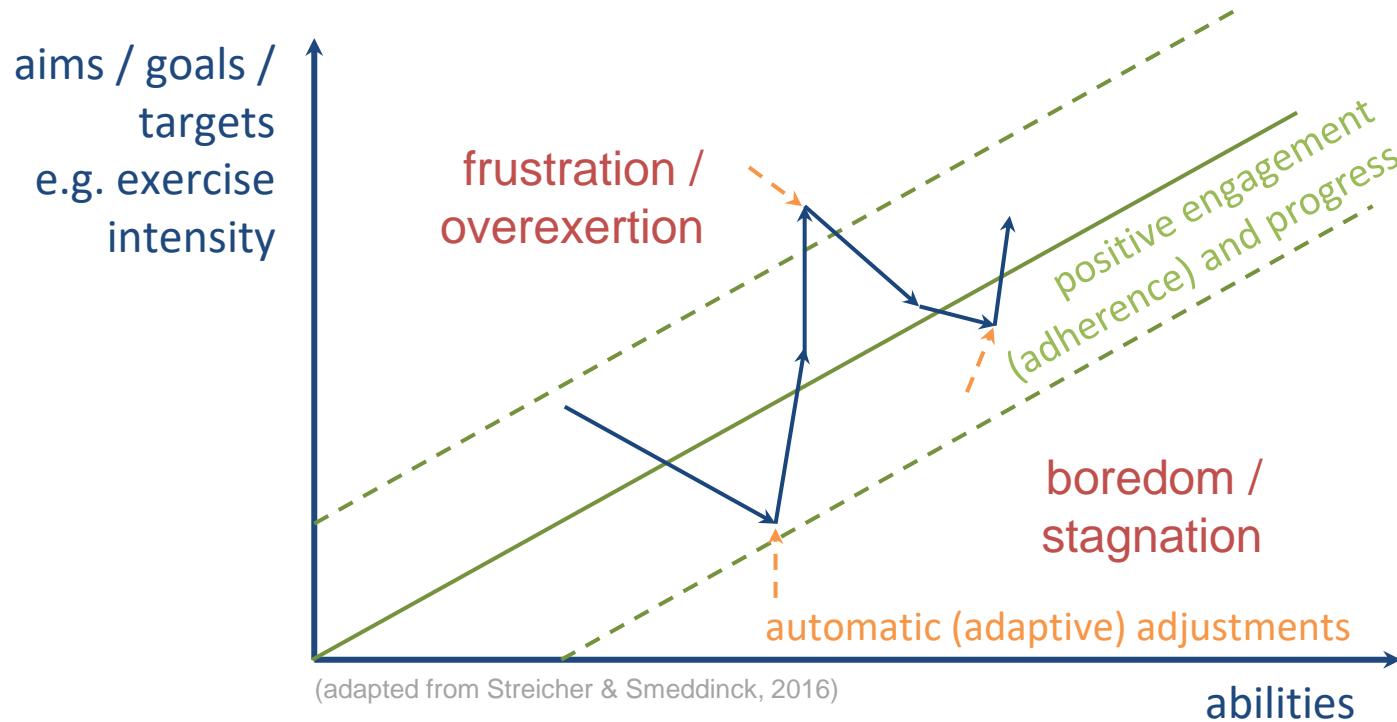
Challenges: The Need for Personalization / Challenging Dynamic Heterogeneities

- Heterogeneous application areas and groups
Heterogeneous stakeholder landscape: *health workers, caregivers, family, friends, etc.*
- Differences in abilities and needs between individuals
 - variance in age-related afflictions
 - differences in the progression of chronic disease
 - differences in permanent physical ability





In The Moment and Over Time: Adaptive Digital Health Interventions for Behavior Change



Need for Personalization / Adaptability & Adaptivity

- Require manual adjustments: **adaptability**
 - Adequate parameter sets for adjustments
 - Translation into application variables
 - Development of interfaces for manual adaptation

BUT: Often not sufficient...

→ *Need for automated adjustments: **adaptivity***

- High frequency and level of detail
- Not overburdening participants or third parties
- Heuristics or more complex models / ML / AI



Facilitate manual ADAPTABILITY
+ automated ADAPTIVITY to achieve:

Personalization

Also in-line with e.g. European Society of Cardiology Guidelines to „*further work to encourage and develop more frequent use of personalised exercise prescription to optimise lifestyle interventions for the prevention and treatment of hypertension*“

Hanssen, H., Boardman, H., Deiseroth, A., Moholdt, T., Simonenko, M., Kränkel, N., Niebauer, J., Tiberi, M., Abreu, A., & Solberg, E. E. (2022). Personalized exercise prescription in the prevention and treatment of arterial hypertension: A Consensus Document from the European Association of Preventive Cardiology (EAPC) and the ESC Council on Hypertension. *European Journal of Preventive Cardiology*, 29(1), 205–215.

Most commonly identified implementation barrier for DHI: “Individual characteristics of end users” → PERSONALIZATION!!!

Kowatsch, T., Otto, L., Harperink, S., Cotti, A., & Schlieter, H. (2019). A design and evaluation framework for digital health interventions. *IT - Information Technology*, 61(5–6), 253–263. <https://doi.org/10.1515/itit-2019-0019>

Alexander Streicher and Jan D. Smeddinck. 2016. Personalized and Adaptive Serious Games. In *Entertainment Computing and Serious Games*, Ralf Dörner, Stefan Göbel, Michael Kickmeier-Rust, Maic Masuch and Katharina Zweig (eds.). Springer International Publishing, Cham, 332–377. Retrieved October 13, 2016 from http://link.springer.com/10.1007/978-3-319-46152-6_14



Traditional Heuristics & Acceptance of Adaptive Motion-Bases Games for Health



Universität Bremen*



Focus on difficulty and input interpretation (parameters):
> **speed, accuracy + amplitude**; parameter targeting **range of motion** of the player (e.g. reach and flexibility of arms)

(Smeddinck, Siegel & Herrlich, 2013. Adaptive Difficulty in Exergames for Parkinson's disease Patients. *Graphics Interface 2013*.)



ADAPTIFY



Early peek into personalised / precision medicine...
... ~ 1.7M€ BMBF-funded project 2015-18.

3rd Generation MGH

Sensor Mat

(Mobile)
Web
Platform

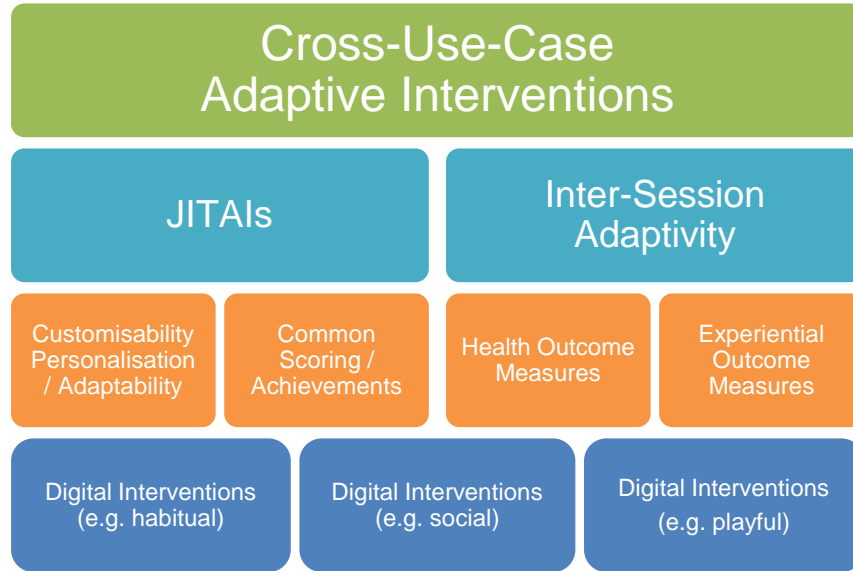
Adaptability
& Adaptivity



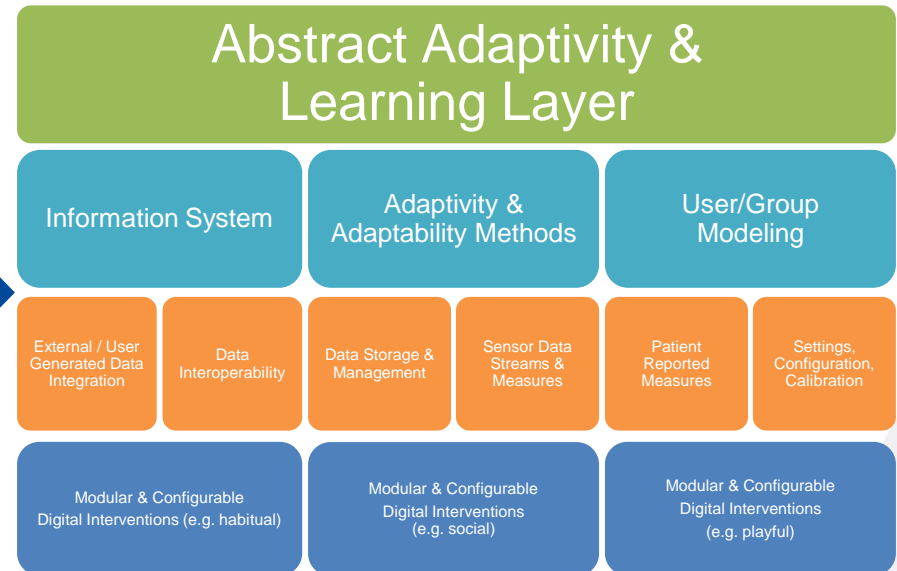


Engineering Personalized Health

Conceptual view:



Implementation view:



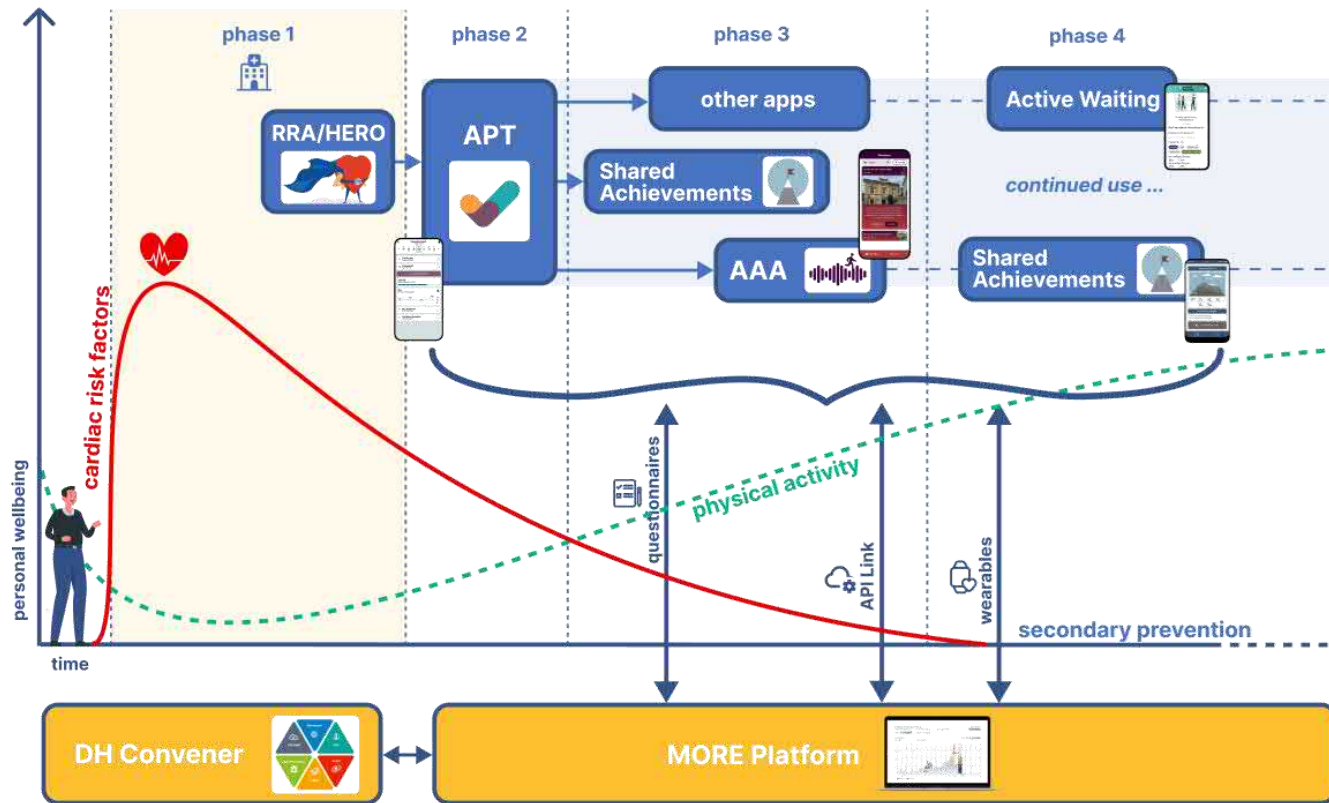
E.g.

Gruber, S., Neumayr, B., Reich, S., Niebauer, J., & **Smeddinck**, J. D. (2022). Towards Adaptability of Just-In-Time Adaptive Interventions. *Proceedings of DHealth 2022*, 2.

Gruber, S., Neumayr, B., & **Smeddinck**, J. D. (2022, accepted). Towards Integration-Preserving Customization of Just-in-Time Adaptive Interventions with Composite Clabjects in RDF and SHACL. 2022 *ACM/IEEE Int. Conf. on Model Driven Engineering Languages and Syst. Companion (MODELS-C)*.



Studying Personalized Health: Integrated Digital Health Innovation Ecosystem



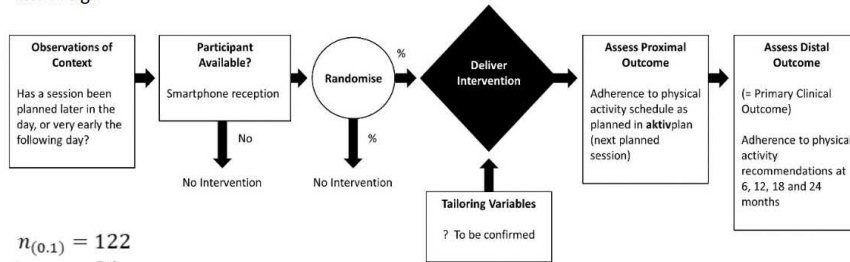


Research Methods for Scalable Studies of Personalization in Digital Health

Continuous evaluation of evolving behavioral intervention technologies (CEEBITS)

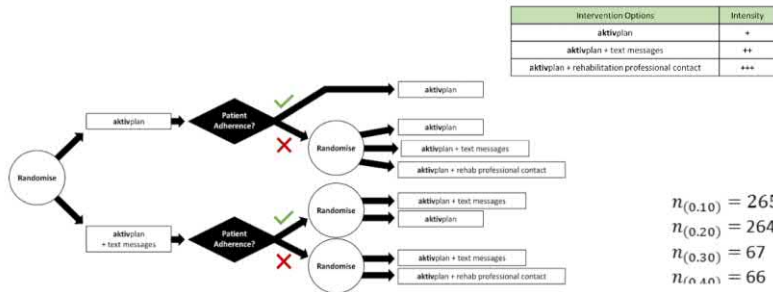
Micro-randomised trial (MRT)

“Intervention” = reminder text message



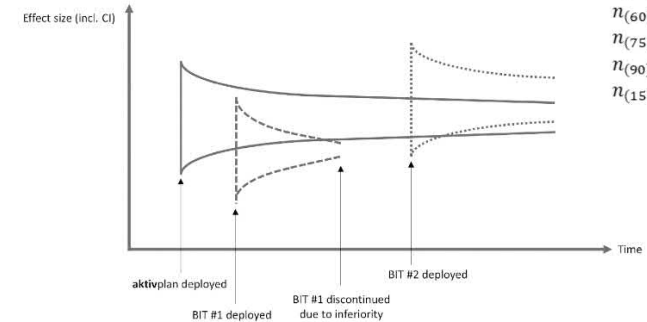
$n_{(0.1)} = 122$
 $n_{(0.2)} = 34$
 $n_{(0.3)} = 18$

Sequential multiple assignment randomised trial (SMART)



Behavioural Intervention Technologies (BITS) for evaluation:

- aktivplan (solid line)
- BIT #1 (dashed line)
- BIT #2 (dotted line)



$n_{(15)} = 7296$
 $n_{(30)} = 1824$
 $n_{(60)} = 456$
 $n_{(75)} = 291$
 $n_{(90)} = 202$
 $n_{(150)} = 73$

Also:

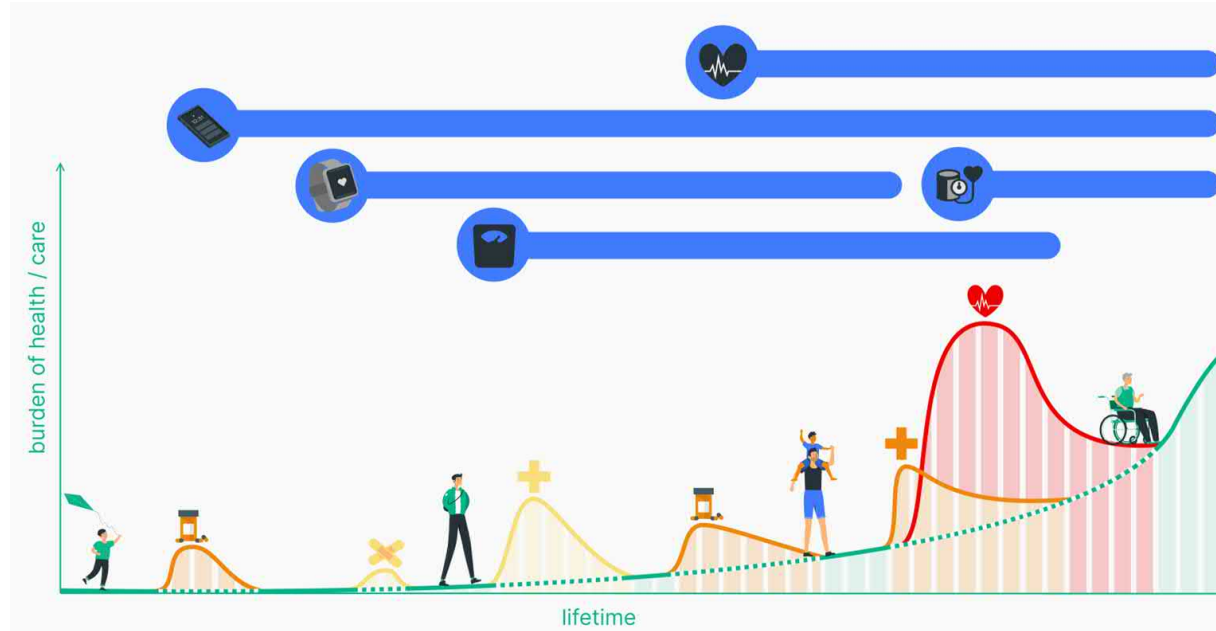
- N-of-1 studies (subject receives treatment(s) and control in randomized order)
- Composite endpoints

	Intervention aim			
	Improvement	Non-deterioration		
Component endpoint 1: Exercise capacity <i>Maximum mechanical power output (Watt)</i>	Change ≥ 15 W	Change > -15 W	Yes	No
Component endpoint 2: Physical activity <i>Moderate to vigorous physical activity (minutes per day)</i>	Change ≥ 10 min/day	Change > -10 min/day	Yes	No

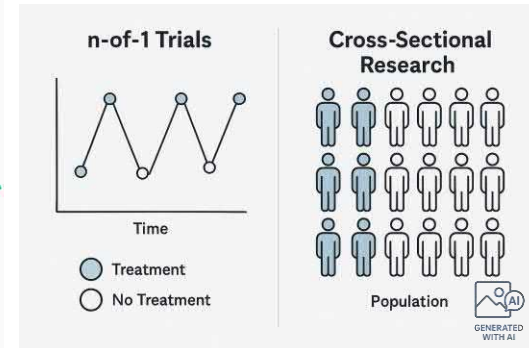
Intervention successful (green arrows)
 Intervention failed (red arrow)



Accompanying Patient Journeys with Digital Health...



Need to rethink scientific methods ...



Lillie, E. O., Patay, B., Diamant, J., Issell, B., Topol, E. J., & Schork, N. J. (2011). The n-of-1 clinical trial: The ultimate strategy for individualizing medicine? *Personalized Medicine*, 8(2), 161. <https://doi.org/10.2217/pme.11.7>

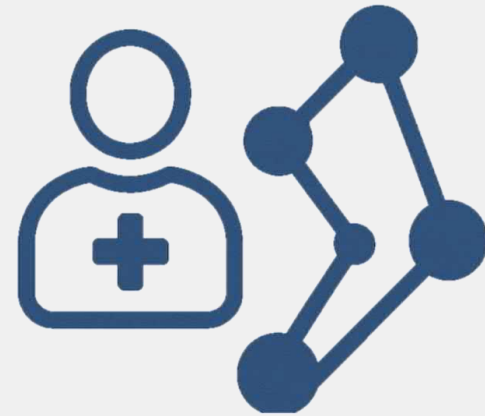
Carrozzo AE, Zimmermann G, Bathke AC, Neunhaeuserer D, Niebauer J, Kulnik ST. Two-Arm Crossover Randomized Controlled Trial Versus Meta-Analysis of N-of-1 Studies: Comparison of Statistical Efficiency in Determining an Intervention Effect. *Biom J.* 2025 Apr;67(2):e70045. doi: 10.1002/bimj.70045. PMID: 40071868; PMCID: PMC11898578.

Generative AI in Health

Adaptive & Personalized Digital Health Interventions



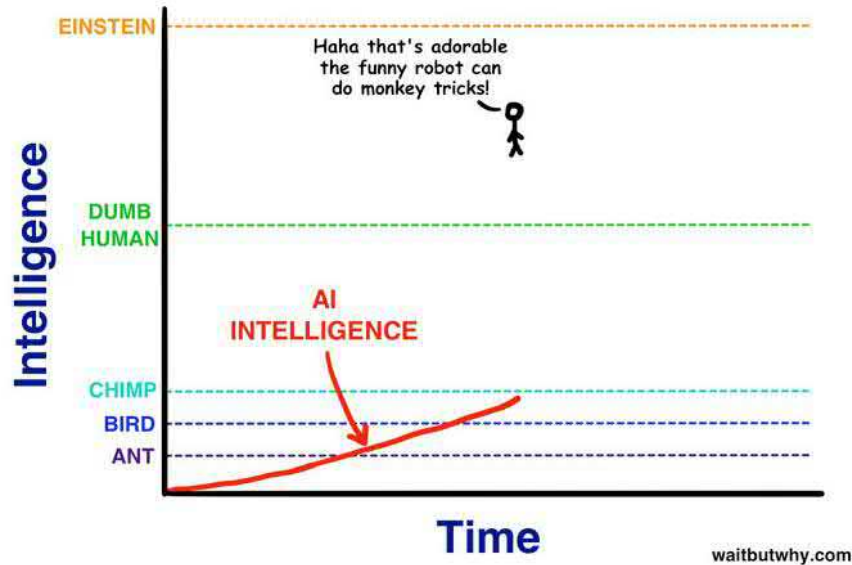
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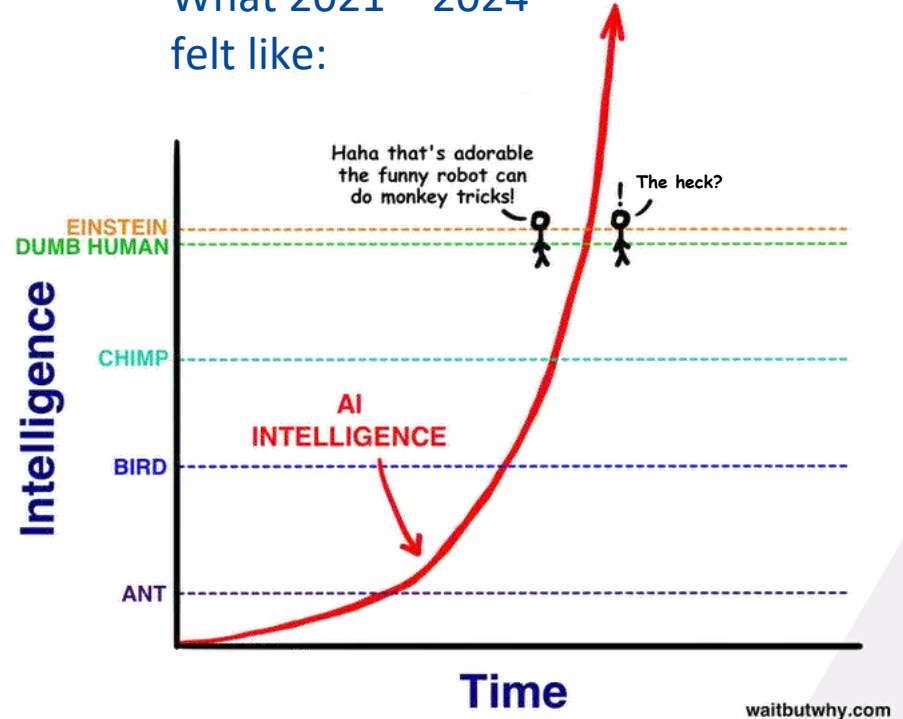


Enter (Recent) Generative AI

Typical view on AI “capabilities”
pre GPT2/3/4 + Dall-E & Co.:



What 2021 – 2024
felt like:





Ubiquitous AI (also in Health) is already here...

- Translation tools etc. have been "in everyone's hands" for many years...
Increasingly rapid introduction of numerous applications also in science and research (e.g. „protein folding diffusion“; Wu et al. 2022)
- Applied (open source) ML/AI model markets are developing rapidly; shortened "time-to-market" ...
- Also longer-term developments in digital health ...
 - Medical image analysis: e.g. skin image scanner (Tschandl et al. 2020)
Speech-based biomarkers (e.g., detection of Alzheimer's dis.; Laguarta et al. 2021)
Cough and breathing analysis (e.g. infectious diseases; Despotovic et al. 2021)

Despotovic, V., Ismael, M., Cornil, M., Call, R. M., & Fagherazzi, G. (2021). Detection of COVID-19 from voice, cough and breathing patterns: Dataset and preliminary results. *Computers in Biology and Medicine*, 138, 104944.

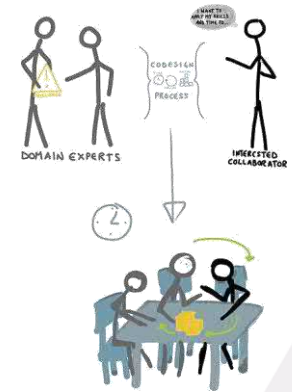
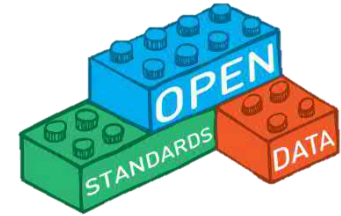
Laguarta, J., & Subirana, B. (2021). Longitudinal Speech Biomarkers for Automated Alzheimer's Detection. *Frontiers in Computer Science*, 3. <https://www.frontiersin.org/articles/10.3389/fcomp.2021.624694>

Tschandl, P., Rinner, C., Apalla, Z., Argenziano, G., Codella, N., Halpern, A., Janda, M., Lallas, A., Longo, C., Malvehy, J., Paoli, J., Puig, S., Rosendahl, C., Soyer, H. P., Zalaudek, I., & Kittler, H. (2020). Human–computer collaboration for skin cancer recognition. *Nature Medicine*, 26(8), 1229–1234.

Wu, K. E., Yang, K. K., Berg, R. van den, Zou, J. Y., Lu, A. X., & Amini, A. P. (2022). Protein structure generation via folding diffusion (arXiv:2209.15611). arXiv. <https://doi.org/10.48550/arXiv.2209.15611>

More Broadly Realizing the Potential of Personalized Digital Health

- exciting developments in sensors, multi-device use ...
- „all data is health data“
- need investment in open platforms and protocols / interop.
 - Open data, protocol and platform initiatives!!!
(e.g. Open mHealth, FHIR HL7, GNU Health, OpenEHR ...)
- data ownership = asset ownership
 - <> equity / social justice in digital health → EHDS
- better data / asset management (regardless where stored)
 - Requires awareness + tools, modular and dynamic informed consent, etc.
- → need for analytics & prediction that tolerates sparsity and unique multimodal personal digital health ecosystems ...
- Now genAI/LLMs and conversational agents to possibly hyper-scale personalized DHIs (Martinego et al. 2023)



**AN INTRIGUING MATCH FOR
GENERATIVE AI (ESP. ON
THE EDGE / FEDERATED)!!**



LLM in Digital Health: HealthGPT



Varun Shenoy

@varunshenoy_

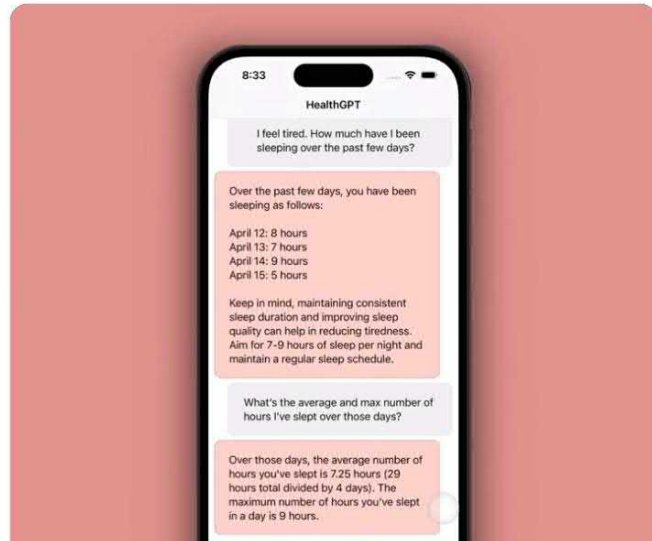
...

I connected ChatGPT to my personal health data on my iPhone.

Now, I can have a conversation with my digital health history.

The code is also public.

Say hello to HealthGPT 🤖



https://twitter.com/varunshenoy_/status/1648374949537775616

“Query your Apple Health data with natural language”

GPT-4 take: HealthGPT Potential Functionalities:

- Personalized health recommendations
- Medical literature summarization
- Disease diagnosis assistance
- Virtual health assistant

“HealthGPT.” Stanford Biodesign Digital Health, May 04, 2023. Accessed:

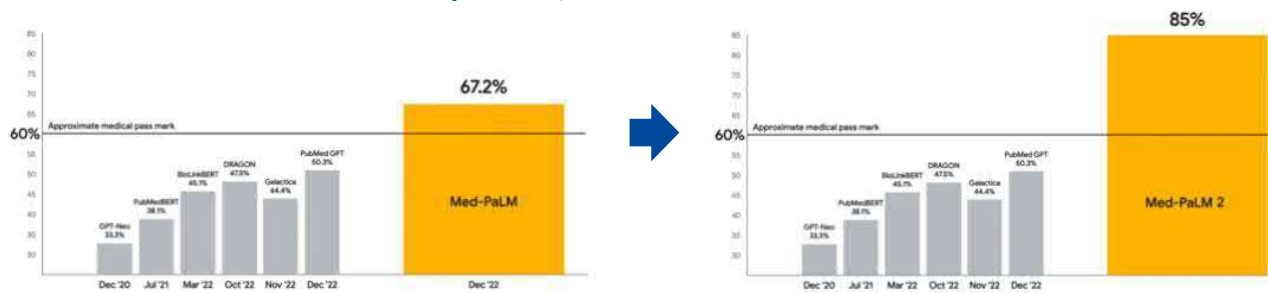
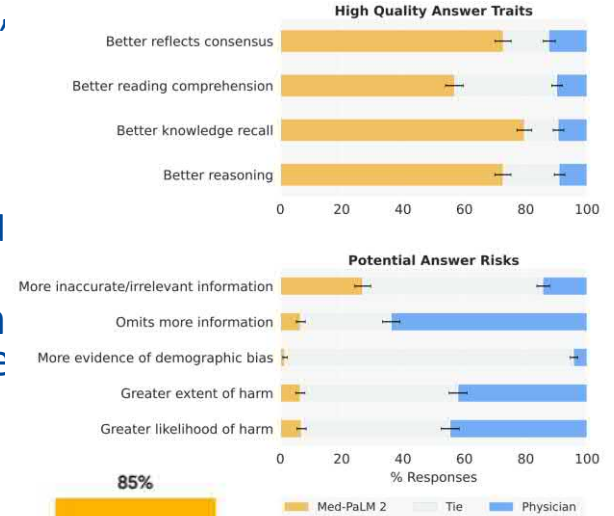
May 04, 2023. [Online]. Available:

<https://github.com/StanfordBDHG/HealthGPT>



Generative and Foundation Models in Health: Key Related Work: Med-PaLM2 (LLM)

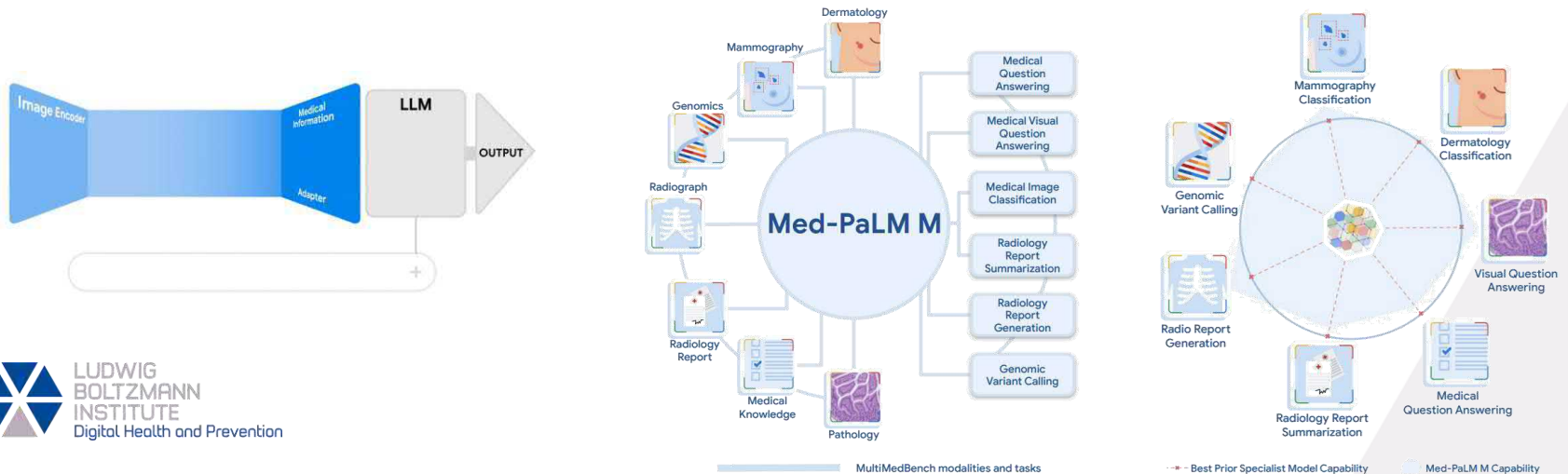
- Med-PaLM first model (Dec. '22) to exceed “passing” score on the US Medical Licensing Examination (USMLE)
- Med-PaLM 2: 85% score on USMLE; multimodal
 - base LLM improvements, medical domain finetuning and prompting strategies
- Med-PaLM 2 answers were preferred over physician answers by a panel of physicians across eight of nine axes in evaluation framework (pairwise ranking w. >1k consumer med. quest.)





Med-PaLM → Multimodal

- Data foundation: MultiMedBench - 14 task dataset incl. medical Q&A, mammography + dermatology image interpretation, radiology report generation + summarization, genomic variant calling
- Claim: system exhibits novel emergent capabilities such as generalisation to novel medical concepts and tasks
- Alternative lighter-weight approach: ELIXR grafts language-aligned vision encoders onto a fixed LLM; requires less compute to train and shows promise across tasks incl. visual QA, semantic search, zero-shot classification. <https://arxiv.org/pdf/2307.14334.pdf> (Med-PaLM-M), <https://arxiv.org/abs/2308.01317> (ELIXR)

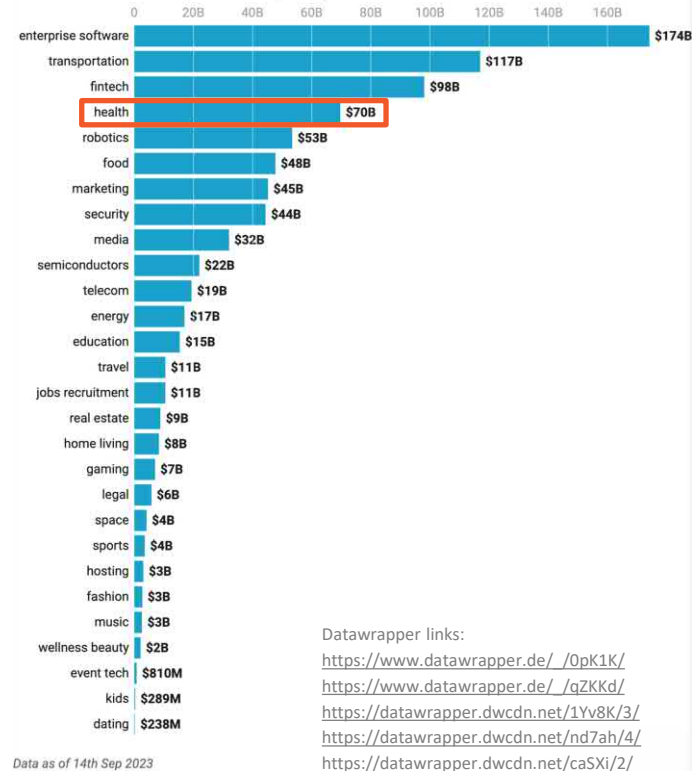




Health as a Top AI Investment Field

\$ invested in AI categories 2010-23

Amount invested in startups and scaleups using AI 2010-2023 YTD



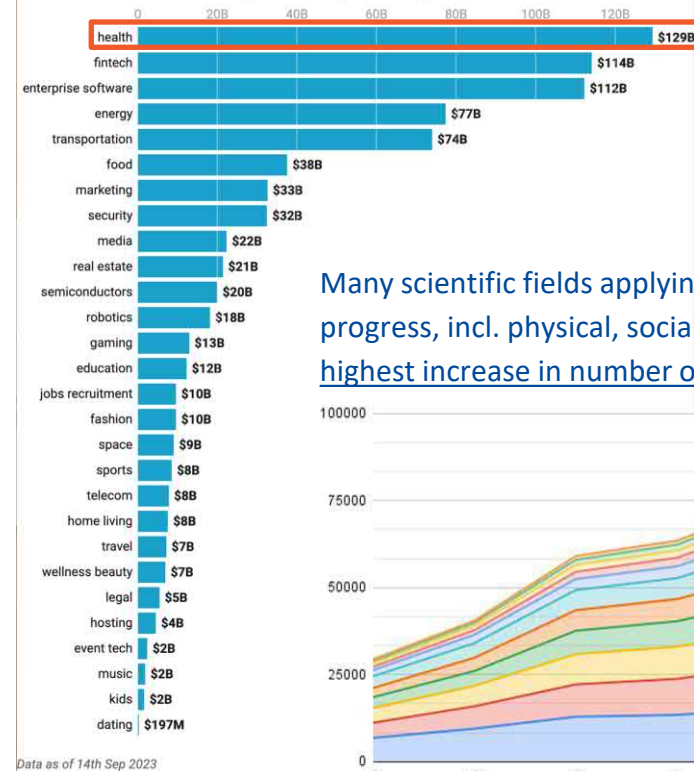
Datawrapper links:

- https://www.datawrapper.de/_/0pK1K/
- https://www.datawrapper.de/_/qZKKd/
- <https://datawrapper.dwcdn.net/1Yv8K/3/>
- <https://datawrapper.dwcdn.net/nd7ah/4/>
- <https://datawrapper.dwcdn.net/caSXi/2/>

Data as of 14th Sep 2023

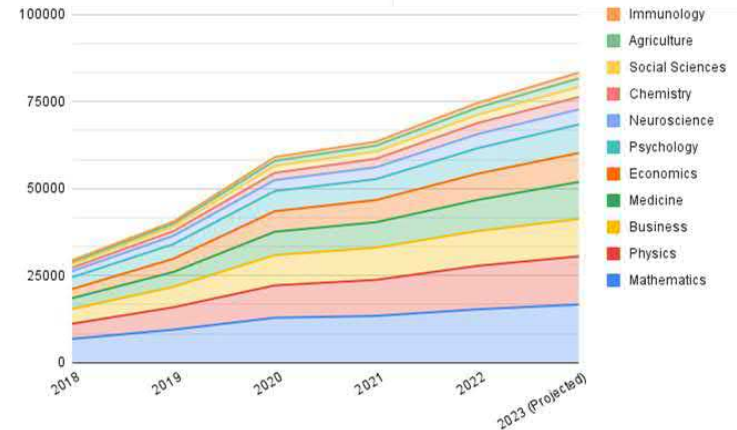
Deal volume in AI categories 2022-23

2022-2023 Amount invested startups and scaleups by industry



Data as of 14th Sep 2023

Many scientific fields applying AI to accelerate progress, incl. physical, social, life and health sciences; highest increase in number of publications: medicine

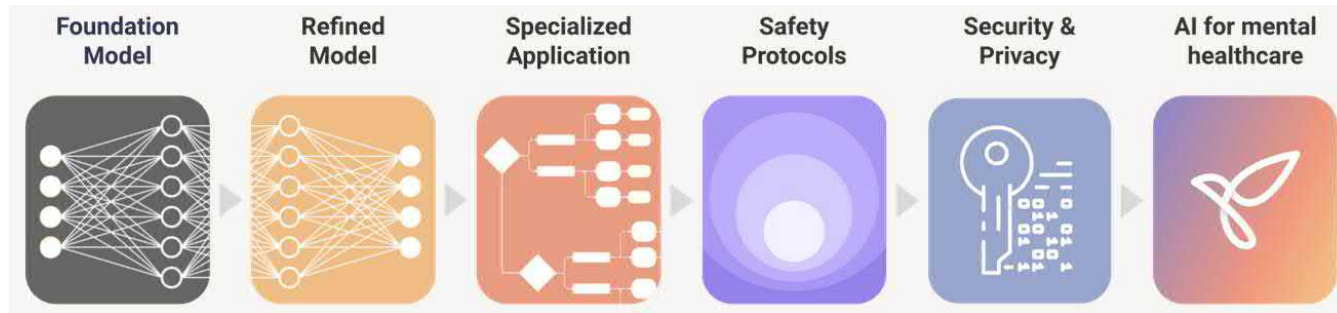




Recent Examples of Large AI Models in Digital Health: Mental Health Support



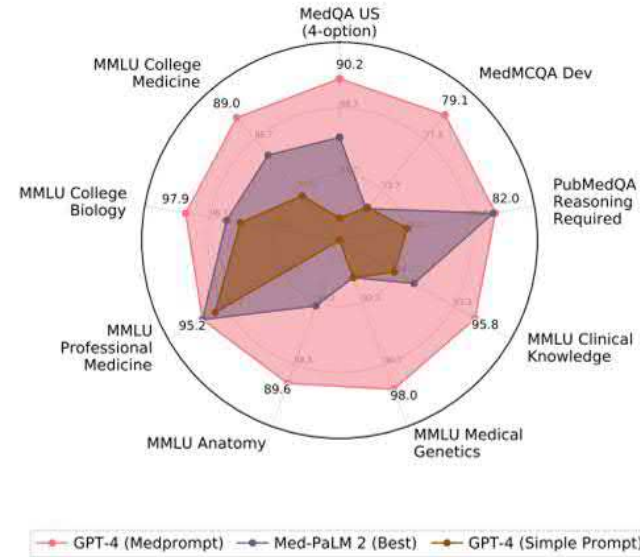
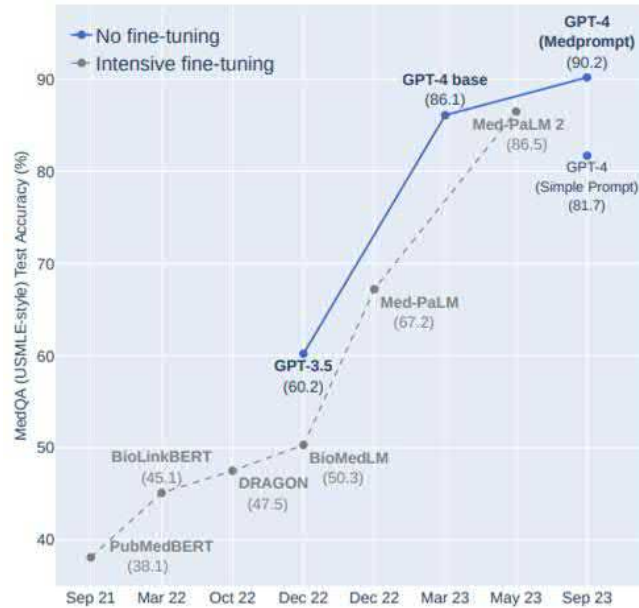
- Mental health chatbot (CBT)
- Found to be effective in reducing symptoms of depression and anxiety in users (study n > 1000, 4 wks)
- Emerging patterns: „Wrapping“ around foundation model (likely still GPT-4) + X (e.g. fine-tuning, pre-formulated prompting, personal data via embeddings, etc.)



- Not positioned as a replacement of professionals! ❓ „flanking“



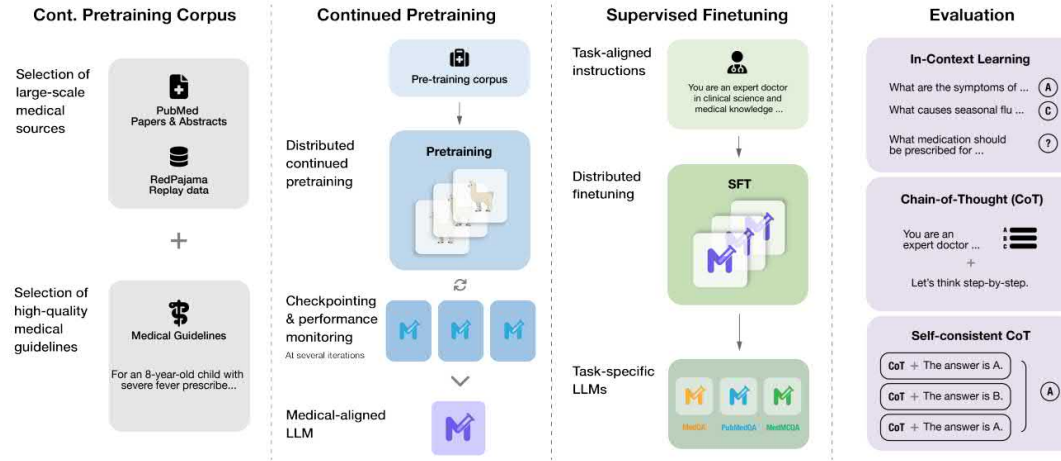
GPT-4 with Medprompt > MedPaLM



Nori, H., Lee, Y. T., Zhang, S., Carignan, D., Edgar, R., Fusi, N., King, N., Larson, J., Li, Y., Liu, W., Luo, R., McKinney, S. M., Ness, R. O., Poon, H., Qin, T., Usuyama, N., White, C., & Horvitz, E. (2023). Can Generalist Foundation Models Outcompete Special-Purpose Tuning? Case Study in Medicine (arXiv:2311.16452). arXiv. <https://doi.org/10.48550/arXiv.2311.16452>

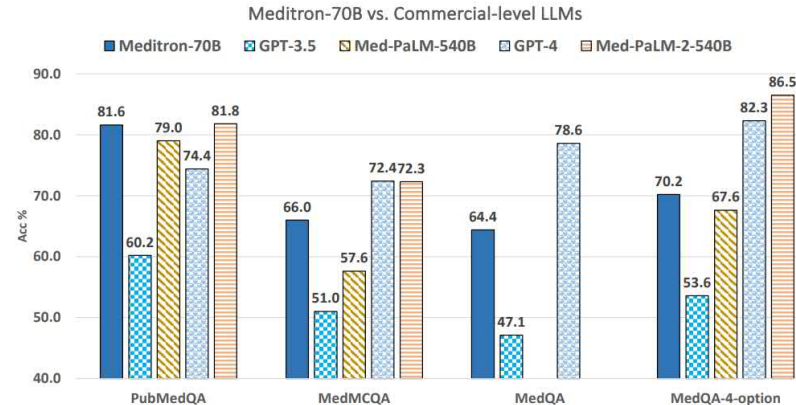


Open Source: Meditron-70B

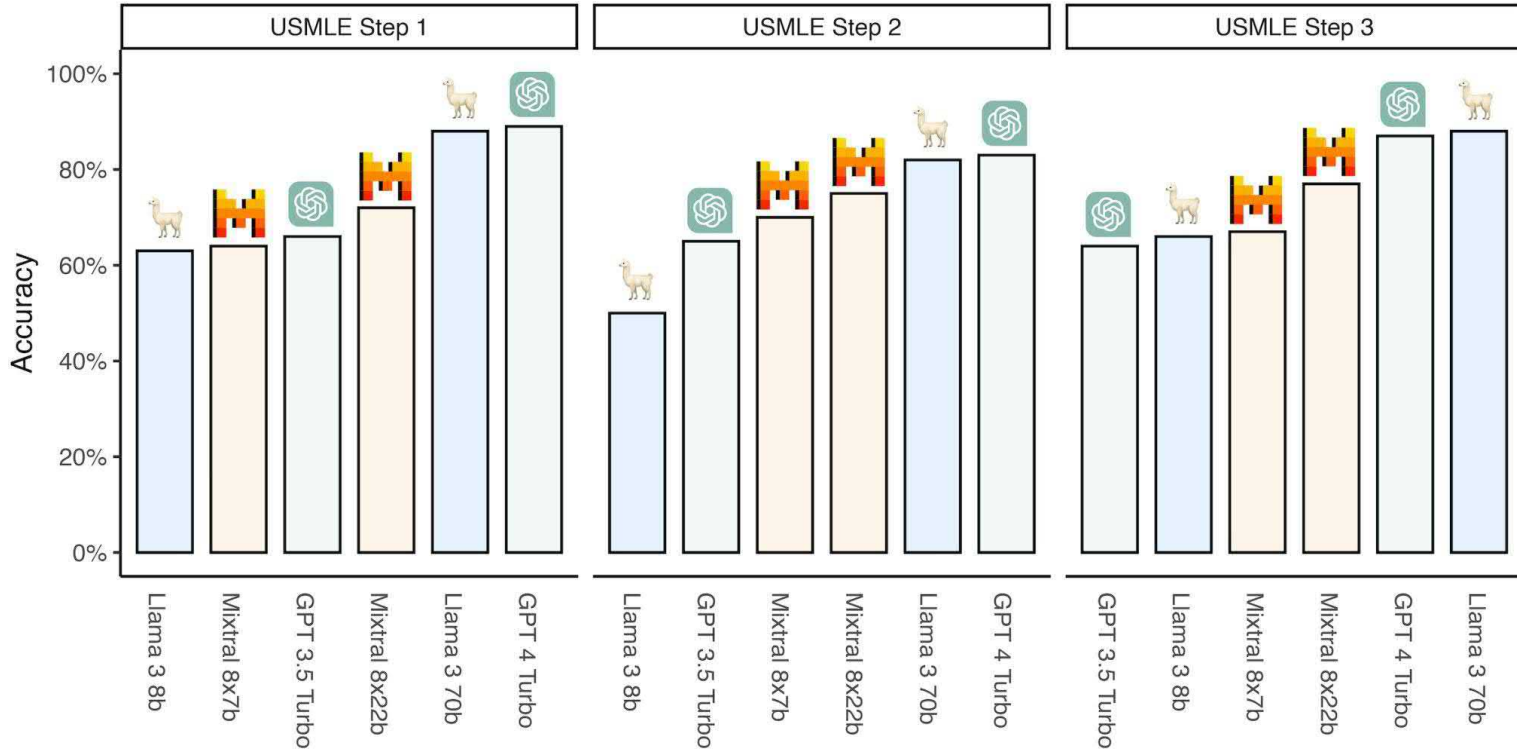


Chen, Z., Cano, A. H., Romanou, A., Bonnet, A., Matoba, K., Salvi, F., Pagliardini, M., Fan, S., Köpf, A., Mohtashami, A., Sallinen, A., Sakhaeirad, A., Swamy, V., Krawczuk, I., Bayazit, D., Marmet, A., Montariol, S., Hartley, M.-A., Jaggi, M., & Bosselut, A. (2023). MEDITRON-70B: Scaling Medical Pretraining for Large Language Models (arXiv:2311.16079). arXiv. <https://doi.org/10.48550/arXiv.2311.16079>

Figure 2: **MEDITRON**. The complete pipeline for continued pretraining, supervised finetuning, and evaluation of MEDITRON-7B and MEDITRON-70B.



„Open Source“ Models Health Topics Performance:



USMLE: United States Medical Licensing Examination

<https://ai-assisted-healthcare.com/2024/04/21/llama3-70b-performs-on-par-with-gpt-4-turbo-on-answering-usmle-questions/>



On-Device / Edge-Ready (Medical) Models

7B-range (workstation): BioMistral series (without fine-tuning)

Labrak, Y., Bazoge, A., Morin, E., Gourraud, P.-A., Rouvier, M., & Dufour, R. (2024). BioMistral: A Collection of Open-Source Pretrained Large Language Models for Medical Domains (arXiv:2402.10373). arXiv. <http://arxiv.org/abs/2402.10373>

	MMLU					
	Clinical KG	Medical Genetics	Anatomy	Pro Medicine	College Biology	College Medicine
BioMistral 7B	60.9 ^{a1.5}	61.7 ^{a2.1}	49.6 ^{a1.2}	55.1 ^{a1.3}	56.9 ^{a1.0}	55.5 ^{a1.7}
Mistral 7B Instruct	57.0 ^{a0.8}	56.7 ^{a0.5}	46.9 ^{a0.3}	51.0 ^{a1.1}	58.6 ^{a0.9}	50.1 ^{a1.0}
BioMistral 7B Ensemble	62.8 ^{a0.5}	62.7 ^{a1.7}	46.9 ^{a0.3}	57.0 ^{a0.6}	60.6 ^{a0.9}	56.3 ^{a0.3}
BioMistral 7B DARE	61.3 ^{a0.4}	61.0 ^{a2.8}	49.9 ^{a0.9}	55.3 ^{a0.7}	64.4 ^{a0.9}	53.9 ^{a1.4}
BioMistral 7B TIES	62.3 ^{a0.5}	61.3 ^{a1.9}	48.1 ^{a2.2}	55.8 ^{a0.8}	57.2 ^{a0.7}	56.5 ^{a1.5}
BioMistral 7B SLERP	63.1 ^{a1.6}	63.3 ^{a0.9}	49.9 ^{a1.9}	57.4 ^{a0.3}	63.4 ^{a0.9}	57.8 ^{a0.9}
MedAlpaca 7B	49.1 ^{a1.3}	49.0 ^{a3.7}	48.4 ^{a1.9}	63.8 ^{a0.8}	47.2 ^{a0.6}	43.5 ^{a1.8}
PMC-LLaMA 7B	25.3 ^{a1.5}	26.0 ^{a3.7}	31.9 ^{a1.8}	16.9 ^{a0.5}	28.0 ^{a2.4}	24.9 ^{a1.2}
MediTron-7B	37.9 ^{a1.5}	47.0 ^{a3.7}	39.3 ^{a1.6}	34.2 ^{a1.0}	42.6 ^{a1.4}	30.4 ^{a0.7}
BioMedGPT-LM-7B	50.1 ^{a1.0}	52.0 ^{a0.8}	46.2 ^{a1.8}	47.3 ^{a1.7}	47.9 ^{a2.5}	45.5 ^{a0.7}
GPT-3.5 Turbo 1106	74.71 ^{a0.3}	74.00 ^{a2.2}	65.92 ^{a0.6}	72.79 ^{a1.6}	72.91 ^{a1.7}	64.73 ^{a2.9}

Model	Size	BBH	Commonsense Reasoning	Language Understanding	Math	Coding
Llama-2	7B	40.0	62.2	56.7	16.5	21.0
	13B	47.8	65.0	61.9	34.2	25.4
	70B	66.5	69.2	67.6	64.1	38.3
Mistral	7B	57.2	66.4	63.7	46.4	39.4
Phi-2	2.7B	59.2	68.8	62.0	61.1	53.7

Table 1. Averaged performance on grouped benchmarks compared to popular open-source SLMs.

Model	Size	BBH	BoolQ	MBPP	MMLU
Gemini Nano 2	3.2B	42.4	79.3	27.2	55.8
Phi-2	2.7B	59.3	83.3	59.1	56.7

Table 2. Comparison between Phi-2 and Gemini Nano 2 Model on Gemini's reported benchmarks.

2-3B-range (mobile): Focus on very high quality training data → Phi-2

Gunasekar, S., Zhang, Y., Aneja, J., Mendes, C. C. T., Del Giorno, A., Gopi, S., Javaheripi, M., Kauffmann, P., de Rosa, G., Saarikivi, O., Salim, A., Shah, S., Behl, H. S., Wang, X., Bubeck, S., Eldan, R., Kalai, A. T., Lee, Y. T., & Li, Y. (2023). Textbooks Are All You Need (arXiv:2306.11644). arXiv. <https://doi.org/10.48550/arXiv.2306.11644>



Hughes, A. (2023, Dec 12). Phi-2: The surprising power of small language models. MS Research. <https://www.microsoft.com/en-us/research/blog/phi-2-the-surprising-power-of-small-language-models/>

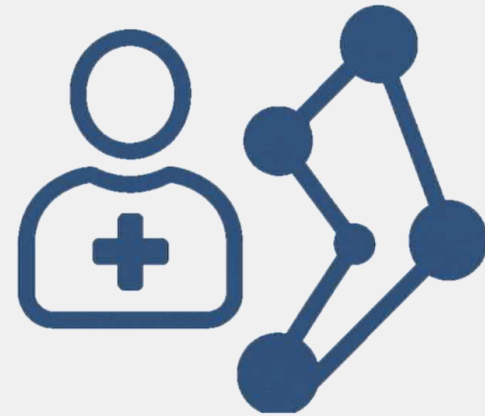
Generative AI in Health

Amazing possibilities!

But what do we do with them?



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Capabilities of DHI in Personal Health:

MAGnify: A set of Digital Health Intervention Lenses

DHI have especially noteworthy capabilities in ...

- Motivation: Help build / maintain motivation (esp. for adherence to beh. ch.)
- Analysis: Esp. based on multi-modal sensing and interaction traces:
Enable analyses and (objective) understandings
- Guidance: Foster guidance (esp. where gaps in coverage by HCP exist)



Adapted from: Smeddinck, J. D. (2016). Games for Health. In R. Dörner, S. Göbel, M. Kickmeier-Rust, M. Masuch, & K. Zweig (Eds.), *Entertainment Computing and Serious Games* (Vol. 9970, pp. 212–264). Springer International Publishing.

Fostering Motivation in Personalized Digital Health Interventions with Generative AI

SmartPA, „The Last JITA!“
!: data biases & i: Theory of Mind



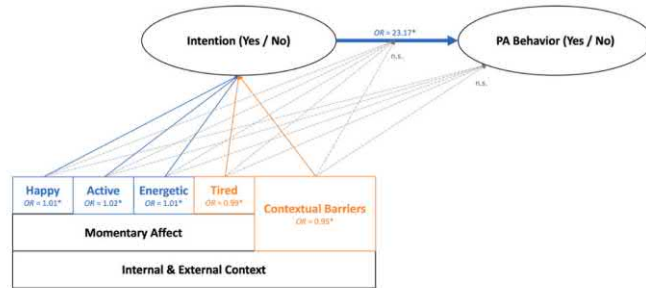
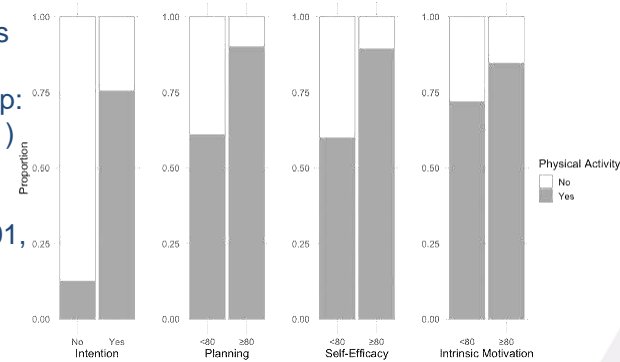


Just-in-Time Adaptive Interventions: Traditional Approach & Which Variables Matter?

SmartPA Study: 3-week EMA Design



(Transitional) Intention predicts PA: OR = 27.87, $p < .001$
 Bridging the Intention Beh. Gap:
 - Planning (OR = 1.03, $p < .001$)
 - Self-Efficacy (OR = 1.02, $p = .014$)
 - Intrinsic Motivation (OR = 1.01, $p = .015$)



- Individuals more likely to form PA intentions when feeling happy, active, or energetic
- Less likely when external/contextual barriers high or when feeling tired
- only PA intentions significant precursors of subsequent PA behavior
- neither contextual barriers, nor momentary affect directly affected PA behavior.

Fig. 2. Observed Determinants of PA Intentions and Behavior
 Note. * $p < .05$; boxes and arrows for Intention (yes – no) were proportionally partitioned to reflect how often intentions were reported and how often participants engaged in PA dependent on their intention report.

Haag, D., Carrozzo, E., Pannicke, B., Niebauer, J., & Blechert, J. (2023). Within-person association of volitional factors and physical activity: Insights from an ecological momentary assessment study. *Psychology of Sport and Exercise*, 68, 102445. <https://doi.org/10.1016/j.psychsport.2023.102445>

Haag, D., Smeddinck, J. D., Vogelsang, A., & Blechert, J. (2025). Contextual and affective precursors of physical activity intention and enactment examined through ecological momentary assessment. *Psychology of Sport and Exercise*, 77, 102796. <https://doi.org/10.1016/j.psychsport.2024.102796>

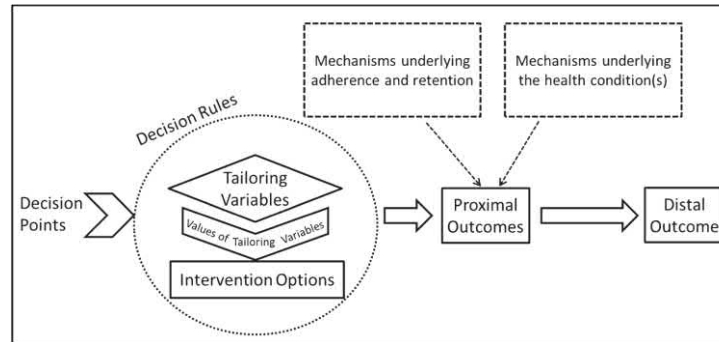
Revolutionary Potential of Generative AI: The Example of Just-in-Time Adaptive Interventions

A type of personalization for e.g. DH:

„The just-in-time adaptive intervention (JITAI) is an intervention design aiming to provide the right type/amount of support, at the right time, by adapting to an individual’s changing internal and contextual state.“

(Nahum-Shani et al. 2018)

E.g. support with retaining PA adherence in longer-term rehabilitation or prevention journeys...

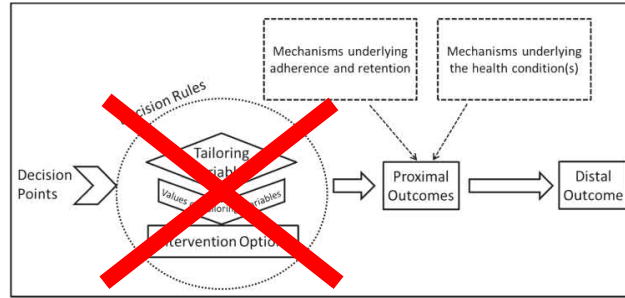
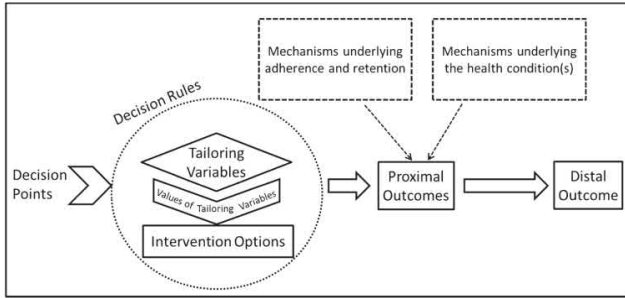


Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-Time Adaptive Interventions (JITAI) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine*, 52(6), 446–462. <https://doi.org/10.1007/s12160-016-9830-8>

Prediction & Personalization: Just-in-Time Adaptive Interventions with Large Language Models



JITAIxLLM: explore viability of decision-making and content generation for JITAIs with LLMs



Haag, D., Kumar, D., Gruber, S., Hofer, D., Sareban, M., Treff, G., Niebauer, J., Bull, C., Schmidt, A., & Smeddinck, J. D. (2025, accepted). The Last JITAI? Exploring Large Language Models for Issuing Just-in-Time Adaptive Interventions: Fostering Physical Activity in a Conceptual Cardiac Rehabilitation Setting. Proceedings of the ACM SIGCHI CHI 2025 Conference. CHI 2025, Yokohama, Japan. <https://doi.org/10.1145/3706598.3713307>

From: Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-Time Adaptive Interventions (JITAs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine*, 52(6), 446–462. <https://doi.org/10.1007/s12160-016-9830-8>

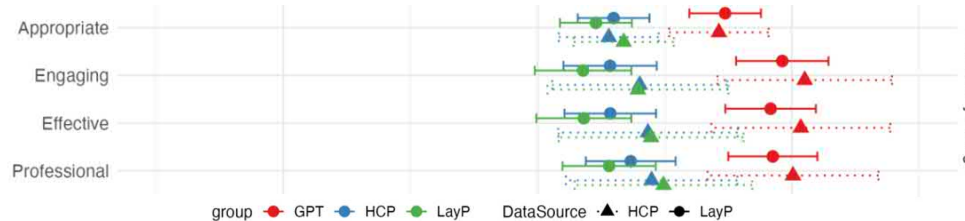
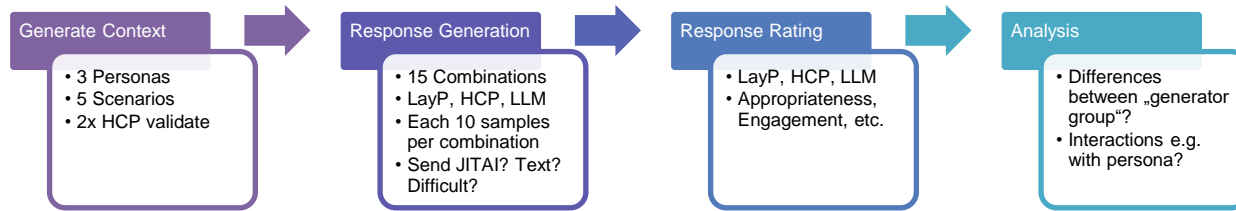
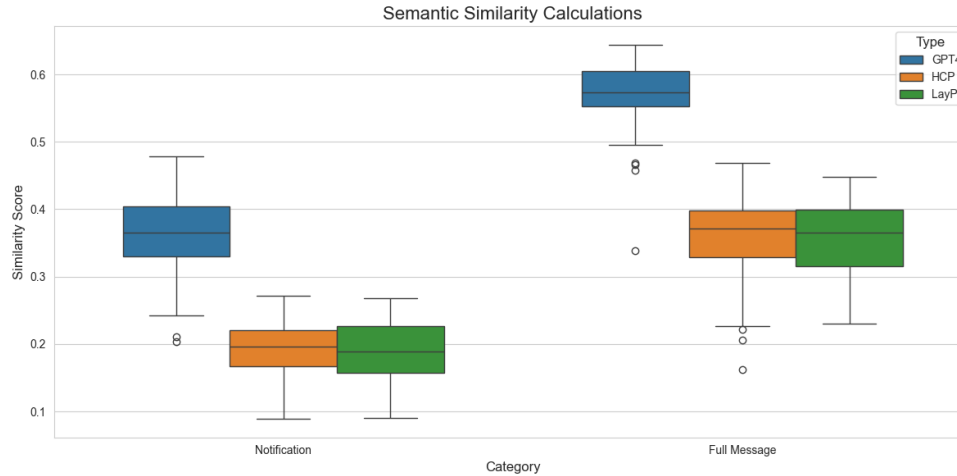


Figure 3: Mean and 95% confidence interval indicators for ratings of JITAI quality and expected affective responses by generator groups assessor category.

- Sig. diff. for appropriateness, engagingness, effectiveness, professionalism + implied positive and negative affect
- GPT responses consistently most highly ranked for decision and texts
- No sig. interaction betw. „rater group“ and „persona“ ... i.e. no „notable weakness“ in one area
- No „bias“ against AI by LayP when „unblinded“ ...

Revolutionary Potential of Generative AI: The Example of Just-in-Time Adaptive Interventions



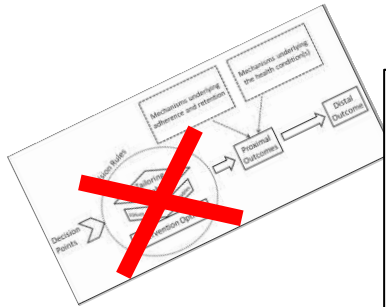
- Requires further validation in practice; common „issues“ with GenAI/LLMs do appear to apply and may lead to e.g. faster „messaging fatigue“

Revolutionary Potential of Generative AI: The Example of Just-in-Time Adaptive Interventions

- Complimentary concept: NOT a task HCP would ever execute at scale!
- Accuracy, safety concerns etc. ... BUT what if more rare than decision-making errors by humans (even experts)? → cf. autonomous driving!?!



Key LLM / GenAI ability: handle sparse and varying contextual variables (NOTE: need to combine „vibing“ & tool use; we used pre-computed parameters); transform between structured and natural language representations (see also plugins / agents / GPTs)



INSTEAD:

“Opportunistic” / “as rich as possible” data and information about the individual and their context
 e.g., goals, mood, weather, calendar, preferences, medical conditions, ...

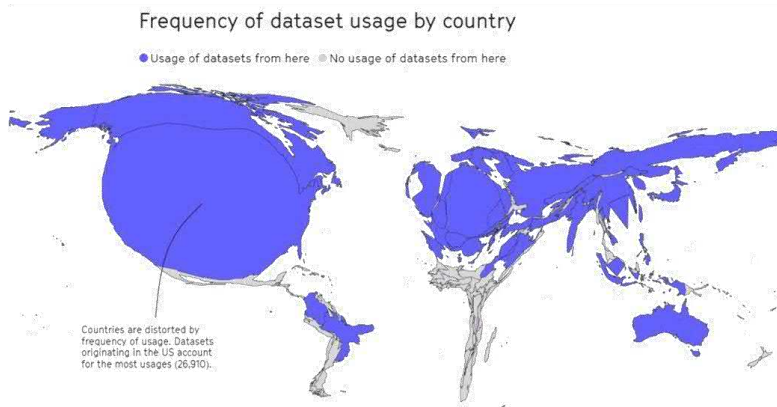


“Hey there! You've already crushed your weekly goal for moderate-intensity aerobic activity, but it's important to keep the momentum going. Since you have some free time in the evening, why not schedule a run or group fitness class? Remember, every step counts towards your overall fitness goal. Keep up the great work!”

Common key concerns DO apply ...



The World Map according to the data AI sees



Sources

Research by: [Koch, Denton, Hanna, and Foster \(2021\)](#)

Visual by: [The Mozilla Internet Health Report 2022](#)

- Accuracy and transparency
- Bias / fairness
- Transparency / explainability
- Privacy
- Ethics & regulatory (EU AI Act!)
- Accessibility & inclusivity
- ...

Sensitive Application Area & „Litmus Test for Acceptability“



- Challenges are particularly prominent / are particularly to be avoided
- Digital health is sensitive in general e.g. considering:
 - Parkinson's disease patients (Smeddinck et al. 2013)
 - Older adults (Smeddinck et a. 2015)
 - Wheelchair users (Gerling et al. 2014)
 - Therapy with perpetrators of domestic violence (Bellini et al. 2021)
 - ... currently: CVD patients



Bellini, R., Wilson, A., & Smeddinck, J. D. (2021). Fragments of the Past: Curating Peer Support with Perpetrators of Domestic Violence. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–14. <https://doi.org/10.1145/3411764.3445611>

Smeddinck, J. D., Herrlich, M., & Malaka, R. (2015). Exergames for Physiotherapy and Rehabilitation: A Medium-term Situated Study of Motivational Aspects and Impact on Functional Reach. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 4143–4146.

Gerling, K. M., Miller, M., Mandryk, R. L., Birk, M. V., & Smeddinck, J. D. (2014). Effects of Balancing for Physical Abilities on Player Performance, Experience and Self-esteem in Exergames. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2201–2210.

Smeddinck, J., Siegel, S., & Herrlich, M. (2013). Adaptive Difficulty in Exergames for Parkinson's Disease Patients. *Proceedings of the 2013 Graphics Interface Conference*, 141–148.



Digital health specific high-level guidelines emerging ... (e.g. European Patients Forum 2023)



Akin to „Guidelines for Human-AI Interaction“ (MSFT) or „People + AI Guidebook“ (GOOG)...

2023 Survey Results: What can AI do for patients?



9 Principles to Regulate AI in Healthcare

1. RESPECT HUMAN DIGNITY
2. ADDRESS DATA QUALITY AND INTEGRITY
3. ENGAGE PATIENTS AND HEALTHCARE PROFESSIONALS
4. ENSURE ACCESSIBILITY AND INCLUSIVITY
5. KEEP HUMANS IN CONTROL
6. PROTECT HEALTH DATA AND PATIENT CONFIDENTIALITY
7. FOSTER RESPONSIBILITY AND ACCOUNTABILITY
8. ENHANCE TRANSPARENCY
9. PRIORITISE EDUCATION, TRAINING, AND DIGITAL LITERACY

Why does this work so well?

GenAI / LLMs and Theory of Mind (ToM)



- ToM: ability to attribute mental states to oneself and others, crucial for social cognition (Premack & Woodruff, 1978; Baron-Cohen et al., 1985)
- Recent LLMs show improved performance on ToM tasks: GPT-4: ~75% accuracy on false-belief tasks ~ 6-year-old (Kosinski, 2023)
 - Instruction-tuned models outperform children on advanced ToM evals (van Duijn et al., 2023)
- LLMs likely imitate rather than truly understand mental states (rely on stat. patterns, not “genuine cognitive processes” (Shapira et al., 2023; Ullman, 2023)
- Even illusion of ToM can be beneficial: LLMs can enhance social reasoning and support behavior change, e.g. in personalized health interventions (Kim et al. 2023; Haag et al., 2024)

Baron-Cohen, S., Leslie, A. M., & Frith, U. (1985). Does the autistic child have a “theory of mind”? *Cognition*, 21(1), 37–46. doi:10.1016/0010-0277(85)90022-8
van Duijn, M. W. A., van Dijk, B., Kouwenhoven, T., de Valk, W., Spruit, M., & van der Putten, P. (2023). Theory of mind in large language models: Examining performance of 11 state-of-the-art models vs. children aged 7–10 on advanced tests. In *Proceedings of the 27th Conference on Computational Natural Language Learning (CoNLL 2023)* (pp. 389–402).

Kim, D. S., Khera, A. V., Hafez, A., Kelliher, J. M., Nah, J., Harrington, R. A., ... Ashley, E. A. (2023). Fine-tuning large language models in behavioral psychology for scalable physical activity coaching. *medRxiv*. doi:10.1101/2023.05.15.23290055

Kosinski, M. (2023). Theory of mind may have spontaneously emerged in large language models. *arXiv preprint arXiv:2302.02083*.

Premack, D., & Woodruff, G. (1978). Does the chimpanzee have a theory of mind? *Behavioral and Brain Sciences*, 1(4), 515–526. doi:10.1017/S0140525X00076512

Shapira, N., Levy, M., Alavi, S. H., Zhou, X., Choi, Y., Goldberg, Y., Sap, M., & Shwartz, V. (2023). Clever Hans or neural theory of mind? Stress testing social reasoning in large language models. *arXiv preprint arXiv:2305.14763*

Ullman, T. D. (2023). Large language models fail on trivial alterations to theory-of-mind tasks. *arXiv preprint arXiv:2302.08399*

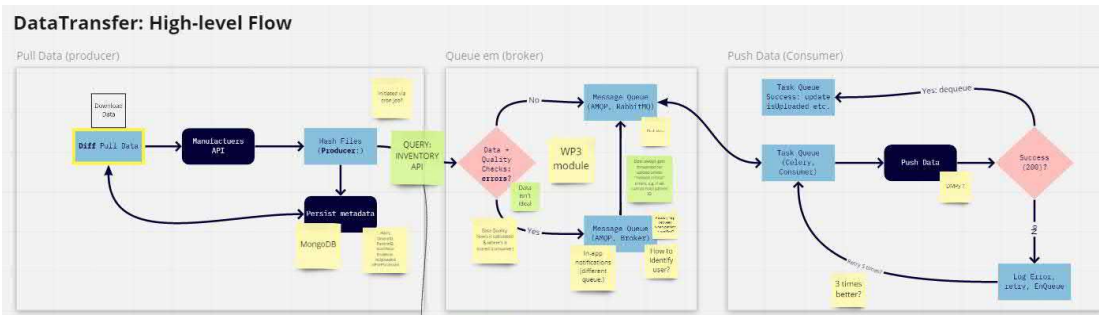
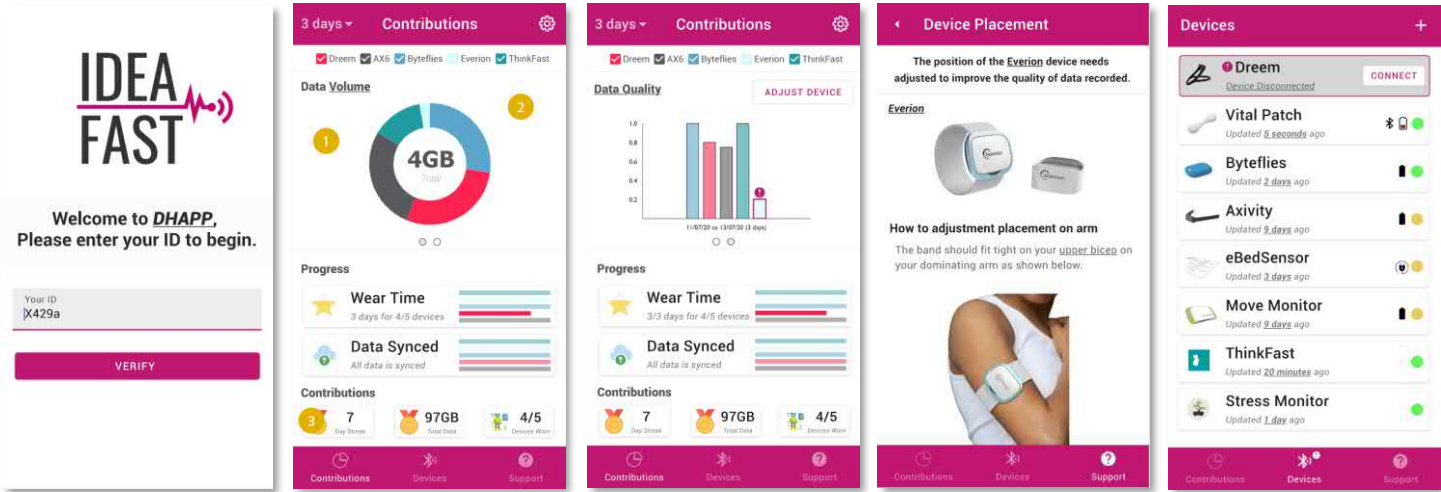
Augmenting Health Sensing and Shared Decision-Making with Generative AI for Analysis

Patient-Generated Health Data, Insight(AI)
!: anthropomorphologization & i: triadic relationships



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Multi-modal Health Data Example: IDEA-FAST: Device Hub Application & Data Flows



Rainey, J., Verweij, D., Dodds, C., Graeber, J., Farhadi, F., Ali, R., Zhang, V., Bull, C. N., & Smeddinck, J. D. (2021). Data Contribution Summaries for Patient Engagement in Multi-Device Health Monitoring Research. *Adjunct Proceedings of the 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2021 ACM International Symposium on Wearable Computers*, 536–541. <https://doi.org/10.1145/3460418.3479371>

Potential / Benefits of patient-generated data

1. Provide complete picture about patients to HCPs
2. Objectify information provided by patients
3. Promote communication between HCPs and patients
4. Allows for reflection
5. Patients are better informed
6. Promote precision medicine



Image: A patient sharing their health data (from wearables) with a HCP thereby engaging in Shared decision making

Interoperability, Standards & Strategy: Connected Health Model in Cardiac Rehabilitation



Persona: Markus (57-year-old)

- Heart attack
- Needs to lower the cardiovascular risk factor
- Having average digital skills
- Willing to commit to using Cardiac Rehabilitation (CR) apps and wants to avoid traveling to the clinic

CVD Risk factors

- Overweight
- Hypercholesterolemia
- Smoking
- Arterial hypertension
- Sedentary lifestyle

+ patient journey & HCP / CVD res. input



Conceptually:
Patient Health-Data Journeys

01

Medical history

His hospital care team retrieved Markus' personal profile and reviewed his medical history. Markus reviewed his information and contacted his GP to correct an element of his medical history (Markus can't edit his EHR directly).

His rehabilitation care team retrieved data related to **medical risk factors** (lipid management, blood pressure, diabetes), **lifestyle risk factors** (physical activity, tobacco use, alcohol use), and Information on **prescribed medication**.

Health assessment

02

03

Activity prescription and care goals

Markus used a **smart CR app** for tracking his biometric & lifestyle data and his care goals. Data were transferred to his physician through the app and his care team recorded the main findings in ELGA.

Markus plans to use a **CR self-referral tool** when he will engage independently to sustain his behaviour change towards a healthy, physically active lifestyle to prevent future attacks.

Lifelong secondary prevention

04

Source: Hussein R et al, Can PCD leverage connected health model for cardiac rehabilitation in Austria. 2023 May 18;302:8-12

56



Digital Health Twins in Personalized Medicine

- Integrate continuous data streams to mirror individual health status; with generative AI enable personalized care (Mann, 2024)
- Combine physiological and behavioral data with clinical records; may update in real time, enabling simulations and predictions (Mann, 2024)
- Applications in Chronic Disease Management:
 - Diabetes: Digital twins provided tailored diet and exercise recommendations, improving glucose control and reducing medication needs (Mayo Clinic Platform, 2024)
 - CVD: Expected to transform prevention and treatment by fusing physiologic, environmental, and clinical data into machine learning models (Thangaraj et al., 2024)
- Learning Loop: Projections refine future predictions as more data accumulates, enhancing accuracy

JokeGPT:

“I asked my digital twin to help improve my health, but now it meditates daily, sleeps early, and judges my pizza habit.”



Making practical use of patient-generated health data...



Barriers and Enablers in Integrating Patient-Generated Health Data for Shared Decision-Making

Objective:

Identify **barriers and enablers** of integrating patient generated health data for shared decision making.

Search:

Databases: PubMed, IEEE and ACM Digital Library

Time period: 2013 to 2023

Included papers: 52

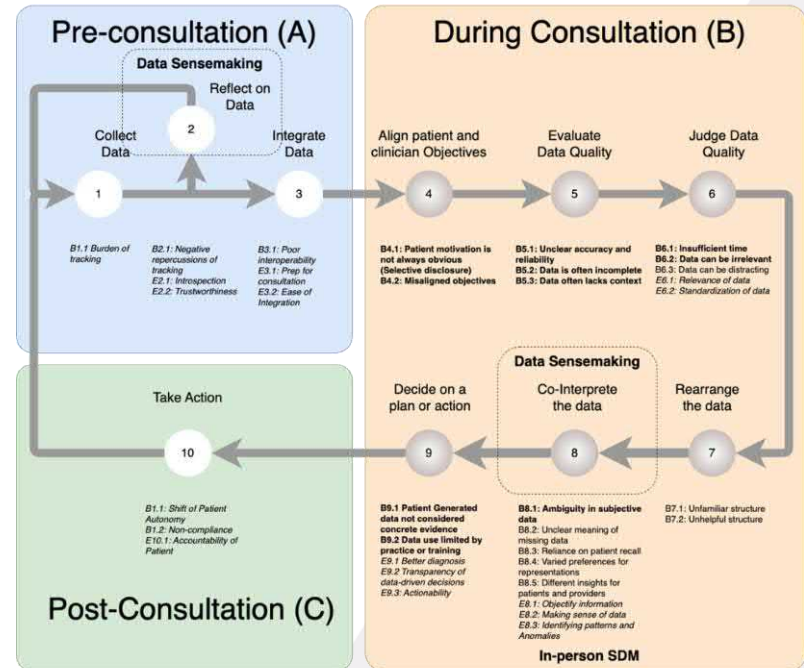
Identified Themes

1. Data
2. Patient Provider Relationship
3. Patient Characteristics
4. Organizational Factors
5. Medical Ethics and Law
6. Design and Technology

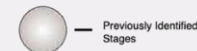
Pavithren V S Pakianathan, Devender Kumar, Prabath Jayatissa, Hussein Rada, Josef Niebauer, Albrecht Schmidt, Jan Smeddinck (in review). Barriers and Enablers in Integrating PatientGenerated Health Data for Shared Decision-Making Between Healthcare Professionals and Patients: A Scoping Review Preprint; <https://s3.ca-central-1.amazonaws.com/assets.jmir.org/assets/preprint/1.amazonaws.com/assets.jmir.org/assets/preprint/60490-submitted.pdf>

10-stage workflow model adapted based on 6-stage model in: West P, Van Kleek M, Giordano R, Weal MJ, Shadbolt N. Common Barriers to the Use of Patient-Generated Data Across Clinical Settings. Proc 2018 CHI Conf Hum Factors Comput Syst New York, NY, USA: Association for Computing Machinery; 2018. p. 1–13. doi: 10.1145/3173574.3174058

10-stage workflow for using patient-generated data: Patient and HCP Perspectives



Newly identified enablers and barriers in *italics*
Previously established enablers and barriers in **bold**



Making practical use of patient-generated health data...



Insight study: Identify challenges and opportunities of patient generated health data (from consumer devices) for physical activity planning and rehabilitation

Part 1 - Situated study and Interviews with:

Participants (n= 6)

Healthcare Professionals (HCP) (n=2)

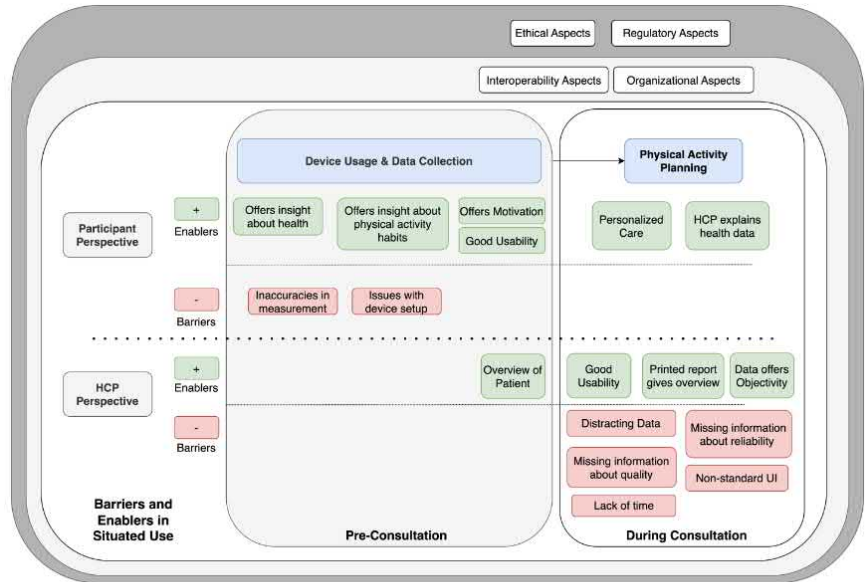
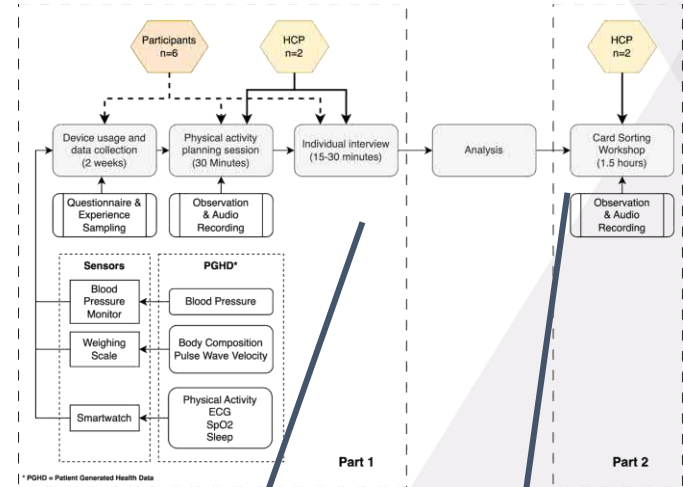
Withings devices + HealthMate app

Part 2 - Workshops with:

HCPs to consider data needs / best-practices



Designing for Patient-Clinician Collaboration in Data-Enabled Physical Activity Planning: Exploring Shared Decision-Making with Patient-Generated Health Data (in review)



What are the potential benefits for patients and clinicians?
31 responses

Word Cloud:

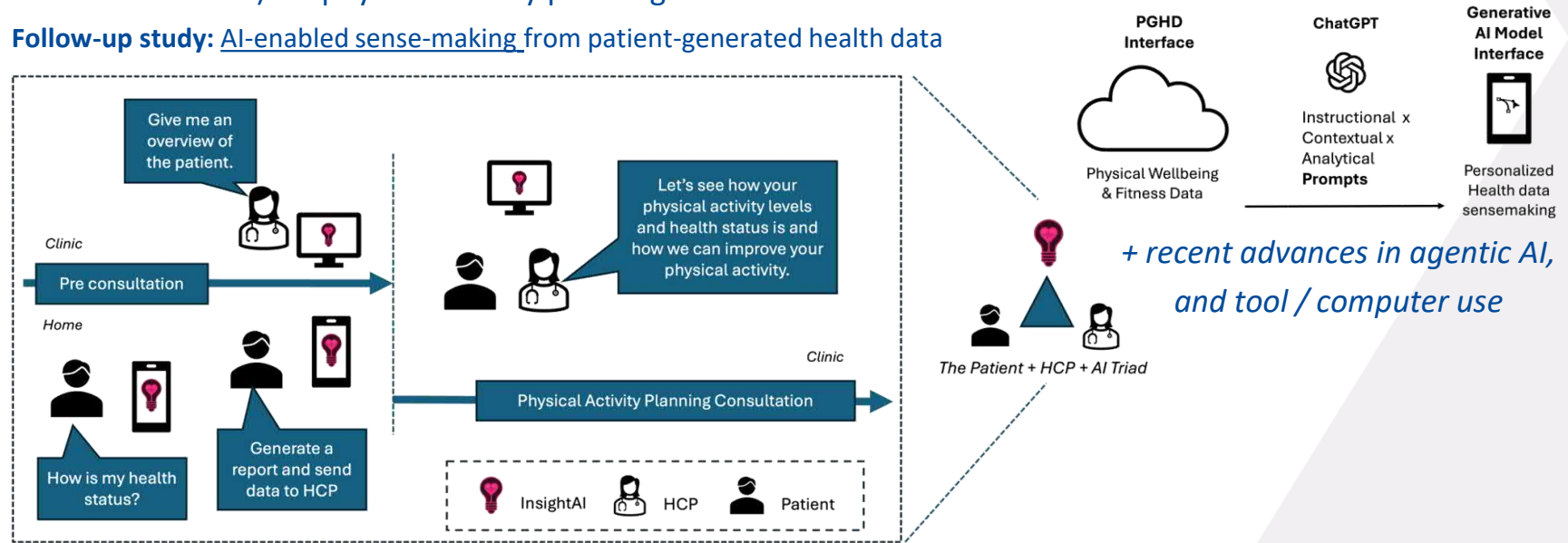
- patients better informed
- personalized
- time saving
- easy to visualize
- increased understanding
- more adherence
- data offers objectivity
- missing information about reliability
- non-standard UI
- lack of time
- lack of social contacts
- lower level of support
- poor accuracy of source 1
- data management cost
- accuracy
- misused data
- 59



Making practical use of patient-generated health data...

Insight study: Identify **challenges** and **opportunities** of **patient generated health data** (from consumer devices) for physical activity planning and rehabilitation

Follow-up study: AI-enabled sense-making from patient-generated health data



V S Pakianathan, P., Fatehi, A., & Smeddinck, J. (2024). *Towards AI Augmented Personalized Data Sensemaking*. 10.18420/muc2024. <https://dl.gi.de/handle/20.500.12116/44311>

Why is this so interesting / important to consider?



Key Concerns: Interacting with Systems that Produce Complex, Unpredictable Output

Traditional digital "tools" don't change by themselves (generative AI breaks with established technology design rules on consistency, reliability, learnability, etc.); if changing:

L1: rule-based (can be complex, but typically predictable)

L2: learning (pattern-based, may be predictable)

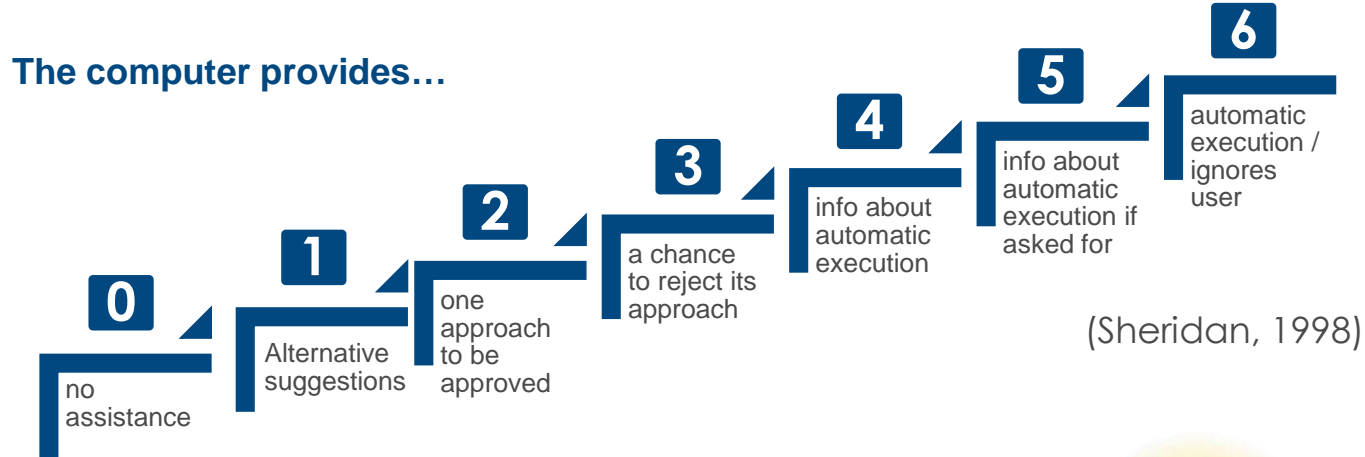
L3: generative („creative“, less / not predictable)



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Still a Helpful Tool: Sheridan's Scale of Automation



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Anthropomorphologization



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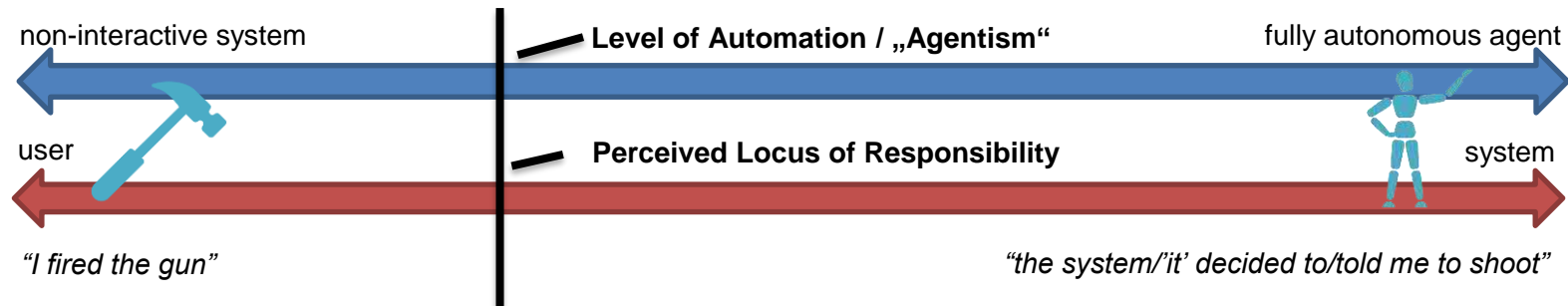
This Photo by smilekiddo is licensed under [CC BY-NC-ND](#)

- *"The computer didn't like me today."*
"I feel let down by my Word editor."
"The system doesn't want to do what I want."
...



Justification Practices, Responsibility, Accountability

AI technology is problematic when it obscures who is making a decision
→ shift in perceived „*locus of responsibility*“? → *accountability!*?!



Smeddinck, J.D. 2023. “That’s What It Told Me”: On the Need of Understanding Justification Practices and of Positioning Accountability in Decision Support Systems in Digital Health. CHI’23 workshop on Identifying Challenges and Opportunities for Intelligent Data-Driven Health Interfaces to Support Ongoing Care (IDDHI2023)



Emerging research field: Human-AI Interaction

Terminology still developing ...

- Human-AI Interaction (HAI/HAIH/HAIx)
- Human-Centred/Centric AI (HCAI)
- AI Interaction Design (AIxD)
- AI User Experience (AIUX)

... differences in emphasis / angles ...

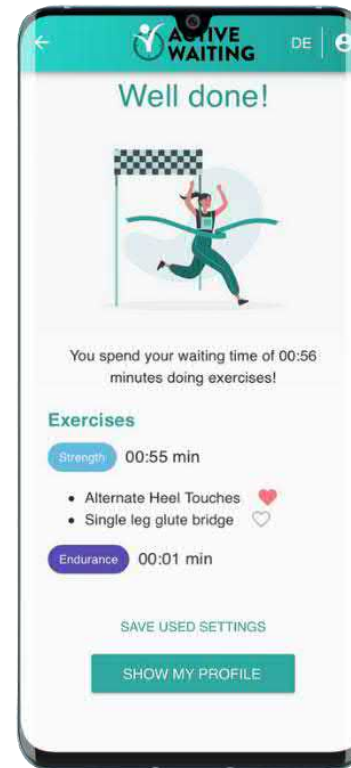
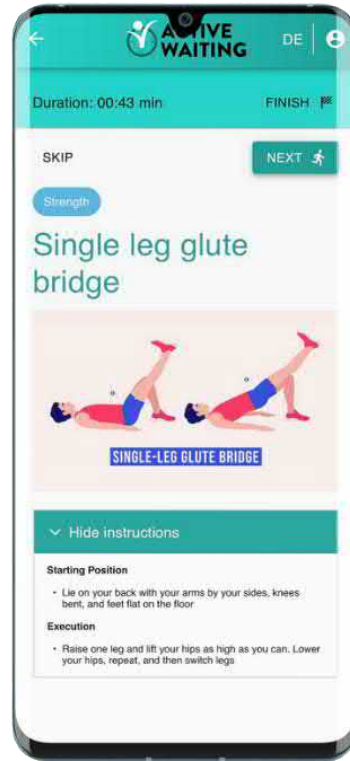
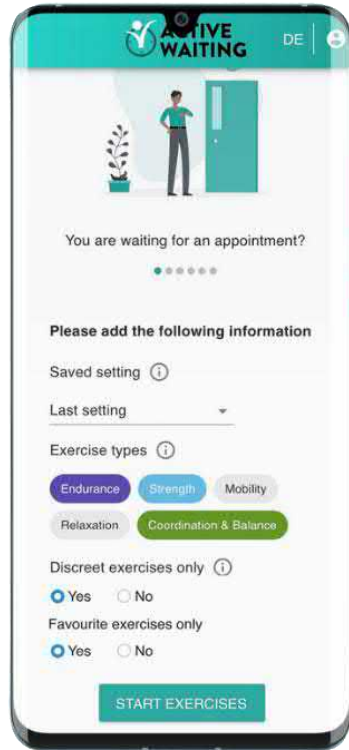
Generative AI for Providing Guidance where / when HCP are not Available

GPT-Coaches, Active Waiting, Venting
!: hyperchondriacs & i: intelligence augmentation



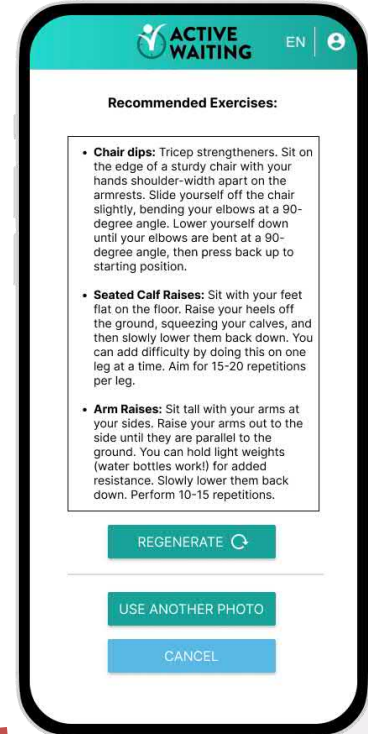
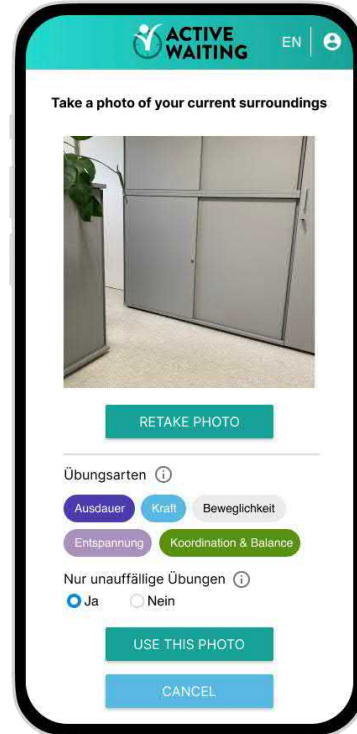
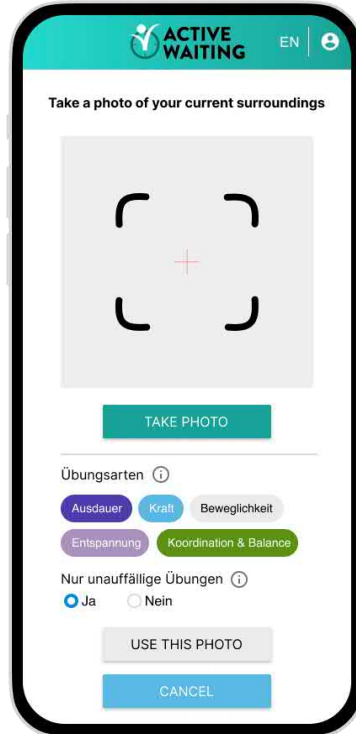
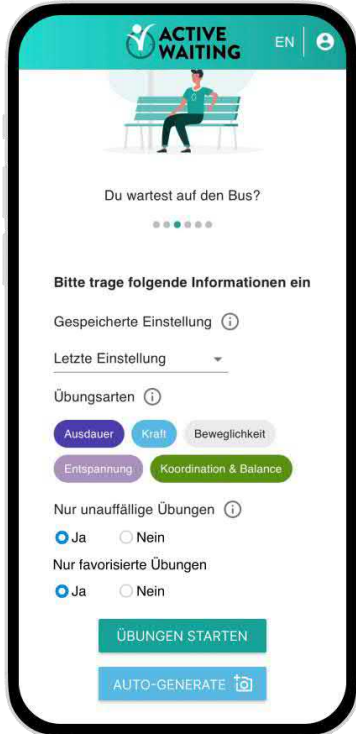
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Digital Health and Prevention

Active Waiting: „Swiss Knife“ for „Opportunistic PA“



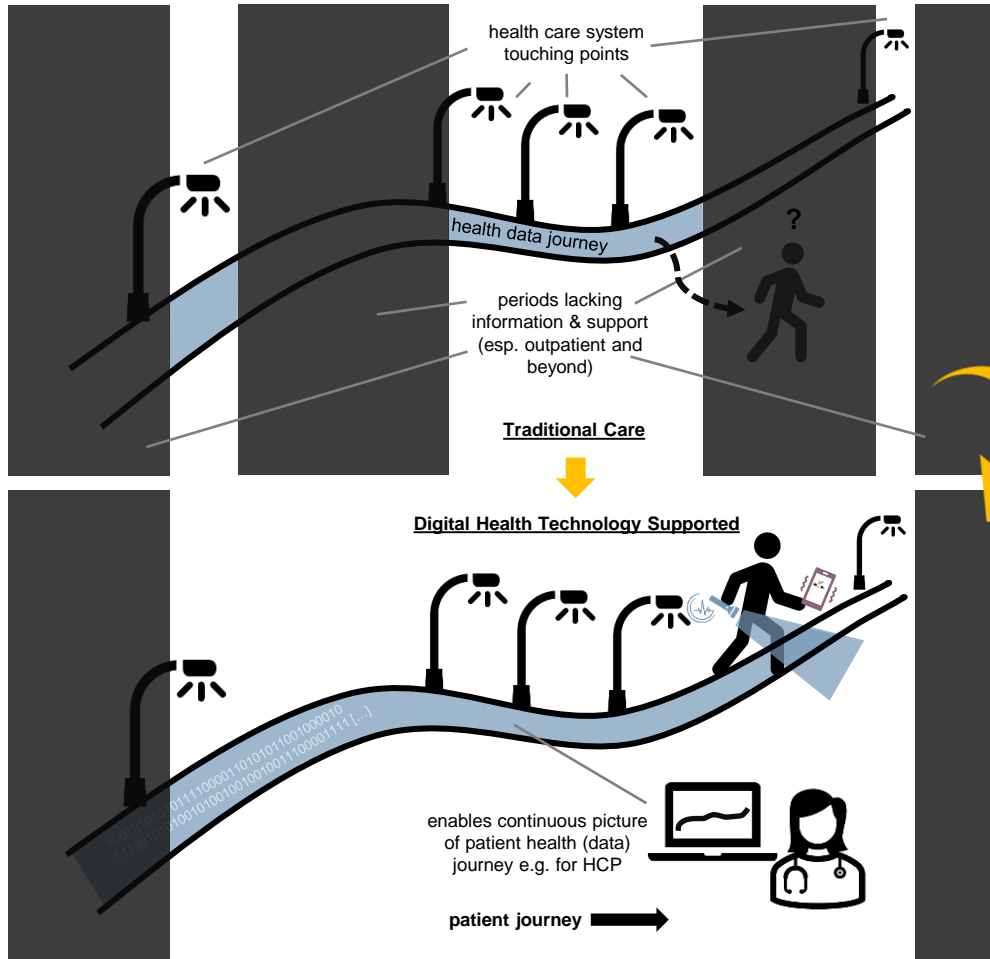


Active Waiting – GenAI-enabled AR version

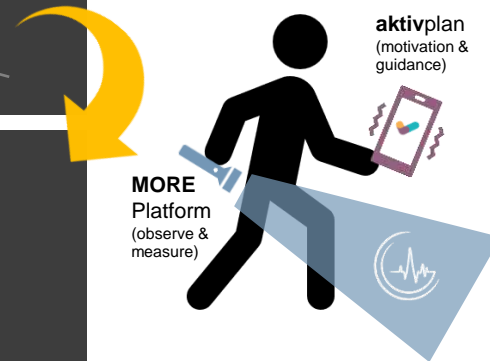
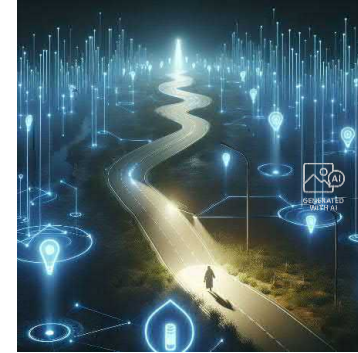


Before our „AI assumes there will be chairs“ fix! 😊

Longer-Term Guidance: Assess & Support



e.g. **Modular Open Research Platform (MORE)**: Study manager + companion app for „life-accompanying studies“

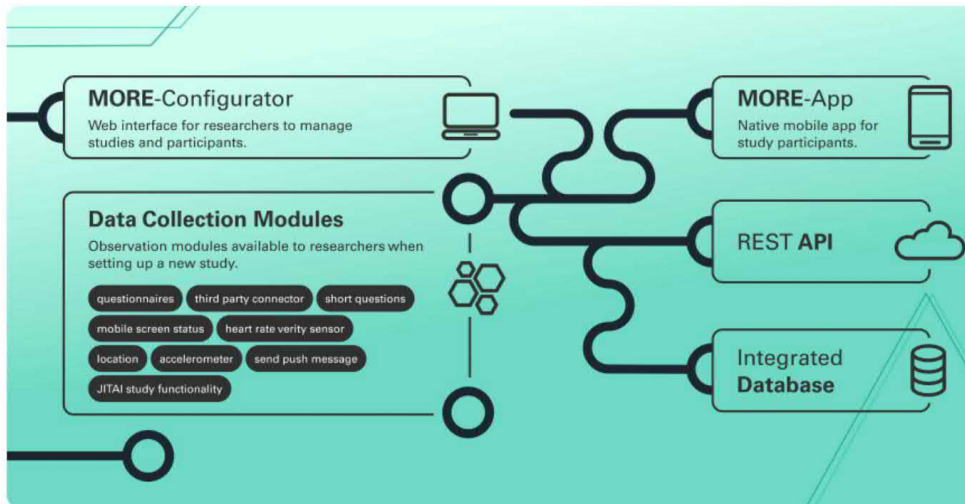


e.g. **aktivplan**: patient companion application for activity planning, reporting + motivation, guidance and support



MORE

A Modular Open Research Platform for Situated
and Longitudinal Human-Subject Research



The Modular Open Research Platform [MORE] is a GDPR-compatible and source-available web and mobile application to assist researchers in gathering data and running studies accompanying people in daily living. With near real-time data transfer, personalized interventions, and seamless integration with sensors and surveys, MORE streamlines research.

features

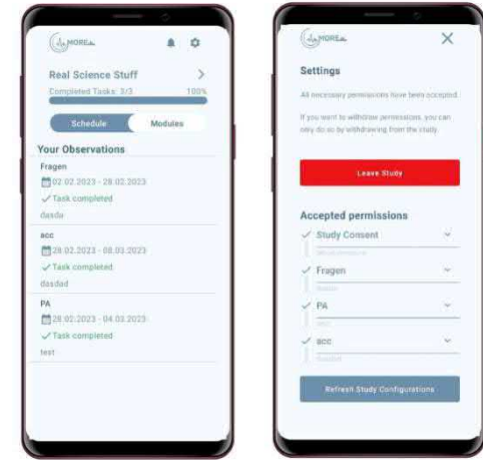
- modular near real-time sensor data collection
- flexible and modular self-reported data
- study role delegation
- safe and secure data collection
- desktop/web and mobile apps

<https://more-platform.at/>

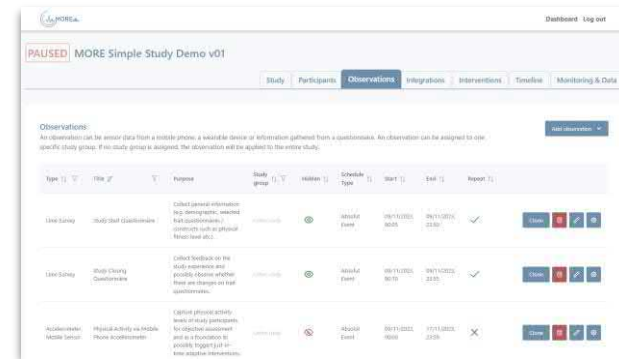
Research Automation, Continuous Assessment & Adaptive Interventions



MORE: Modular open research platform for conducting longer-term, lifelong studies with multimodal data collection (questionnaires + sensor technology);
WISS 2025 Research Infrastructure: Planning tool (professionals) + study-participation app



- Iteratively developed with stakeholders (Pakianathan et al. 2023), use in several test studies and two independent studies (SmartPA2 and ActiveWaiting <https://clinicaltrials.gov/study/NCT06321926>)
- External inquiries / interest in use (local and international, e.g. PLUS, TNO, KU Leuven, EPFL) and possible commercial exploitation
- Available as research infrastructure + source code
- Use in ongoing projects (e.g. FFG KlimaFIT)



Pakianathan PVS, Wurhofer D, Kumar D, Niebauer J, Smeddinck J. Multi-Stakeholder Design for Complex Digital Health Systems: Development of a Modular Open Research Platform (MORE). Stud Health Technol Inform. 2023;301:204-209. doi:10.3233/SHTI230040

Ludwig Boltzmann Institute for Digital Health and Prevention. (2024). Evaluation of the “ActiveWaiting App”; Encouraging Active Exercise-related Use of Waiting Time. A Waitlist Control Study (Clinical Trial Registration NCT06321926). clinicaltrials.gov. <https://clinicaltrials.gov/study/NCT06321926>



Multi-level Modeling for Customization of Just-in-Time Adaptive Interventions: Scalable with Generative AI

- Towards integration-preserving customization of JITAIs in RDF and SHACL (consistent, modular, comparable)
- Needed to systematically build / share insights about approaches / components of adaptive interventions
- GenAI-enabled conversion + formal check
- Persistence and structure + real-world

MORE-Configurator
Web interface for researchers to manage studies and participants.

MORE-App
Native mobile app for study participants.

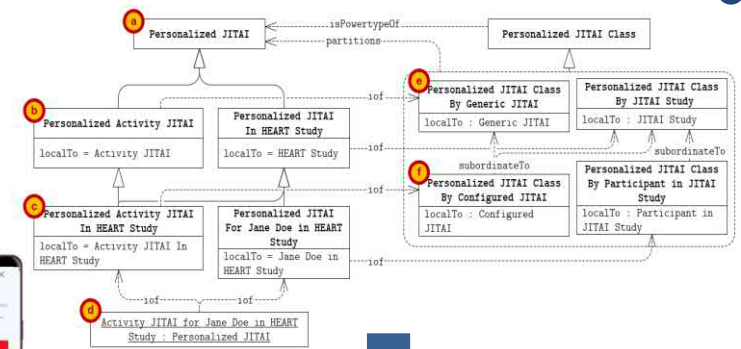
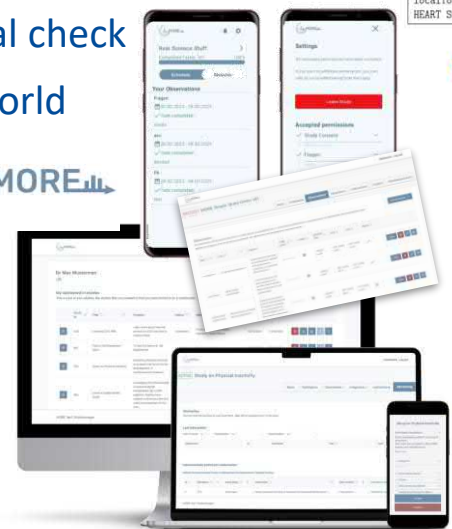


Research Modules
Available to researchers when setting up a new study.

- questionnaires
- third party connector
- weight
- accelerometer
- track push notifications
- track phone calls
- location
- usage of phone apps
- screen on/off
- noise
- light
- send push message
- JITAI interface

REST API

Time Series Database



```

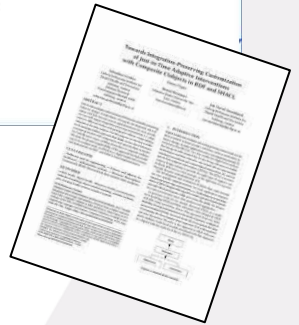
@prefix : <http://example.org/Study>.
@prefix owl: <http://www.w3.org/2002/07/owl#>.
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#>.
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>.

:Study1 owl:Class,
  rdfs:subClassOf :PersonalizedJITAI,
  rdfs:label "Study 1",
  rdfs:comment "Study 1: Personalized JITAI".

:Study2 owl:Class,
  rdfs:subClassOf :PersonalizedJITAI,
  rdfs:label "Study 2",
  rdfs:comment "Study 2: Personalized JITAI".

:Study1 rdfs:subClassOf :Study2.

:Study1 rdfs:localTo "Study 1".
:Study2 rdfs:localTo "Study 2".
  
```



Funded by (WISS2025):  **LAND SALZBURG**



Gruber, S., Neumayr, B., & Smeddinck, J. D. (2022). Towards Integration-Preserving Customization of Just-in-Time Adaptive Interventions with Composite Clabjects in RDF and SHACL. *2022 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C)*. 2022 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C).

Conversational Interfaces (Chatbots) for Venting & Emotional Wellbeing Support

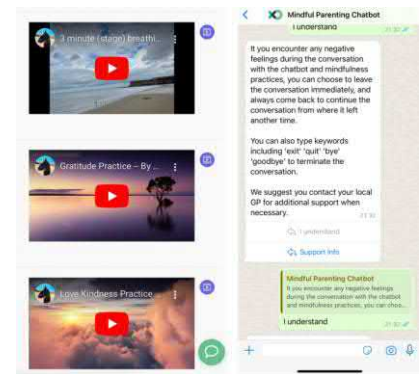
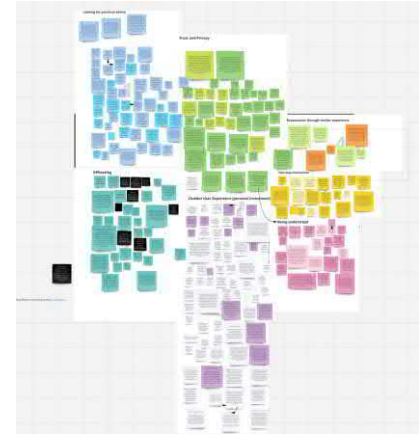


(Viana (Nijia Zhang), 2024; supervisee, PhD Thesis)

- UK Working Parents (mothers, fathers, lone parents) report significant emotional strain, stress, guilt, and work-family conflict, often lacking accessible, private, non-judgmental support channels (Zhang, 2024; ONS, 2022)
- Specific needs include offloading emotions, seeking reassurance/practical advice, and feeling understood

"Venting Bot" Concept:

- Purpose-built conversational interfaces (rule-based or AI-driven) designed as dedicated, interactive channels for users to articulate, offload ('vent'), and process negative emotions and challenging experiences



Conversational Interfaces (Chatbots) for Venting & Emotional Wellbeing Support

(Viana (Nijia Zhang), 2024; supervisee, PhD Thesis)



Mechanisms & potential impact:

- Support Pillars: achieved via accessibility (24/7), Non-Judgmental Space (encourages candid disclosure, Potts et al., 2021), Simulated Validation ("being heard"), Cognitive Structuring (organising thoughts, Pennebaker, 1993), and User Control (privacy, low social burden)
- Wellbeing outcomes: Studies (ES1-ES3) indicate potential for increased calmness/control, decreased short-term anxiety, improved emotional regulation (especially when paired with mindfulness - ES3), and enhanced self-awareness
- Functional integration: Venting valued alongside practical info, reminders, & recording features

Key design considerations & challenges:

- Empathy/Authenticity Balance: Crucial to avoid perceived insincerity; trust is key
- Reliability & robustness: Contextual understanding (AI models) & error handling are vital for user retention
- Context & personalisation: Relevance > generic responses; difficult but important
- Ethics: Non-negotiable focus on privacy, transparency, managing expectations, & clear signposting to human/professional support...



“Coaches in Your Pocket”

- **24/7 personalized support:** LLMs act as always-available health coaches across domains like mental health, fitness, and chronic care (Hegde et al., 2024)
- **Expert-level quality:** Generative AI can match or exceed human health coaches in perceived appropriateness and helpfulness (Ong et al., 2024; Jacobson et al., 2025)
- **Mental health:** Systems like Therabot use fine-tuned LLMs to deliver CBT-based conversations, showing clinical impact in anxiety and depression (Jacobson et al., 2025)
- **Fitness / PA coaching:** GPTCoach applies behavior change theory and wearables to generate personalized workout plans and messages (Jörke et al., 2024; Hegde et al., 2024)
- **Chronic disease:** LLMs help patients manage conditions like diabetes and hypertension with tailored advice and health education (Al-Anezi, 2024)
- **Multimodal assistants:** LLMs fine-tuned on wearable and health data offer holistic coaching across domains like sleep and physical activity (Cosentino et al., 2024)

Al-Anezi, F. M. (2024). Exploring the use of ChatGPT as a virtual health coach for chronic disease management. *Learning Health Systems*, 8(3), e10406. <https://doi.org/10.1002/lrh2.10406>

Cosentino, J., Belyaeva, A., Liu, X., Furlotte, N. A., Yang, Z., et al. (2024). Towards a personal health large language model. *arXiv preprint*, arXiv:2406.06474

Hegde, N., Vardhan, M., Nathani, D., Rosenzweig, E., Speed, C., & Seneviratne, M. (2024). Infusing behavior science into large language models for activity coaching. *PLOS Digital Health*, 3(4), e0000431 <https://doi.org/10.1371/journal.pdig.0000431>

Jacobson, N. C., Heinz, M. V., Mackin, D., Trudeau, B., Bhattacharya, S., et al. (2025). Evaluating Therabot: A randomized controlled trial of a generative AI therapy chatbot for depression, anxiety, and eating disorders. *NEJM AI*, 1(1). <https://doi.org/10.1056/Aloa2400802>

Jörke, M., Sapkota, S., Lee, S., Liao, Z., Brunskill, E., & Patel, S. (2024). GPTCoach: Towards LLM-based physical activity coaching. *arXiv preprint*, arXiv:2405.06061

Ong, Q. C., Ang, C.-S., Chee, D. Z. Y., Lawate, A., Sundram, F., et al. (2024). Advancing health coaching: A comparative study of large language model and health coaches. *Artificial Intelligence in Medicine*, 157, 103004. <https://doi.org/10.1016/j.artmed.2024.103004>



HYPERchondriasis in the Era of Pervasive Health Tracking

Hypochondriasis: Excessive concern about having a serious illness despite medical reassurance

- Misinterpretation of normal bodily sensations as indicators of severe disease
- Frequent medical consultations seeking validation
- Persistent health-related anxiety impacting daily life

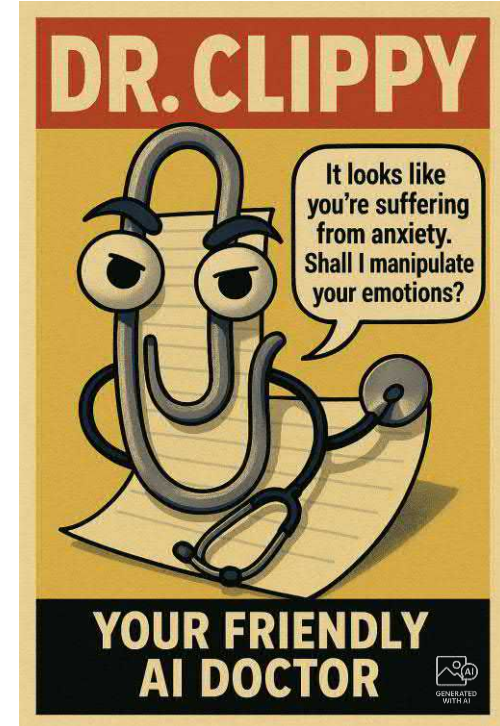
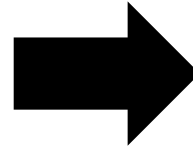
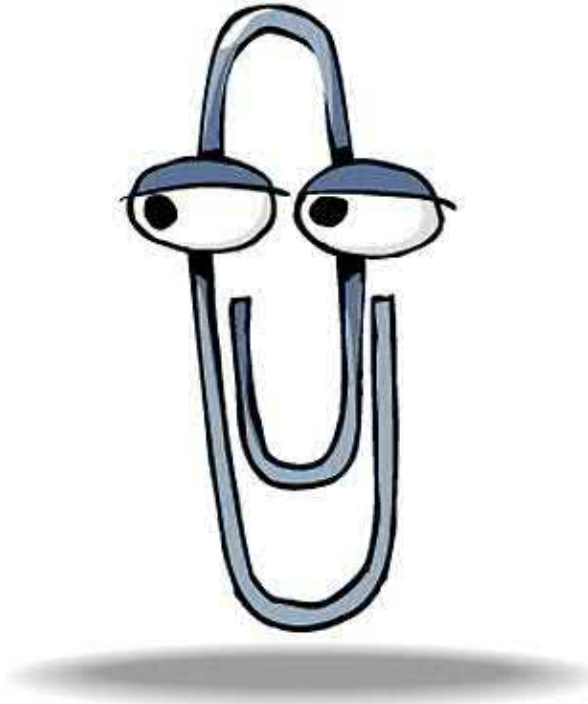


Hyperchondriasis: Heightened health anxiety fueled by constant monitoring and analysis of personal health data from wearable devices and health apps
(term not formally coined, but see also: <https://www.hcplive.com/view/hyperchondriasis>)

Similar potential consequences as above; contributing factors:

- Continuous health data tracking: Real-time data on metrics like heart rate and sleep patterns.
- Information overload: Easy access to medical information online leading to potential misinterpretation; now bottomless and genAI
- Confirmation bias: Seeking information that aligns with existing health fears, exacerbating anxiety → genAI is the ultimate custom echochamber multiplier

Clippy's Revenge?



https://en.wikipedia.org/wiki/Office_Assistant

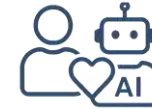
Joke-GPT:

*“Shurely you’d want to be a ‘better’ version of yourself!?!
Because what could go wrong with digital paternalism?”*



Longer-Term: Intelligence Augmentation & Human-AI Relations

- AI and ML systems as permanent interaction partners; increasingly in conversational / agent-like interaction modalities ... possibly highly immersive (see also Nißen et al., 2022; temp. dyn.)
 - more complex "patterns of behaviour" or outcomes that are difficult to predict
- Impact of continuous / life-accompanying interactions
 - Research into successful design principles
 - Interdisciplinary approach (incl. psychological & sociological backgrounds)
- AI / IA: Computing machines will do routine work; prepare the way for insights and decisions in technical and scientific thinking (Licklider); *"elegant combination(s) of reasoning machinery and direct manipulation"* (Horvitz)
- "Flanking" use-cases "abstaining from decision-making" can be relevant approach, but: !decision-making != !decision-influencing ... (cf. „locus of responsibility“)



... AI is „increasingly agent-like“ ...

artificial
intelligence
hand-in-hand with
intelligence
augmentation

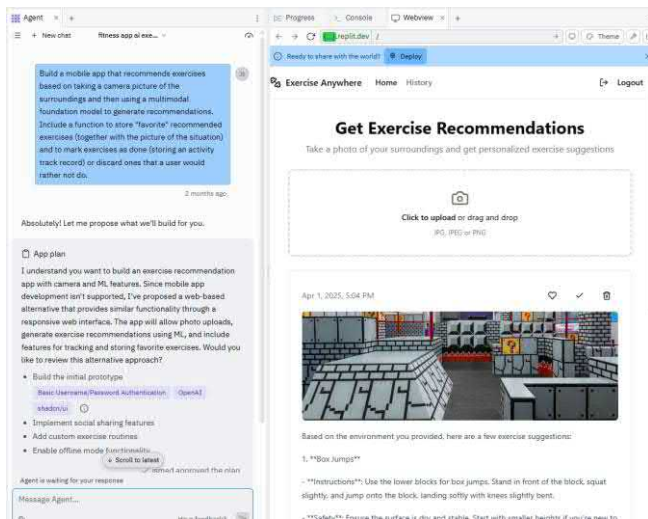


... AI as „rocketships for our minds“ ...

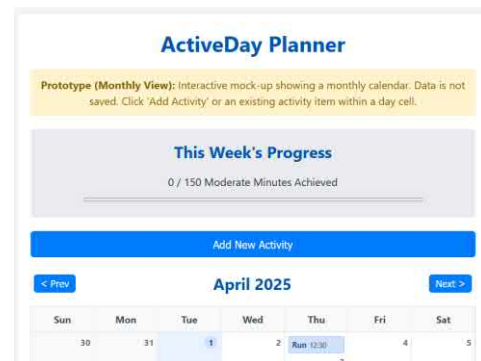


The Future is Already Here: Health apps on request ...

- AW+AI with Replit
- aktivplan concept prototype with Gemini 2.5



“generate a behavior change support application for fostering physical activity as a preventative measure for people living with CVD risk factors (pre-clinical / not yet patients); optionally make it link with google fit if the user wants to enable it. make the web app centered around a calendar for scheduling and reporting planned activities. optionally implement this as an augmentation of an existing calendar tool, such as google calendar, so that people can easily overlay planned activities with other planned elements of their day. make sure to implement as a progressive web app that is also mobile-ready.”



- Manual implementation costs: 4 – 5 figures
- AI compute cost: cents

Generative AI in Personalized Digital Health

Amazing possibilities!

But what do we do with them?



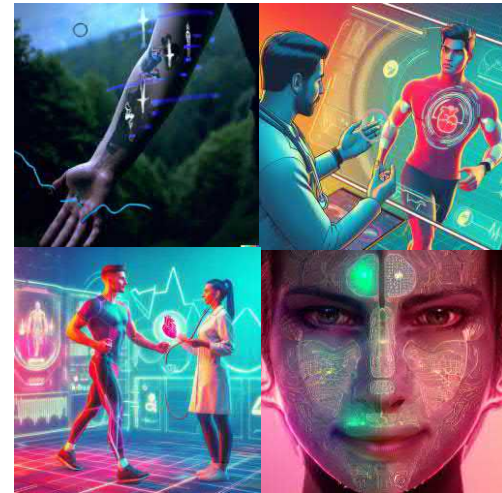
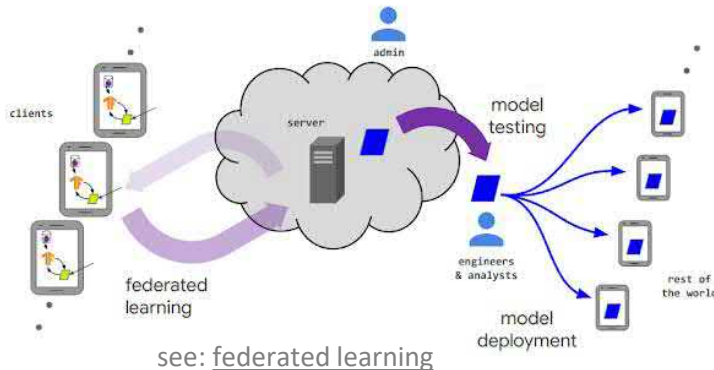
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Generative AI in Digital Health: yay/nay?

- Interaction with more prominent role of individual model users also offers opportunities for model improvement
In digital health applications: privacy and security particularly relevant → new approaches, such as federated learning ...
- Local execution and control over model(s)
e.g. OS foundation models “democratizing” AI



Dall-E: "a person with digital tatoos on the arms that show vital signs and health information standing in beautiful nature digital art"

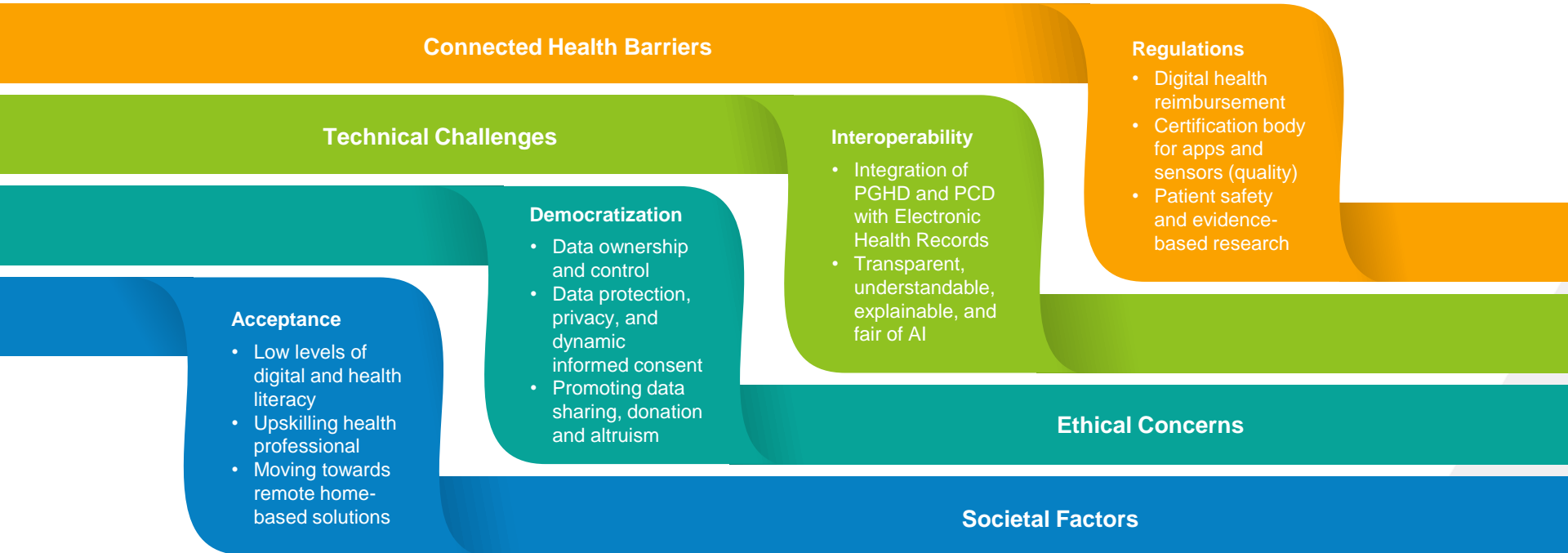
StableDif: "face with intricate and detailed light-emitting tatoos showing health information and vital sign visualizations heart rate ultra HD realistic wide focus"

StableDiffusion: "digital health tricorder used to scan a human body in the future unreal engine hyperdetailed realistic 4k octane"

StableDiffusion: "a virtual doctor helping a patient with a cardio training app"



Key Implementation Challenges: esp. regulations (akin to health data interoper.)



via Rada Hussein et al.



Challenges in Digital Health: “Scalability Issues” / Technology to Practice Gap

- Great opportunities in rapid technological development
(E.g. AI in DH: Topol, 2019)
- Advancements often do not reach the general public
 - “Digital Divide”: gap between those who have access to tech. and those who don’t
 - Limiting general factors on affordability / accessibility; geographical location, socioeconomic status, age, education (OECD 2019, WHO 2021)
- **AI is (getting) cheap;**
it WILL be used ... !!!

This Photo by Arz is licensed under [CC BY-SA](#)

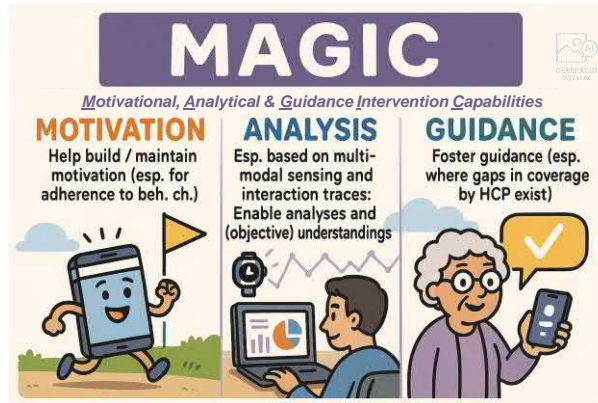


Capabilities of DHI in Personal Health:

MAGnify: A set of Digital Health Intervention Lenses

DHI have especially noteworthy capabilities in ...

- Motivation: Help build / maintain motivation (esp. for adherence to beh. ch.)
- Analysis: Esp. based on multi-modal sensing and interaction traces: Enable analyses and (objective) understandings
- Guidance: Foster guidance (esp. where gaps in coverage by HCP exist)

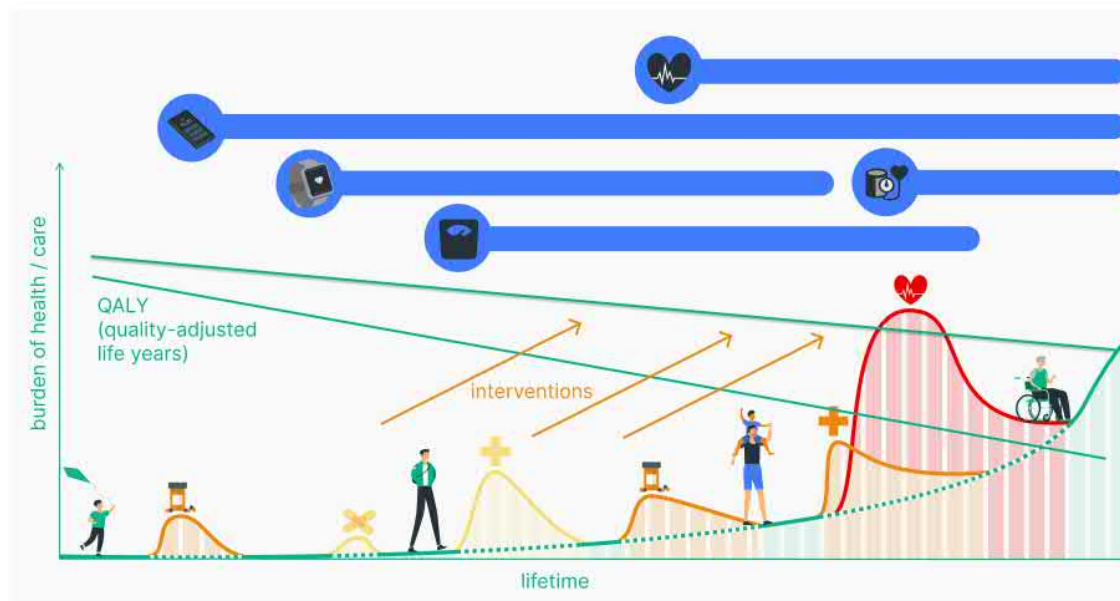


Adapted from: Smeddinck, J. D. (2016). Games for Health. In R. Dörner, S. Göbel, M. Kickmeier-Rust, M. Masuch, & K. Zweig (Eds.), *Entertainment Computing and Serious Games* (Vol. 9970, pp. 212–264). Springer International Publishing.



Immense Value of Digital Health Interventions

- Key towards more quality-adjusted life years
- Urgent need for longer-term research as most conv. Agents in DH already long-term oriented (Car et al., 2020)



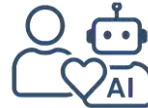
Key Talking Points

1. The growing importance of digital health solutions in addressing challenges of aging populations and chronic diseases ... **prevention > treatment**
2. Why **personalized health** (esp. in long-term health considerations)?
3. How **AI enables personalized healthcare interventions** that adapt to individual needs and contexts?
4. Scoping Digital Health Interventions with the **MAGnify** Framework of Lenses
 - a) Use-Cases / Worked Examples on GenAI in Digital Health Interventions for Beh. Ch.
5. Key **concerns** including privacy, biases, accountability, responsibility, explainability, etc.
6. Human-AI interaction design and development considerations
7. **Need for long-term and integrated / holistic perspectives ... Human-AI Relations** in digital health and real-world implementations
-> LBI-DHP digital health technology ecosystem



Key Takeaway Messages

1. GenAI can transform personalization: to drive personalized & adaptive digital health interventions, especially for chronic care and prevention
2. GenAI for health data sensemaking: can unearth value from patient-generated (health) data (PGHD) to enable timely, context-aware support & decision-making
3. AI capabilities advancing: State-of-the-art models (domain-specific, multimodal, edge, open source) show strong medical knowledge + already diverse health apps
4. Critical concerns: Must tackle biases, privacy, accountability, explainability, and regulatory issues for safe, ethical use
5. Human-AI collaboration is crucial: Effective interaction design (HAI/AIUX) and perspective on augmenting human capabilities are vital for trust & adoption
6. Long-term views & integrated ecosystem needed: Requires long-term vision, robust research methods, interoperability, and bridging the practice gap



THANK YOU!

Questions? Comments? Feedback?

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