TOWARDS AGENTIC PERSONAL HEALTH AND ORGANIZATIONAL DOMAIN COORDINATION IN OCCUPATIONAL NUTRITION

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Workplace meal choices shape dietary behavior and health outcomes, while individuals increasingly generate health-related data through wearables. Although both domains relate to the same meal event, they remain digitally separate because they operate under different governance conditions and data sensitivities. This creates a coordination problem: individuals lack structured access to organizational meal information, while meal-service providers should not access raw personal health data. This paper develops a coordination model for cross-domain interaction between the personal and organizational domains. Drawing on coordination theory, the model specifies how locally computed personal indicators and organizational meal-related information can interact within a governing coordination infrastructure centered on the meal event as the unit of coordination. A prototype instantiation illustrates the design through bounded coordination artifacts and tool-mediated interaction. An initial controlled benchmark indicates the technical feasibility of the approach, while questions of real-world adoption and organizational impact remain for future research.

Keywords:
digital health,
coordination,
agentic AI,
wearables,
cross-domain

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1 Introduction

Cardiovascular disease, diabetes and related metabolic risk make everyday food choices increasingly relevant for prevention and self-management. In occupational settings, canteens shape these choices because they determine which meals are offered and how dishes are composed (Friedman & Mozaffarian, 2016). Reviews of workplace cafeteria interventions show that changes in the food environment can influence dietary behavior and health-related outcomes (Naicker et al., 2021). Nutrition research further shows that meal composition and preparation matter for postprandial glycemic response. Carbohydrate amount, fiber, protein, fat and cooking can all change how a meal affects glucose after eating (Murillo et al., 2022; Pasmans et al., 2022). At the same time, nutrition-related data are generated on the personal side. Individuals use meal logs and wearable devices to observe related health outcomes (George et al., 2023). This also includes continuous glucose monitoring, especially in the context of prediabetes, gestational diabetes and type 2 diabetes. Research on personalized nutrition has shown that people can react very differently to the same meal and that glucose meal responses can support individualized dietary guidance (Zeevi et al., 2015). Although both domains are relevant to the same meal event, they rarely interact digitally. Privacy regulation, data-management challenges and the sensitivity of health-related information constrain direct sharing of personal insights in organizational settings (Donovan et al., 2025). Individuals usually do not have digital access to recipe, portion or preparation data from the canteen, while food-service actors cannot and should not interpret raw personal health data (Pateraki et al., 2020; Salehzadeh Niksirat et al., 2024; Virgillito et al., 2025). This creates a coordination problem between two domains that each hold only part of the relevant knowledge (Caccamo et al., 2023). In this context, coordination theory provides a useful lens because the challenge is the management of dependencies among activities distributed across multiple actors (Malone & Crowston, 1994). In multi-agent settings, these dependencies are shaped also by infrastructures that mediate and govern the interaction space (Omicini et al., 2004; Rodriguez-Aguilar et al., 2015).

Developments in edge AI, as well as LLM-based tool selection, make it feasible to process sensitive indicators locally and connect them to organizational services through bounded interfaces (Krishnan, 2025; Piccialli et al., 2025; Singh & Gill, 2023; Zhao et al., 2026). Prior coordination-infrastructure research has advanced the structuring of interaction, but it still identifies agent decision support and decentralized coordination design as open challenges (Rodriguez-Aguilar et al., 2015). Related governance research likewise calls for further study of data governance across multi-actor settings, particularly where personal data are involved (Paparova et al., 2023). In occupational nutrition, this gap is particularly salient because personal health-related indicators and organizational meal-service data are jointly relevant to the same meal event but remain separated by different governance regimes and data sensitivities (Donovan et al., 2025). What is missing is a governed coordination model for interaction between personal and organizational domains around shared meal-related and health-related indicators. This paper addresses that gap by developing the Agentic Cross-Domain Coordination Model (ACCM). Its technical feasibility is examined through a prototype instantiation of selected components and evaluated with bounded LLM-based tool calls via a natural-language interface.

RQ: How can a model be conceptualized for cross-domain coordination between the personal health domain and the organizational domain in occupational nutrition settings?

2 Literature Review

2.1 Coordination Infrastructure

"How will the widespread use of information technology change the ways people work together?" (Malone & Crowston, 1994). This question motivates Malone and Crowston's research. They argue that the most significant effect of information technology is its ability to make coordination between individuals and groups both cheaper and more effective. As coordination costs decline, organizations can move beyond traditional hierarchies and adopt more flexible structures. In this way, information technology reshapes the fundamental ways work is organized within and across organizations. This study adopts Malone and Crowston's definition of coordination as "managing dependencies between activities" (Malone & Crowston, 1994). In Computer-Supported Cooperative Work (CSCW), this concept is extended through the incorporation of models of coordinative practices into computational artifacts that support actors in dealing with contingencies in cooperative work (Ciolfi et al., 2023). In the multi-agent system (MAS) literature, this becomes a matter of governing the interaction space through coordination infrastructures. In MAS, the environment is conceived as an explicit part of the system, with the dual role of providing the surrounding conditions for agents to exist and an exploitable design abstraction for building applications (Weyns et al., 2006). Artifact-oriented approaches in MAS distinguish between agents and coordination artifacts or media. Agents exploit coordination artifacts at the coordination stage, while coordination media first enable interactions among agents and then mediate them in a more automated manner. In this sense, coordination artifacts externalize coordination knowledge into the interaction environment or infrastructure. This corresponds to the distinction between subjective and objective coordination: subjective coordination concerns the reasoning processes of agents, whereas objective coordination is enacted through coordination media that embed and enforce social laws and interaction constraints (Omicini et al., 2004). Agent Coordination Contexts (ACCs) refine this further by defining the controlled layer through which an agent can interact with its environment, making coordination and security constraints explicit at the agent-environment boundary (Ricci et al., 2006). This study therefore uses coordination theory as a lens to examine how meal-related dependencies are mediated across domains.

2.2 Large Language Models and Agentic AI

In cross-domain settings, another challenge is that users and services operate with different interpretive contexts. NLP-based interfaces can reduce knowledge barriers between users and information systems by enabling access through natural language (Sawant & Sonawane, 2024). LLMs extend this by offering more flexible natural-language understanding and by supporting semantic interoperability tasks such as schema alignment and knowledge integration across heterogeneous domains (Abu-Salih et al., 2025; Zhou et al., 2025). However, these capabilities do not remove governance concerns. Instead, they increase the need for secure and governed interaction (Abu-Salih et al., 2025). Agentic AI adds a capability beyond language understanding. AI agents can be categorized by their autonomy, capabilities and underlying technologies (Krishnan, 2025). Traditional agents include rule-based systems and agents using machine learning or reinforcement learning for adaptive decision-making (Xi et al., 2025). More advanced forms leverage LLMs, enabling complex reasoning, tool integration and diverse tasks such as scheduling and data summarization (Sapkota et al., 2026). Recent developments introduce Agentic AI, referring to highly autonomous agents capable of dynamic task decomposition and multi-agent coordination, suited for complex domains such as medical decision support (Murugesan, 2025). Emerging standards such as the Model Context Protocol (MCP) enable advanced agents to interact and access external tools in multi-agent systems (Li & Xie, 2025). Their integration also raises challenges, including semantic interoperability and the need for robust governance (Huang & Hughes, 2025). Overall, MCP forms foundational infrastructure for collaborative multi-agent applications (Liao et al., 2025).

2.3 Interoperability & Data Spaces

In Europe, the International Data Spaces (IDS) and Gaia-X promote federated data ecosystems where organizations exchange data under common standards and sovereignty assurances (von Scherenberg et al., 2024). These frameworks emphasize legal agreements, identity management and trusted execution environments but focus mainly on B2B interoperability rather than individuals as distinct stakeholders (Scheider et al., 2023). In parallel, personal information management systems (PIMS) have emerged, exemplified by Solid pods and the MyData movement, which give individuals control over storage and selective sharing (Janssen & Singh, 2022). Despite progress in inter-organizational data spaces and PIMS, most frameworks privilege one over the other. This gap calls for a cross-domain interaction that bridges user-centric control with organization-level interoperability (Delacroix & Lawrence, 2019).

2.4 Synthesis

In the present problem space, a single meal event spans two domains that remain institutionally and technically separated. The core challenge is therefore one of coordination across distributed actors, data sources and governance regimes. Coordination theory defines this challenge as the management of dependencies between activities, while CSCW and MAS show that such dependencies can be managed through computational artifacts and governed interaction infrastructures. However, these perspectives do not address the semantic and knowledge barriers that arise when users, services and data sources operate with different vocabularies and structures across domains. Here, NLP-based interfaces and LLMs add an important capability by enabling semantic mediation and the translation of user intent into structured requests across heterogeneous systems. Agentic AI adds the possibility of actors that can interpret intent and act across services, but data space and governance research make clear that such action must remain bounded by sovereignty and policy requirements. Taken together, these perspectives suggest that the design problem is to create a governed coordination model that links personal and organizational domains through controlled layers. The synthesis informs the formulation of four design requirements concerning local resource control, governed cross-domain interaction, bounded exchange and boundary-specific admissibility. Table 1 summarizes these requirements and their realization in ACCM.

Table 1: Literature-derived requirements and their realization in ACCM

Requirement	Literature	ACCM
R1 Local control of domain resources	PIMS / MyData; data governance	Personal and organizational resources remain local; domain-specific tools compute outputs locally
R2 Governed cross-domain interaction	Coordination-infrastructure theory	A Governing Coordination Infrastructure organizes objective coordination and exchange conditions
R3 Bounded and selective exchange	Coordination-infrastructure theory; governance literature	Cross-domain interaction occurs through bounded coordination artifacts
R4 Boundary-specific admissibility control	ACC theory	Agent Coordination Contexts define admissible actions and perceptions at the domain boundary

3 Methodology

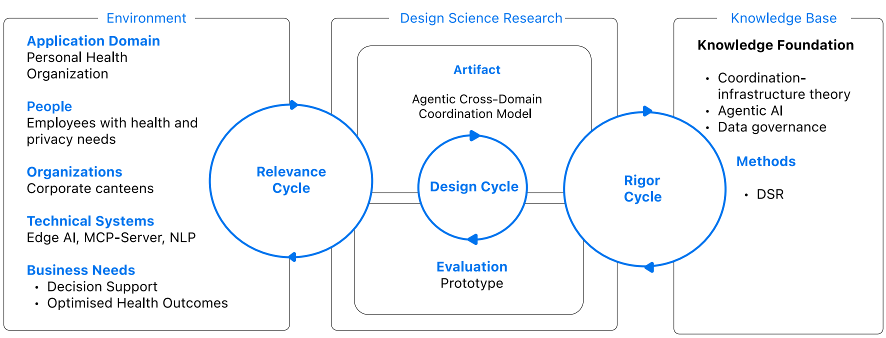

Figure 1: Three Cycle View adapted from
Source: (Hevner, 2007)

This study adopts design science research (DSR) to develop and evaluate an artifact for governed cross-domain interaction in occupational nutrition settings (Hevner, 2007).

Table 2: Illustrative indicators, organizational uses and tools

Domain	Measure	Use & Literature	Related Tools
Organization	Carb & portion size	Portion and starch adjustment (Vlachos et al., 2020)	find_menu_items (T5) get_dish_carbohydrates (T4) find_lowest_carb_dish (T2)
	Fiber, Fat, Protein	Increase fiber-rich components, higher-protein meals, and adjust recipe composition (Kim et al., 2019)	find_menu_items (T6)
	Preparation	Change processing, cooking, or food order (Cesbron-Lavau et al., 2021)	get_dish_preparation_info (T7)
Personal	Pre-meal baseline	Interpret Glucose starting state (Ehlert et al., 2026)	get_premeal_baseline_glucose (T8)
	Rise to peak	Glucose excursion magnitude (Ehlert et al., 2026)	find_highest_postmeal_peak (T1)
	2-h iAUC	Glucose total exposure (Ehlert et al., 2026)	get_postmeal_indicator_bundle
	Time to peak	Glucose response speed (Ehlert et al., 2026)	get_postmeal_indicator_bundle (T3)

Following Hevner's three-cycle view, the study combines relevance, rigor and design activities as show in Figure 1. The relevance cycle is grounded in the challenge of linking personal nutrition-related data with organizational meal-service data while preserving privacy. The rigor cycle draws on the theoretical synthesis from which the design requirements for ACCM were derived and is shown in Table 1. In the design cycle an initial ACCM model was derived from the requirements, implemented through a prototype instantiation of selected components and refined based on the prototype findings. The prototype was developed with real-world data collected during the study intervention by meala (meala GmbH, 2025), a food-tracking diary app that integrates glucose data from FreeStyle Libre and Dexcom and connects to Apple Health and Health Connect for contextual data such as activity and sleep. It contained more than 30,000 glucose values and 955 tracked meals from a company canteen and private settings. The study further used the menu data from a company canteen in Berlin, Germany, including 687 menus with nutritional information and portion sizes collected between August and November 2024. In total, 10 users aged 25 to 55 participated. Seven pursued healthier eating, two aimed at performance improvement and one had no specific goal. To instantiate ACCM, a prototype was implemented with FastMCP (*Fastmcp*, 2026). It operationalized selected elements of the coordination model and exposed a restricted set of indicator tools derived from the Glucose360 platform (Ehlert et al., 2026) and glucose-related nutrition studies listed in Table 2.

Table 3: Benchmark queries and expected tools

ID	User query	Tool	Arguments
Q1	What was my highest post-meal peak between 2024-08-12 and 2024-08-18?	T1	date_range_start=2024-08-12, date_range_end=2024-08-18
Q2	What is the dish with the lowest carbs in all available menu data?	T2	none
Q3	For meal event ME1, how did I react?	T3	meal_event_id=ME1
Q4	For meal event ME1, what was the time to peak in the first 120 minutes?	T3	meal_event_id=ME1
Q5	For meal event ME1, what is the 2-hour incremental AUC (iAUC 0–120)?	T3	meal_event_id=ME1
Q6	How did I react to meal event ME1?	T3	meal_event_id=ME1
Q7	What is the rise to peak for meal id ME1?	T3	meal_event_id=ME1

ME1 – meal id from food diary

The prototype provided a technical instantiation of ACCM to examine the feasibility of governed LLM-based tool selection and local calculated indicators. Evaluation was conducted as a feasibility-oriented ex post assessment using a benchmark of prompt-expectation test cases. For each test case, labels were defined manually before execution by specifying the expected tool call and the expected arguments as shown in Table 3. The benchmark queries were executed three times per mode using the same tool descriptions and instruction setup across models. The evaluated models were qwen3.5:0.8b, granite4:latest, llama3.1:8b and gpt-4o. They were selected to compare smaller models suitable for edge AI settings with a closed cloud-based model. The local open models were run via Ollama on an Apple M1 Pro and 32 GB RAM, while GPT-4o was accessed via API. The evaluation examined tool-selection accuracy, parameter correctness, false positives, false negatives, overcall behavior and latency. Tool-selection accuracy measured whether the labeled tool was selected. False positives captured incorrect or unnecessary tool calls, whereas false negatives captured missed required tool calls. Overcall behavior referred specifically to cases in which a model invoked more tool use than required. Latency was recorded descriptively as end-to-end response time and is interpreted cautiously because execution environments differed across models. This evaluation was used to assess the technical plausibility of the prototype and to derive implications for the design of the governed layer.

4 Model

Figure 2 specifies ACCM as a federated coordination model for workplace meal events. The model draws on coordination theory by treating cross-domain interaction as the management of dependencies between two operationally separate domains: a personal health domain and an organizational meal-service domain. In line with coordination-infrastructure theory, ACCM separates subjective coordination from objective coordination, which is organized through a shared governing infrastructure. Each domain contains local resources, local tools, local agents and user-facing applications or services. In the personal domain, resources consist of employee-held health-related data, while tools derive bounded indicators from these data for local use. In the organizational domain, resources consist of meal-service and nutrition-related data, while tools process menu, recipe and ingredient information. In both domains, agents coordinate locally over these resources and tools. Raw domain data are therefore not exposed to the other side as part of the coordination arrangement. Cross-domain interaction is mediated through Agent Coordination Contexts (ACCs) positioned at the boundary between each domain and the shared infrastructure. The ACC defines the admissible actions and perceptions available to a given agent at the boundary between its domain and the governing coordination infrastructure. It preserves the distinction between local agent autonomy and infrastructural governance: the agent remains responsible for local interpretation and action selection, while the infrastructure regulates the terms under which cross-domain interaction becomes possible. The central coordination device in ACCM is the meal event. The model represents it through bounded coordination artifacts within the governing infrastructure. These artifacts link organizational descriptions of meals with locally computed personal indicators related to the same event. In this way, the meal event becomes the shared coordination object without requiring either domain to relinquish control over its underlying resources. Cross-domain exchange is limited to bounded, decision-relevant outputs produced locally and made available under infrastructural conditions. The participating domains remain distinct, maintain their own resources and interact through a governed coordination infrastructure. ACCM therefore specifies a form of selective interoperability in which cross-domain coordination is achieved through bounded coordination artifacts, governed exchange conditions, and boundary admissibility controls.

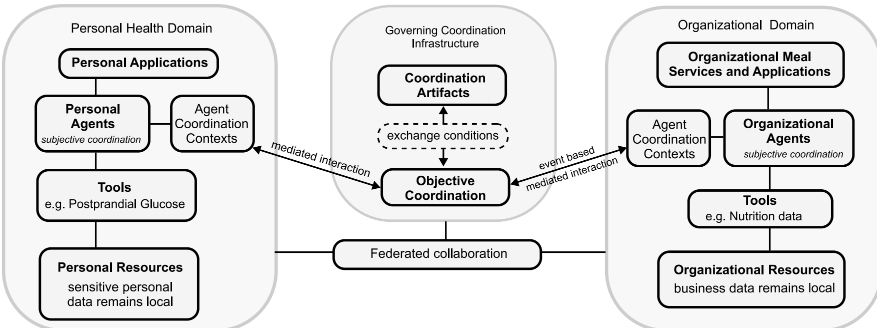

Figure 2: Conceptual Agentic Cross-Domain Coordination Model
Source: Own

5 Results

The prototype was used to generate 21 evaluations per model (7 cases, each repeated three times), gpt-4o achieved 100.0% true positives and the lowest mean latency (1,970 ms). Among the open models, granite4:latest obtained the highest performance (61.9% TP), followed by llama3.1:8b (52.4% TP) and qwen3.5:0.8b (38.1% TP). The complete results are shown in Table 4. At the case level, the cases listed in Table 3 showed different levels of performance across the open models. Q1 ("What was my highest post-meal peak between 2024-08-12 and 2024-08-18?") and Q5 ("For meal event ME1, what is the 2-hour incremental AUC?") each recorded 7/9 correct runs, while Q2 ("What is the dish with the lowest carbs in all available menu data?") recorded 6/9 correct runs. The date-bounded case Q1 achieved a 100.0% date-pass rate across all models. Q4 ("For meal event ME1, what was the time to peak in the first 120 minutes?") recorded 5/9 correct runs. Performance was lower for the semantically similar reaction queries in Q3 ("For meal event ME1, how did I react?"), recorded 3/9 and Q6 ("How did I react to meal event ME1?"), recorded 2/9 correct runs. The same results for Q7 ("What is the rise to peak for meal id ME1?").

Table 2: Tool-invocation benchmark across models

Model	TP (%)	FP	FN	Overcall (%)	Avg. latency (ms)
llama3.1:8b	52.4	0	10	0.0	9,288
granite4:latest	61.9	3	5	14.3	5,608
qwen3.5:0.8b	38.1	11	1	52.4	63,866
gpt-4o	100.0	0	0	0.0	1,970

TP = true positive rate; FP = false positives; FN = false negatives; Overcall = unnecessary tool invocation rate

6 Discussion

This study frames workplace nutrition as a cross-domain coordination challenge in which the relevant dependency is distributed across two operationally separate domains. The design-knowledge contribution of the study lies in an event-centered coordination pattern for selective interoperability in sensitive settings. In ACCM, the meal event functions as a bounded coordination artifact that links organizational meal descriptors with locally computed personal indicators without requiring either domain to expose its underlying resources. The contribution lies in their integration through a governed coordination model in which a shared event structures the scope of coordination, the conditions of exchange, and admissibility at the domain boundary. In this sense, the meal event serves both as a semantic coordination unit and as a practical privacy boundary for cross-domain interaction.

The prototype and benchmark provide preliminary support for this pattern. They show that natural-language requests can be translated into bounded tool calls and cross-domain responses, thereby reducing semantic and knowledge barriers for users. At the same time, the findings indicate that privacy-preserving coordination remains reliable only when AI operates within explicit governance boundaries and restricted action spaces. In the evaluated benchmark, the cloud-based model achieved the strongest tool-selection performance, whereas the tested local models were less reliable, especially for semantically broader formulations. The implication is the continued importance of a governed coordination layer based on local computation, bounded tool mediation and precise event-bounded exchange. Edge AI appears promising for such settings, but further progress in local model quality and edge-specific fine-tuning is needed before it can support this coordination pattern with comparable robustness. The evaluation was limited to a prototype and a controlled benchmark assessing technical feasibility. It did not validate downstream effects. On the personal side, the study did not examine whether the proposed coordination pattern improves health-related outcomes. On the organizational side, it did not evaluate whether the generated indicators improve menu planning or other forms of decision support. The prototype should therefore be understood as a preparatory step toward a future intervention study in which the coordination model can be instantiated in real organizational settings to assess adoption, decision processes and measurable effects on nutrition-related health outcomes

7 Conclusion

This paper presented ACCM as a coordination model for governed cross-domain interaction between personal health platforms and organizational meal-service platforms. The model specifies how locally computed personal indicators and organizational meal-related information can be connected through a governed layer while preserving the local control of sensitive personal data. Beyond assessing technical feasibility, the initial prototype and controlled benchmark also informed the iterative refinement of ACCM by providing preliminary design knowledge about the governed layer. The findings suggest that coordination artifacts can support this interaction pattern and that the meal event serves as a useful coordination and privacy boundary for cross-domain interaction. The paper therefore contributes a conceptual design-oriented model for selective cross-domain interoperability in occupational nutrition. Future research should examine the model in real organizational settings and assess adoption and practical outcome effects.

References

Abu-Salih, B., Alotaibi, S., Alanazi, A. L., Abu Khurma, R., Al-Shboul, B., Khouri, A., & Aljaafari, M. (2025). Using large language models for semantic interoperability: A systematic literature review. *ICT Express*, *11*(4), 819–837. https://doi.org/10.1016/j.icte.2025.06.011

Caccamo, M., Pittino, D., & Tell, F. (2023). Boundary objects, knowledge integration, and innovation management: A systematic review of the literature. *Technovation*, *122*, 102645. https://doi.org/10.1016/j.technovation.2022.102645

Cesbron-Lavau, G., Goux, A., Atkinson, F., Meynier, A., & Vinoy, S. (2021). Deep Dive Into the Effects of Food Processing on Limiting Starch Digestibility and Lowering the Glycemic Response. *Nutrients*, *13*(2), 381. https://doi.org/10.3390/nu13020381

Ciolfi, L., Lewkowicz, M., & Schmidt, K. (2023). Computer-Supported Cooperative Work. *Handbook of Human Computer Interaction*, 1–26. https://doi.org/10.1007/978-3-319-27648-9_30-1

Delacroix, S., & Lawrence, N. D. (2019). Bottom-up data Trusts: disturbing the 'one size fits all' approach to data governance. *International Data Privacy Law*, *9*(4), 236–252. https://doi.org/10.1093/IDPL/IPZ014

Donovan, S. M., Abrahams, M., Anthony, J. C., Bao, Y., Barragan, M., Bermingham, K. M., Blander, G., Keck, A. S., Lee, B. Y., Nieman, K. M., Ordovas, J. M., Penev, V., Reinders, M. J., Sollid, K., Thosar, S., & Winters, B. L. (2025). Personalized nutrition: perspectives on challenges, opportunities, and guiding principles for data use and fusion. *Critical Reviews in Food Science and Nutrition*, *65*(30), 7151–7169. https://doi.org/10.1080/10408398.2025.2461237

Ehlert, B., Aron, D., Perelman, D., Wu, Y., & Snyder, M. P. (2026). Glucose360: An Open-Source Python Platform with Event-Based Integration for Continuous Glucose Monitoring Data Analysis. *Diabetes Technology & Therapeutics*, *28*(2), 130. https://doi.org/10.1177/15209156251374711

fastmcp. (2026). https://github.com/PrefectHQ/fastmcp

Friedman, F., & Mozaffarian, D. (2016). Dietary and Policy Priorities for Cardiovascular Disease, Diabetes, and Obesity. *Circulation*, *133*(2), 187–225. https://doi.org/10.1161/CIRCULATIONAHA.115.018585

George, A. S. H., Shahul, A., & George, Dr. A. S. (2023). Wearable Sensors: A New Way to Track Health and Wellness. *Partners Universal International Innovation Journal (PUIIJ)*, *01*(04), 15–34. https://doi.org/10.5281/ZENODO.8260879

Hevner, A. R. (2007). A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems*, *19*(2). https://aisel.aisnet.org/sjis/vol19/iss2/4

Huang, K., & Hughes, C. (2025). *Agentic AI Communication Protocols and Security*. 81–110. https://doi.org/10.1007/978-3-032-02130-4_4

Janssen, H., & Singh, J. (2022). Personal Information Management Systems. *Internet Policy Review*, *11*(2). https://doi.org/10.14763/2022.2.1659

Kim, J. S., Nam, K., & Chung, S. J. (2019). Effect of nutrient composition in a mixed meal on the postprandial glycemic response in healthy people: a preliminary study. *Nutrition Research and Practice*, *13*(2), 126. https://doi.org/10.4162/nrp.2019.13.2.126

Krishnan, N. (2025). AI Agents: Evolution, Architecture, and Real-World Applications. *ArXiv*. https://doi.org/10.48550/arXiv.2503.12687

Li, Q., & Xie, Y. (2025). From Glue-Code to Protocols: A Critical Analysis of A2A and MCP Integration for Scalable Agent Systems. *ArXiv*, (abs/2505.03864). https://doi.org/10.48550/arXiv.2505.03864

Liao, C. C., Liao, D., & Surya Gadiraju, S. (2025). AgentMaster: A Multi-Agent Conversational Framework Using A2A and MCP Protocols for Multimodal Information Retrieval and Analysis. *ArXiv*, *abs/2507.21105*. https://doi.org/10.48550/arXiv.2507.21105

Malone, T. W., & Crowston, K. (1994). The Interdisciplinary Study of Coordination. *ACM Computing Surveys (CSUR)*, *26*(1), 87–119. https://doi.org/10.1145/174666.174668

meala GmbH. (2025). *meala*. https://www.heymeala.com/en/

Murillo, S., Mallol, A., Adot, A., Juárez, F., Coll, A., Gastaldo, I., & Roura, E. (2022). Culinary strategies to manage glycemic response in people with type 2 diabetes: A narrative review. *Frontiers in Nutrition*, *9*, 1025993. https://doi.org/10.3389/fnut.2022.1025993

Murugesan, S. (2025). The Rise of Agentic AI: Implications, Concerns, and the Path Forward. *IEEE Intelligent Systems*, *40*(2), 8–14. https://doi.org/10.1109/MIS.2025.3544940

Naicker, A., Shrestha, A., Joshi, C., Willett, W., & Spiegelman, D. (2021). Workplace cafeteria and other multicomponent interventions to promote healthy eating among adults: A systematic review. *Preventive Medicine Reports*, *22*, 101333. https://doi.org/10.1016/j.pmedr.2021.101333

Omicini, A., Ossowski, S., & Ricci, A. (2004). Coordination Infrastructures in the Engineering of Multiagent Systems. *Methodologies and Software Engineering for Agent Systems*, 273–296. https://doi.org/10.1007/1-4020-8058-1_17

Paparova, D., Aanestad, M., Vassilakopoulou, P., & Bahus, M. K. (2023). Data governance spaces: The case of a national digital service for personal health data. *Information and Organization*, *33*(1), 100451. https://doi.org/10.1016/j.infoandorg.2023.100451

Pasmans, K., Meex, R. C. R., van Loon, L. J. C., & Blaak, E. E. (2022). Nutritional strategies to attenuate postprandial glycemic response. *Obesity Reviews*, *23*(9), e13486. https://doi.org/10.1111/obr.13486

Pateraki, M., Fysarakis, K., Sakkalis, V., Spanoudakis, G., Varlamis, I., Maniadakis, M., Lourakis, M., Ioannidis, S., Cummins, N., Schuller, B., Loutsetis, E., & Koutsouris, D. (2020). Biosensors and Internet of Things in smart healthcare applications: challenges and opportunities. *Wearable and Implantable Medical Devices: Applications and Challenges*, 25–53. https://doi.org/10.1016/B978-0-12-815369-7.00002-1

Piccialli, F., Chiaro, D., Sarwar, S., Cerciello, D., Qi, P., & Mele, V. (2025). AgentAI: A comprehensive survey on autonomous agents in distributed AI for industry 4.0. *Expert Systems with Applications*, *291*, 128404. https://doi.org/10.1016/J.ESWA.2025.128404

Ricci, A., Viroli, M., & Omicini, A. (2006). Agent coordination contexts in a MAS coordination infrastructure. *Applied Artificial Intelligence*, *20*(2–4), 179–202. https://doi.org/10.1080/08839510500484207

Rodriguez-Aguilar, J. A., Sierra, C., Arcos, J. L., Lopez-Sanchez, M., & Rodriguez, I. (2015). Towards next generation coordination infrastructures. *The Knowledge Engineering Review*, *30*(4), 435–453. https://doi.org/10.1017/S0269888915000090

Salehzadeh Niksirat, K., Velykoivanenko, L., Zufferey, N., Cherubini, M., Huguenin, K., Humbert, M., Velykoivanenko, L., Zufferey, N., Cherubini, M., Huguenin, K., & Humbert, M. (2024). Wearable Activity Trackers: A Survey on Utility, Privacy, and Security. *ACM Computing Surveys*, *56*(7), 183. https://doi.org/10.1145/3645091

Sapkota, R., Roumeliotis, K. I., & Karkee, M. (2026). AI Agents vs. Agentic AI: A Conceptual taxonomy, applications and challenges. *Information Fusion*, *126*, 103599. https://doi.org/10.1016/J.INFFUS.2025.103599

Sawant, P., & Sonawane, K. (2024). NLP-based smart decision making for business and academics. *Natural Language Processing Journal*, *8*, 100090. https://doi.org/10.1016/j.nlp.2024.100090

Scheider, S., Lauf, F., Möller, F., & Otto, B. (2023). A Reference System Architecture with Data Sovereignty for Human-Centric Data Ecosystems. *Business and Information Systems Engineering*, *65*(5), 577–595. https://doi.org/10.1007/s12599-023-00816-9

Singh, R., & Gill, S. S. (2023). Edge AI: A survey. *Internet of Things and Cyber-Physical Systems*, *3*, 71–92. https://doi.org/10.1016/J.IOTCPS.2023.02.004

Virgillito, D., Catalfo, P., & Ledda, C. (2025). Wearables in Healthcare Organizations: Implications for Occupational Health, Organizational Performance, and Economic Outcomes. *Healthcare*, *13*(18), 2289. https://doi.org/10.3390/HEALTHCARE13182289

Vlachos, D., Malisova, S., Lindberg, F. A., & Karaniki, G. (2020). Glycemic Index (GI) or Glycemic Load (GL) and Dietary Interventions for Optimizing Postprandial Hyperglycemia in Patients with T2 Diabetes: A Review. *Nutrients*, *12*(6), 1561. https://doi.org/10.3390/nu12061561

von Scherenberg, F., Hellmeier, M., & Otto, B. (2024). Data Sovereignty in Information Systems. *Electronic Markets 2024 34:1*, *34*(1), 1–11. https://doi.org/10.1007/S12525-024-00693-4

Weyns, D., Omicini, A., Odell, J., Weyns, D., Omicini, A., & Odell, J. (2006). Environment as a first class abstraction in multiagent systems. *Autonomous Agents and Multi-Agent Systems 2006 14:1*, *14*(1), 5–30. https://doi.org/10.1007/s10458-006-0012-0

Xi, Z., Chen, W., Guo, X., He, W., Ding, Y., Hong, B., Zhang, M., Wang, J., Jin, S., Zhou, E., Zheng, R., Fan, X., Wang, X., Xiong, L., Zhou, Y., Wang, W., Jiang, C., Zou, Y., Liu, X., … Gui, T. (2025). The rise and potential of large language model based agents: a survey. *Science China Information Sciences*, *68*(2), 1–44. https://doi.org/10.1007/S11432-024-4222-0

Zeevi, D., Korem, T., Zmora, N., Israeli, D., Rothschild, D., Weinberger, A., Ben-Yacov, O., Lador, D., Avnit-Sagi, T., Lotan-Pompan, M., Suez, J., Mahdi, J. A., Matot, E., Malka, G., Kosower, N., Rein, M., Zilberman-Schapira, G., Dohnalová, L., Pevsner-Fischer, M., … Segal, E. (2015). Personalized Nutrition by Prediction of Glycemic Responses. *Cell*, *163*(5), 1079–1094. https://doi.org/10.1016/j.cell.2015.11.001

Zhao, L., Liu, S., Xin, T., Tan, J., Wang, X., Li, Y., Bian, Z., Chen, Y., Kong, F., Bian, J., Qian, C., & Zhang, Z. (2026). AI agent in healthcare: applications, evaluations, and future directions. *Npj Artificial Intelligence 2026 2:1*, *2*(1), 31-. https://doi.org/10.1038/s44387-026-00076-4

Zhou, J., Li, H., Chen, S., Chen, Z., Han, Z., & Gao, X. (2025). Large language models in biomedicine and healthcare. *Npj Artificial Intelligence 2025 1:1*, *1*(1), 44-. https://doi.org/10.1038/s44387-025-00047-1