MUSAE

D4.5 UX Interaction guidelines

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Executive summary

MUSAE, a project on art-driven innovation in the food sector, employs the Design Future Art-driven (DFA) methodology to explore novel scenarios and inspire industrial prototypes that envision the future of food through the lens of sustainability, health, and societal well-being. This deliverable outlines findings and recommendations regarding the human-machine interaction (HMI) aspects of these scenarios, with a particular focus on human-robot interaction (HRI) and the design of multimodal interfaces. Building upon a comprehensive analysis of 12 artistic scenarios developed within MUSAE (Deliverables D2.1-D2.12), this document identifies both explicitly stated and inferred technological components, emphasising those related to robotics and advanced interaction modalities. This analysis is underpinned by a commitment to humanising technology, aiming to ensure that prototypes are not only functional but also intuitive, accessible, engaging, and ethically sound. The deliverable provides a detailed technological review of each scenario, followed by a set of **comprehensive HRI guidelines** for developers. These guidelines, informed by established HRI and HCI literature, cover key aspects such as **robot appearance and embodiment, behavior and movement, multimodal communication, human-robot collaboration, ethical considerations, and specific evaluation metrics**. Key areas of focus include the development of multimodal interfaces, the integration of conversational AI, immersive technologies (AR/VR), various forms of robotics (e.g. collaborative, social, bio-inspired), sensor-based systems, and their evaluation using relevant metrics. The overarching goal is to provide artists and developers with actionable recommendations to ensure that the MUSAE prototypes are both technologically advanced and deeply human-centered, fostering broader acceptance, facilitating social interaction, and promoting a more profound impact on the future of food.

Introduction

Within the MUSAE project, "scenarios" serve as powerful tools for envisioning potential futures in the realm of food, art, and technology. Developed through the unique Design Future Art-driven (DFA) methodology, each scenario paints a vivid picture of a possible future, exploring how societal shifts, technological advancements, and evolving cultural values might intersect to shape our relationship with food. These narratives are not meant to be predictive, but rather provocative, sparking dialogue and inspiring innovation by presenting a unique ecosystem of interconnected elements. These elements can be trends, personas, describing fictional characters representing different user types, and technologies. For example, the aforementioned scenario delves into a world where agroforestry initiatives, driven by AI, robotics, and a philosophy of interconnectedness, are reshaping urban landscapes and challenging traditional notions of food production and consumption, prompting us to consider the implications and opportunities that such a future might hold.

Each MUSAE scenario, while presenting a cohesive vision of a potential food future, serves as a springboard for the development of diverse projects, each interpreting and realising the scenario's essence in a tangible way. While a scenario outlines a specific goal and positioning, for instance, highlighting the importance of local food ecosystems and community engagement, it can inspire a variety of projects, from interactive educational tools to prototypes of innovative food-sharing platforms. Although the specific user interactions, workflows, and detailed functionalities will naturally differ based on each project's scope and aims, the foundational technological components can be anticipated and generalised. These might include, for example, user-friendly interfaces for connecting local producers and consumers, data visualisation tools for showcasing the environmental impact of local food systems, and potentially sensor networks to gather data from community gardens. Implementing these technologies involves addressing practical challenges, such as ensuring ease of use for diverse audiences, presenting data in a meaningful and accessible way, and potentially integrating different technological components. Thus, each project emerging from a scenario must thoughtfully adapt these core technological elements to its specific needs and context, while remaining aligned with the overarching vision of the scenario.

The task underpinning this deliverable is focused on mentoring and supporting artists and developers to improve the human-machine interaction component of their projects. By anticipating their potential requirements, we provide guidance on state of the art tools and methods to design multimodal and social interfaces. Complex project requirements originating from the new scenarios within the MUSAE project also extend these tools and methods to the human-robot interaction of computationally creative solutions, thereby assisting and mentoring artists and end-users in refining the interaction of people with their product when developing their industrial prototype. This contributes to humanising the technological prototype enhancing their acceptance by the larger audience.

To achieve these goals, this deliverable embarks on a thorough technological review of the twelve MUSAE scenarios, identifying both explicitly stated and implied technological components that underpin each vision. Building upon this foundation, we abstract these diverse technological needs into broader categories, such as Generative AI, Conversational Agents, Immersive Technologies, Robotics, and Sensor Networks, highlighting their potential applications and associated challenges within the context of the scenarios. This process allows us to anticipate the technological landscape of potential projects, even in the absence of concrete project specifications. Furthermore, we delve into relevant Human-Computer Interaction (HCI) and Human-Robot Interaction (HRI) literature to establish a framework for designing effective and engaging multimodal interfaces. This framework informs a set of practical interaction guidelines, tailored to each scenario, that developers can utilise to implement their projects, ensuring that the resulting prototypes are not only technologically sound but also user-friendly, accessible, and aligned with the humanistic spirit of the project.

This investigation is driven by several key considerations, shaping both the scope and the methodology of our analysis.

Focus on Multimodal Interfaces: This deliverable prioritises multimodal interfaces for human-machine interaction, exploring how speech, gesture, touch, visual displays, and other modalities can be potentially reused and integrated to create rich, natural, and intuitive interactions. We advocate for a holistic approach, assuming a rich and vast sensory input landscape. For example, we consider how visual data from cameras, tactile feedback from sensors, auditory input, and even olfactory or gustatory information, where applicable, can be combined to enhance the user experience. In this regard, we leverage the Human-Robot Interaction (HRI) literature as a valuable framework, given its established methodologies for addressing interactions between humans and complex computational systems in a variety of contexts, including scenarios with a strong emphasis on a social, collaborative, or educational component. This framework helps us generalise the potential needs of computational systems where a human-machine interaction component is anticipated or envisioned. This is mostly motivated by our team's expertise in this area.

Humanising Technological Prototypes through Interaction Design: A key objective is to enhance the acceptance and impact of the technological prototypes by a wider audience. By applying human-centered design principles, a project can make the interaction more natural, intuitive, and engaging. Crucially, the efficacy of a system often hinges on the design of the interaction workflow. A well-designed interaction can significantly influence user acceptance, perceived usability, and overall satisfaction. Therefore, we emphasise the importance of considering key HRI metrics, such as task completion time, error rate, user satisfaction, perceived workload, and learnability, to ensure that the interaction is not only functional but also enjoyable and efficient. By anticipating and addressing potential usability issues through careful interaction design, we aim to create prototypes that are readily adopted and seamlessly integrated into users' applications.

Assisting and Mentoring Artists and End Users: While the analysis provided in this deliverable is scenario-centric, aiming to generalise across various potential projects and implementations that share the same vision and direction, our team is also actively involved in providing ongoing guidance and support to artists and end-users. This involves sharing state-of-the-art tools, methods, and best practices in HMI design, drawing upon expertise developed in previous projects. This mentoring process is iterative and collaborative, ensuring that the prototypes evolve in a way that aligns with both the artistic vision and the principles of effective human-machine interaction. At the time of submission, we are still actively supporting artists and other stakeholders of the consortium.

Research questions

The primary research question (**RQ1**) providing the basis for this investigation is to explore which technology can support the development of the scenarios, and how this can be shaped to address the foreseen expectations and challenges. Whenever a scenario explicitly envisions elements of human-machine interaction, principles and methodologies in HCI and HRI can be utilised to humanise the technological prototypes developed in the MUSAE project. To address this main research question, we have identified four sub-questions:

- **RQ1-1: Technological Components of a MUSAE scenario**: This sub-question aims to identify the technological components that make up a MUSAE scenario. A clear understanding of these components is essential for determining the feasibility of implementing effective interactions.
- **RQ1-2: Explicit HM Interaction Component**: This sub-question investigates whether a particular scenario explicitly envisions a human-machine (HM) interaction. This influences the extent to which HCI/HRI research can be applied.
- **RQ1-3: Humanising the Interaction Component**: This sub-question explores how to humanise the interaction component of a scenario to enhance its acceptance by a broader audience. This involves identifying and implementing design principles and strategies that make the interaction more natural, intuitive, and engaging.
- **RQ1-4: Risks Associated with the Use of Technologies**: If applicable, this sub-question examines the main risks associated with the use of specific technologies in a scenario. It is important to consider ethical, societal, and environmental implications to ensure responsible and sustainable development.

By answering these sub-questions, we aim to enable a comprehensive analysis of how HRI research can contribute to the humanisation of technological prototypes in MUSAE. Our findings aim to inform the design and development of future prototypes, ensuring that they are more user-centered, engaging, and ethically aligned.

Methodology and approach

To gain a comprehensive understanding of the technological requirements for the 12 scenarios developed in MUSAE, we conducted a review, taking inspiration for the process from Semeraro et al. (2023), of their projects described in Deliverables 2-1 to 2-10. Our primary goal was to identify the technological components envisioned by the artists following the application of the Design Future Art-driven (DFA) method. This review allowed us to abstract the underlying technological needs and provide tangible support for the implementation of prototypes driven by our research questions.

We paid close attention to instances where the artists explicitly mentioned technological elements, either by identifying them as trends or within the defined domains and scenarios. These components were further elaborated to ensure a clear understanding of their intended functionality. However, we also encountered cases where the technological components were not explicitly stated. In such instances, we carefully examined the project proposals, considering aspects such as the desired user experience, interaction modalities, and the overall artistic vision. Through diligent analysis, we inferred the technological needs that were implied but not explicitly expressed. It is important to note that our focus was on identifying technological components at a high to medium level of detail. Rather than specifying specific models or solutions, which is beyond the scope of the deliverables, we aimed to capture the broader categories of technology required to realise the artistic concepts. For example, we might identify the need for an image generation system or wearable technologies, without delving into specific product recommendations.

Once we had collected and summarised the main technological needs from all projects, we proceeded to the second step. Recognising that several projects envisioned or implied an interaction component, we turned to the human-computer and human-robot interaction literature for guidance. Drawing on established principles and best practices from these fields, we provided guidelines to support the design and development of effective and engaging interactive experiences within the MUSAE art projects.

By combining a thorough review of the project proposals with insights from human-computer and human-robot interaction research, we aimed to provide a solid foundation for the implementation of MUSAE's prototypes. Our goal was to empower the artists with the technological knowledge and design principles necessary to bring their artistic visions to life in a meaningful and impactful way. This analysis was completed in July 2024, and is based on the information that was released prior to that date, which is available at Technical Reporting D2
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Structure of the Deliverable

This deliverable begins with an introduction outlining the MUSAE project's goals, the role of scenarios, and the importance of human-centered design, followed by the research questions and the methodology used for analysing the 12 scenarios. A detailed technological review of each scenario is then presented, outlining their main elements and identifying both explicitly stated and inferred technological components. This is followed by a consolidated outline of the identified technologies across all scenarios, categorised for clarity. The core of the deliverable focuses on Human-Robot Interaction (HRI) design guidelines, providing actionable recommendations for developers. These guidelines cover crucial aspects such as robot appearance and embodiment, behaviour and movement, multimodal communication, human-robot collaboration, and ethical considerations. A dedicated section expands on guidelines for multimodal HRI, emphasising the appropriate choice of modalities, seamless integration, redundancy, feedback, and cognitive load. Finally, the deliverable concludes with a section on HRI evaluation metrics, outlining key performance indicators relevant to the MUSAE context, including task performance, safety, interaction quality, and context-specific metrics such as educational impact and community engagement.

1) Technological review of MUSAE scenarios

As described before, a scenario can be defined as an archetypical description of the vision and the desiderata behind its tangential implementations . It relies on an imaginative and iterative process – stimulating creative expression and divergent thinking. Each scenario is made of several associated: **trends**, which can be seen as related work addressing similar desiderata; **elements**, the main components, or building blocks of the scenario; and **personas**, as fictional characters trying to generalise different categories of users involved. In this deliverable, the level of detail of each scenario varies depending on the technical positioning of its original proposition. For example, a scenario that has already anticipated a number of technological aspects related to either trends, elements, or persona, will include more information in order to properly contextualise the interaction guidelines.

S1: The Microbial Renaissance: a Culinary Tech Revolution

Outline. The Microbial Renaissance era uses cutting-edge technology to transform culinary practices and promote sustainable food innovation. Microbes can be used as 'cell factories' to produce animal-based ingredients and reduce the depletion of natural resources. Precision fermentation enables the creation of specific proteins, carbohydrates, fats, vitamins, or aromas. These ingredients can be shaped, flavored, and textured using digital production techniques. Imagining novel food products that are edible and distinct from existing products is a challenge.

By leveraging artificial intelligence and food engineering technologies, this scenario aims to transcend the constraints of our imagination and bring about a paradigm shift in the products we consume. However, mere dietary modifications are insufficient to catalyse this culinary transformation. Instead, a cultural revolution is needed - one that permeates the entire community and ignites a shared passion for an alternative approach to food production, preparation, consumption, and social interactions centered around food.

What are the main technological components that can be inferred from this project?

- **Content generation (inferred).** Generative AI methods can be used to create visuals and immersive graphics that can anticipate how these facilities (e.g. the High Fermentation Labs), food creations, recipes and new ingredients may look like. In this case, Generative AI is used as a tool for explorative computational creativity to project users in the scenario defined by the artists. This can involve generating images, videos, or even interactive 3D models of novel food products, allowing users to visualise and interact with them before they physically exist. Furthermore, generative AI can be used to create virtual environments simulating the experience of visiting and working in the High Fermentation Labs, enhancing the sense of immersion and engagement.
- **Conversational agents for education and training (inferred).** In the education and training section of the high-tech fermentation facilities, both consumers and professionals are welcomed to ask questions and gain knowledge about microbial-based foods. In an interactive and visual way, visitors can gain insight into what microorganisms are, how they can be used to produce ingredients, and get inspiration on how to grow microbes themselves at home and cook with these new ingredients. Conversational AI methods specialised on domain knowledge can be used to implement personalised learning pathways in order to educate users and eventually persuade those who are sceptical about the food transition. These agents can be designed to adapt to different learning styles and levels of expertise, offering customised explanations, demonstrations, and even interactive quizzes. They could also guide users through virtual tours of the fermentation facilities, providing real-time information and answering questions as they arise. Further expanding the concept, conversational agents can act as virtual mentors, providing personalised feedback on users' microbial cultivation and cooking experiments. They can offer suggestions for improvement, troubleshoot issues, and even provide emotional support to encourage persistence and exploration, using principles of motivational interviewing and other behaviour change techniques.
- **Immersive environments (inferred).** Augmented reality technologies can replace the holographic interactive displays envisioned by the artist to show “the latest microbial strains” that are expected to decorate the streets in the foreseen scenario. AR overlays can provide real-time information about the showcased strains, their properties, and their potential applications in food production. Furthermore, AR can be used to create

interactive games and simulations that educate the public about microbial-based food in an engaging and memorable way. For example, users could participate in a virtual scavenger hunt, using their mobile devices to locate and learn about different microbial strains hidden throughout their city. AR can also be used to enhance the dining experience, providing interactive visualisations of the nutritional content, origin, and sustainability impact of the food on their plate.

Other devices, and technologies envisioned by this project are purely speculative in nature. These include devices to analyse their latest microbial-based food creations for nutritional values, safety, texture, taste and aroma before moving on to tasting; as well as the “Microbial Synthesiser” and the “Microbe Spectrum Scanner”.

Does this project envision a HM interaction?

Although not explicitly stated, this project implicitly envisions a strong HM interaction component, particularly in the areas of education, training, and persuasion. The scenario highlights the need for a cultural shift towards embracing microbial-based foods, and technology is seen as a key enabler in achieving this transition. The personas identified in the scenario further emphasise the importance of addressing different levels of acceptance and skepticism towards microbial food, suggesting the need for tailored interactions.

As highlighted in the initial text, communication and persuasion are central to the proposal. Conversational AI, particularly through **empathetic conversational agents** and social robots, has the potential to play a significant role in achieving personalisation and persuasion in this context. These agents could infer users' emotional states, desires, and intentions, creating a more personalised and effective interaction. For example, a conversational agent could detect a user's hesitation or concern about microbial food through their language and adapt its responses accordingly, providing reassurance, addressing specific concerns, and highlighting the benefits that are most relevant to that individual. Furthermore, the use of social robots can enhance the interaction by providing a **physical presence** and **leveraging non-verbal cues**, such as gestures and facial expressions, to build rapport and trust. A social robot could, for instance, offer a friendly smile and a welcoming gesture when greeting a visitor to a fermentation facility, creating a more positive and engaging experience. Robots could guide visitors through the labs.

The text correctly identifies that societal and cultural biases, as exemplified by Persona 3 (Johan), who is completely skeptical, and Persona 2 (Omar), who is not yet fully convinced, can pose a significant challenge. Conversational agents and social robots can address this challenge by providing a **non-judgmental space** for individuals to express their views and concerns. The ability of these agents to empathise and respond appropriately can create a safe and supportive environment for open dialogue, potentially leading to a shift in attitudes.

If so, how can this technology be made more human?

To make the technology more human-centered, the following guidelines can be considered:

- **Personalisation:** Conversational agents and social robots should be designed to adapt to individual users' needs, preferences, and levels of understanding. This can be achieved through:
  - **User profiling:** Gathering information about users' prior knowledge, attitudes, and motivations regarding microbial food.
  - **Adaptive dialogue:** Tailoring the conversation style, language complexity, and information provided based on the user profile.
  - **Emotional intelligence:** Detecting and responding to users' emotional states, providing empathy and support. For instance, if a user expresses frustration or confusion, the agent can adjust its approach, offering encouragement or simplifying the information.
- **Transparency and Explainability:** The decision-making processes of AI systems, particularly in the context of content generation and personalised recommendations, should be transparent and explainable to users. This can foster trust and understanding. For example, if a Gen AI system creates a novel food product, it should be able to explain the reasoning behind its design, highlighting the microbial strains used and their properties.
- **User Control and Agency:** Users should have control over their interactions with the technology and be able to customise their experience. This can include options to adjust the level of detail provided, choose different learning pathways, or opt-out of certain features. For instance, a user should be able to ask a conversational agent to provide more in-depth information about a particular topic or to skip a section they are already familiar with.
- **Multimodal Interaction:** Combining different interaction modalities, such as voice, touch, and gesture, can create a more natural and intuitive user experience. For example, a user could interact with a social robot using voice commands, touch its screen to access information, and use gestures to navigate through menus or control virtual objects in an AR environment. In addition, users could use their smartphones to interact with robots (Wu et al 2020).
- **Context Awareness:** Conversational agents and robots should be aware of the context of the interaction, including the physical environment, the ongoing conversation, and the user's past interactions. This can enable them to provide more relevant and timely information and assistance. For example, a robot guiding a visitor through a fermentation facility should be able to adapt its explanations based on the visitor's location and the specific exhibits they are viewing. Similarly, a conversational agent should remember previous interactions with a user, avoiding repetition and building upon their existing knowledge.

What are the main risks associated with the use of these technologies?

While the envisioned technologies offer exciting possibilities, it is crucial to consider the potential risks.

- **Bias and Fairness:** AI systems, including generative AI and conversational agents, can inherit and perpetuate biases present in the data they are trained on. This could lead to unfair or discriminatory outcomes, such as promoting certain types of microbial food over others based on cultural biases or reinforcing existing stereotypes. To mitigate this risk, it is essential to use diverse and representative training data, carefully evaluate AI models for bias, and implement mechanisms for detecting and correcting biased outputs.

- **Misinformation and Manipulation:** Generative AI could be used to create realistic but false or misleading information about microbial food, potentially harming public perception and trust. Conversational agents could also be used to manipulate users' opinions or behaviors through persuasive techniques. To address this, it is crucial to develop methods for detecting and countering AI-generated misinformation, promote media literacy among users, and design conversational agents that adhere to ethical guidelines for persuasion.
- **Privacy and Security:** The use of personal data to personalise interactions raises concerns about privacy and data security. It is essential to implement robust data protection measures, obtain informed consent from users, and be transparent about how data is collected, used, and stored.
- **Overreliance and Deskilling:** Overdependence on technology for information and guidance could lead to a decline in critical thinking and traditional skills related to food production and preparation. It is recommended to strike a balance between leveraging technology and preserving valuable human skills and knowledge.
- **Accessibility and Equity:** Unequal access to technology could exacerbate existing social and economic inequalities, creating a divide between those who can benefit from the Microbial Renaissance and those who cannot, in the context of the envisioned scenario. Design efforts should be made to ensure that the technology is accessible to all, regardless of socioeconomic status, location, or ability.
- **Ethical Considerations of Persuasive Technology**: The use of conversational agents and social robots to persuade individuals to adopt microbial-based foods raises ethical questions about autonomy and informed consent. It is important to ensure that persuasive techniques are used responsibly and transparently, avoiding manipulation and respecting individuals' right to make their own choices. Guidelines for ethical persuasion in human-computer interaction should be followed, such as providing users with clear and accurate information, avoiding deceptive tactics, and allowing users to easily opt-out of persuasive interactions.

S2: Soil Skinships: soil fertility and our reproductive futures

Outline. The narrative of human creation deeply intertwined with soil, shaping our cultural landscapes and reflecting our bond with this fundamental life-giving element. However, intensive agriculture practices have endangered our soil, leading to the loss of fertile topsoil and a looming crisis. This demands a reimagining of our relationship with soil.

The Symbiocene era, set in 2034, introduces the concept of "skinship" between human skin and Earth's skin, emphasising the symbiotic connection between the two. This future embraces technological innovations like augmentation devices that provide real-time data on soil health and mirror this information through sensations felt by the wearer. This intimate connection fosters a profound understanding of the interplay between soil fertility and human reproductive health.

Technological trends

Augmented embodiment and immersive experiences were identified as the main technological trends extending and enhancing human physicality and sensory experiences, by immersing individuals in their environments. In the "Soil Skinships" scenario, this trend materialises through advanced augmentation devices integrated with human skin. These devices not only enable a profound, tactile connection with the Earth's soil but also provide real-time feedback on its health and fertility. This symbiotic interaction fosters a unique understanding and appreciation of the earth, blurring the lines between the human body and the natural world. By physically feeling the state of the soil and aligning it with their own health and reproductive capacities, individuals experience an unprecedented level of immersion in their ecosystem, embodying a future where human well-being is inextricably linked to the health of our planet. This trend encapsulates a transformative approach to environmental stewardship and sustainable living, rooted in a deep, sensory connection with the Earth. Overall, this project aligns with the identified technological trend.

What are the main technological components that can be inferred from this project?

The project identifies the main technological component in the envisioned Augmentation devices (*Scenario Element 5*). These are described as sophisticated sensors and implants seamlessly integrated with human skin. Through these devices, people become connected with the land beneath their feet. When in contact with the soil, it collects real-time data about its nutrients, health and fertility. This data is translated into physical sensations that the wearer can feel. These can be comfortable sensations when in balance, but can also feel uncomfortable, like simulated menstrual cramps. The devices also collect data and provide personalised insights into personal reproductive health. Balancing the different outputs takes active engagement, learning and understanding.

Overall, the augmentation devices can be associated with the following technologies.

- **Sensors and IoT** allow to trace the status of the soil, in order to collect data regarding. A variety of sensors exist to collect valuable data from soil, aiding in precision agriculture, environmental monitoring, and research. **Soil moisture sensors** are perhaps the most common, measuring the volumetric water content or soil tension to optimise irrigation and water management. These sensors can utilise capacitance, resistance, or electromagnetic technologies. **Temperature sensors** help track soil heat fluctuations, important for seed germination and plant growth. **Electrical conductivity sensors** determine the salinity levels, influencing crop selection and fertiliser application, while additional sensors can measure soil **pH**, **nutrient content** (e.g., nitrogen, phosphorus, potassium), and even the presence of specific gases like carbon dioxide. This wealth of data, often collected continuously and wirelessly transmitted, typically allows for informed decision-making in the context of resource conservation and improved crop yields. In the context of this project, these sensors would provide the data that can be processed in further steps.
- **Modality transformations (inferred)** offer a powerful means to diversify and enhance how we interact with soil data. By converting it into different modalities such as colours, images, and sound, we unlock new possibilities for data exploration, understanding, and communication. Example of modality transformations include:
    - **Visualising soil data as colours** allows us to perceive patterns and variations that might not be readily apparent in numerical or textual formats. For instance, different colours can represent different levels of soil moisture, nutrient content, or pH, creating a visual map of soil health. This approach can be particularly useful for quickly identifying areas of concern or for communicating complex data to non-expert users (e.g. Sacha et al., 2017).
    - **Converting soil data into sound** introduces an auditory dimension to data exploration. By mapping soil properties to musical notes or sound frequencies, users can "listen" to the soil. This auditory representation can be particularly effective in conveying temporal changes or trends in soil data. For instance, a time series of soil moisture measurements can be transformed into a soundscape where the pitch or volume of the sound reflects the moisture levels over time. For example, a similar sonification strategy in this domain was attempted from colleagues of UWE Bristol[1].
- **Wearable devices and haptic technologies** are natural candidates to implement the augmentation devices. On one hand, this would facilitate the collection of physiological data from the users, which is necessary to achieve the expected level of symbiosis between soil and human; and, on the other hand, to actuate the (modality transformed) soil data through haptic feedback, so that the user can perceive its conditions in real time. Haptic feedback can be delivered through various means, such as vibration,

[1] https://www.uwe.ac.uk/news/sound-of-the-underground

pressure, or texture changes, providing a rich and nuanced sensory experience (e.g. Culbertson et al., 2018). For example, a wearable device could vibrate gently to indicate healthy soil conditions or deliver a more intense sensation to signal a problem, such as low nutrient levels or excessive dryness.

Does this project envision a HM interaction?

Users' engagement is envisioned to control the interactions between the soil and the personal inputs. The interaction is thus expected to balance/gate these two input streams. However, the interaction appears to be unidirectional, meaning that the conditions of the soil can affect the human, but the physiological data collected from the latter does not affect the soil. By interacting with the device, users can thus balance the personal and the soil signals. This suggests a human-in-the-loop system, where the user actively interprets and responds to the feedback provided by the augmentation device.

If so, how can this technology be made more human?

To make this technology more human-centered and enhance the user experience, several approaches can be considered.

- **Personalised Data Fusion and Interpretation:** Integrating physiological data with soil data requires sophisticated data fusion techniques. Machine learning algorithms, particularly deep learning models, can be employed to analyse patterns and correlations between the user's physiological state (e.g., heart rate, skin temperature, hormonal levels) and soil conditions (e.g., moisture, nutrient levels, pH). These models can learn individual user profiles and adapt the feedback accordingly. For example, a user who is particularly sensitive to environmental changes might receive more subtle haptic feedback, while a user who prefers more direct feedback might receive stronger sensations. This is inline with research on personalised affective computing (e.g. Chanel et al., 2011).
- **Adaptive and Context-Aware Feedback:** The system should be able to adapt the feedback based on the user's current context and activity. For instance, if the user is engaged in strenuous physical activity, the system might reduce the intensity of haptic feedback to avoid distraction or discomfort. Conversely, if the user is in a resting state, the system could provide more detailed and nuanced feedback. Context awareness can be achieved through the integration of various sensors and data sources, such as GPS, accelerometers, and environmental sensors. Research on context-aware computing provides relevant methodologies (e.g. Baldauf et al., 2007).
- **Multimodal Feedback Integration:** While haptic feedback is central to this scenario, integrating other modalities, such as visual or auditory feedback, can enhance the user experience. For example, a visual display on a wearable device could provide supplementary information about soil health, while subtle auditory cues could reinforce haptic sensations. The design of multimodal feedback should follow principles of perceptual congruence, ensuring that different modalities complement each other and avoid creating cognitive overload (e.g. Spence & Driver, 2004). For instance, a visual display could be used to show trends in soil data over time, while haptic feedback provides real-time information about the current state of the soil.

- **User Control and Customisation:** Users should have control over the intensity, frequency, and type of feedback they receive. This can be achieved through a user interface that allows them to adjust settings, set preferences, and even create custom feedback profiles. Allowing users to tailor the system to their individual needs and preferences is essential for user acceptance and satisfaction (e.g. Nielsen, 1993). Users should be able to adjust the sensitivity of the haptic feedback, choose which soil parameters they want to be informed about, and even define their own mappings between soil data and sensory feedback.
- **Explainable AI (XAI):** As AI plays a crucial role in data processing and feedback generation, it is important to incorporate principles of explainable AI (XAI). Users should be able to understand why the system is providing certain feedback and how it is interpreting their physiological data and soil data. This can be achieved through visualisations, textual explanations, or even conversational interfaces that allow users to query the system (e.g. Miller, 2019). For example, the system could explain why it is suggesting a particular course of action, such as reducing watering or adding nutrients to the soil, based on the data it has collected and the user's physiological state.

What are the main risks associated with the use of these technologies?

The envisioned technology presents several potential risks that need to be addressed:

- **Data privacy and security:** The collection and use of sensitive physiological data raise significant privacy concerns. Robust data encryption, anonymisation techniques, and strict access control measures are necessary to protect user data. Compliance with relevant data protection regulations (e.g., GDPR in Europe) is essential. Furthermore, users should be fully informed about what data is being collected, how it is being used, and with whom it might be shared.
- **Data misinterpretation and overreliance:** The accuracy and reliability of the data collected by sensors and its interpretation by AI algorithms are crucial. Errors or misinterpretations could lead to inappropriate actions, potentially harming both the user and the environment. Regular calibration of sensors, validation of algorithms, and clear communication of the limitations of the technology are essential. Users should be educated about the potential for errors and encouraged to use their own judgment in conjunction with the feedback provided by the system.
- **Health and safety:** The use of wearable devices that deliver haptic feedback raises potential health and safety concerns, particularly regarding long-term use. It is important to ensure that the intensity and frequency of haptic sensations are within safe limits and do not cause discomfort, pain, or injury. Ergonomic design and thorough testing are necessary to minimise risks. Furthermore, the potential psychological effects of continuous sensory feedback should be investigated.
- **Equity and accessibility:** Access to this technology may be unevenly distributed, potentially exacerbating existing inequalities. Efforts should be made to ensure that the technology is affordable and accessible to diverse populations, including those in developing countries and rural areas. Design for inclusivity and universal accessibility should be considered from the outset. For instance, providing alternative feedback

modalities, such as visual or auditory cues, can make the technology accessible to individuals with different sensory abilities.

- **Unintended consequences:** The widespread adoption of this technology could have unintended social, environmental, or ethical consequences. For example, it could lead to a commodification of soil health or create new forms of social stratification based on access to technology. Careful consideration of potential impacts and engagement with stakeholders from diverse backgrounds are crucial to anticipate and mitigate negative consequences. For example, if the technology becomes widely used by farmers, it could lead to changes in land use practices or agricultural policies that have broader environmental implications.

S3: Food Beyond Food: what is food without its origin?

Outline. Food is a powerful political force that defines borders, shapes identities, and forges alliances. Traditionally, the origin of a product was considered a major determinant of its quality, with distinguished products from diverse regions gaining prestige. However, climate change has reshaped the planet, making it necessary to embrace innovative methods to ensure the continued production of desired products sustainably.

This project fast-forwards to 2044, where the widespread acceptance of scientific advancements and the urgent need to impose new ways of producing food have led to the introduction of lab-grown meat, genetically modified fermented ingredients, and hydroponically grown vegetables in regular supermarkets. A movement called 'Anti-Extinction Ac' aims to redistribute global food production, leveraging scientific advancements to standardise food quality and characteristics worldwide.

Technological trend

Related to food safety, the artists identified the following technological trends. **Blockchains** are described as emerging as robust solutions to ensure the traceability and authenticity of food products. Additionally, **smart packaging technologies**, such as sensors, are being integrated to monitor critical parameters in real-time, ensuring product integrity from production to consumption. **Connected packaging**, utilising NFC technology, allows consumers to access comprehensive information about a product, including its origin and safety standards.

One element of this project is food testing (*Element 4*) through Food Forensics. Food Forensics, originally dedicated to uncovering food fraud related to authenticity and traceability, has shifted its role to ensure the prevention of trafficking in real animals or wild plants. This transition signifies a departure from human-centric aspects to broader concerns involving environmental conservation and ethical practices.

Based on the technological trends and elements of this project, the artist created and selected the "Forensic Food" domain. Rooted in the investigative methodologies pioneered by Forensic Architecture, this domain delves into the intricate interplay of food-related technologies and forensic analysis, applying emergent forensic technologies to unveil instances of 'less visible' food fraud. Beyond the surface, this exploration peels back layers to expose the deeper dimensions of food crime, emphasising the need to visualise violence against humanity and the environment ("*ecocide*") beyond conventional perceptions of the food chain. Guided by the principles of interdisciplinary investigation, the domain aspires to redefine our comprehension of the less visible impact of the food chain, weaving together technology, ethics, justice, and sustainability. Through this holistic exploration, the vision is to empower individuals, fostering a conscientious approach to our interconnected world and enabling informed dietary choices.

What are the main technological components that can be inferred from this project?

The project encompasses two main challenges: (i) the identification of "food frauds" through food testing; and (ii) the visualisation of a food fraud (ecocide) in raising awareness of the consequential impact of the food chain.

- **Food Fraud Identification:** The first challenge is said to be tackled by using food-related technologies and forensic analysis methods. This can be interpreted as employing data mining and machine learning techniques to analyse data from various sources, such as blockchain records, sensor data from smart packaging, and supply chain databases. These techniques can identify patterns and anomalies indicative of food fraud. For example, classification algorithms can be trained to distinguish between authentic and fraudulent products based on their chemical composition, origin, or processing history. Anomaly detection algorithms can be used to flag unusual patterns in supply chain data that might indicate illicit activities, such as the substitution of ingredients or mislabeling of products (Chandola, 2009).
- **Visualisation and Modality Transformation:** The second challenge can be associated with a broad range of data transformation and visualisation methods. These methods aim to map a source modality (e.g., a description of the ecocide, together with numerical/quantitative evidence outlining its impact on the food chain or the environment) to a target modality that can be effectively communicated to users (sound, music, image, video, an infographic, etc.). This could involve techniques like:
  - **Sonification:** Transforming data into sound to represent different aspects of the ecocide, such as the severity of environmental damage or the scale of illegal activities. For more information on sonification techniques, we refer to (Hermann et al., 2011).
  - **Information/Data Visualisation:** Creating visual representations of data, such as charts, graphs, and maps, to illustrate the impact of food fraud on the

environment and society. This can include interactive visualisations that allow users to explore the data and uncover hidden relationships.
  - **Generative AI:** Using generative models, such as GANs (Goodfellow et al., 2014), VAEs (Kingma & Welling, 2013), or Stable Diffusion (Rombach et al., 2022), to create images, videos, or even virtual environments that depict the consequences of ecocide.

Does this project envision a HM interaction?

The project does not explicitly envision a HM interaction in the traditional sense (e.g., a direct interaction with a robot or a conversational agent). However, it does anticipate the need for a visualisation or modality transformation method to provide sufficient control to the user. This implies an interaction where the user can manipulate parameters or explore the data representation to gain a deeper understanding. This method would likely involve a modality-specific interface (e.g., a graphical user interface with sliders, buttons, and interactive visualisations) that would allow the user to interact with the system in a way that is natural and intuitive.

If so, how can this technology be made more human?

Humanising the technology for visualising ecocide involves designing the interaction and representation to be more intuitive, engaging, and impactful. Here we provide a few insights from an HCI perspective.

- **User-Centered Design:** Applying user-centered design principles (e.g., Norman, 2013) is crucial. This involves understanding the target audience (e.g., general public, policymakers, activists), their needs, and their existing knowledge about food fraud and ecocide. Iterative design and user testing can help refine the interface and ensure usability at deployment.
- **Interactive Exploration:** Instead of presenting a static visualisation, the system should allow users to interactively explore the data. This could involve: (i) **filtering and selecting,** allowing users to filter data based on different criteria (e.g., type of food fraud, geographical location, time period) and select specific aspects they want to investigate further; (ii) **drilling down,** providing the ability to drill down into the data to get more detailed information about specific instances of ecocide; and (iii) **customisation,** enabling users to adapt the visualisation based on their criteria, such as choosing different colour schemes or data representations.
- **Narrative and Storytelling:** Integrating storytelling elements can make the data more relatable and engaging. This could involve presenting case studies of specific ecocide events, highlighting the impact on individuals and communities, or showing the chain of events that led to the environmental damage. Combining data visualisation with narrative techniques can create a more powerful and memorable experience (see e.g., Segel & Heer, 2010).
- **Emotional Engagement:** While maintaining objectivity, the visualisation can be designed to evoke appropriate emotional responses. For example, using colour palettes, sound design, or visual metaphors to convey the severity of the ecocide. However, it's

important to avoid sensationalism and ensure that the emotional impact is aligned with the data, for sustainable HCI deployment (DiSalvo, 2010).
- **Explainability and Transparency:** The system should be transparent about the data sources, the methods used to analyse and transform the data, and any limitations or uncertainties. This can build trust and help users understand the basis for the visualisations. Providing explanations for the system's outputs, such as why a particular instance of food fraud is flagged as high-risk, can enhance user understanding and engagement (e.g., Lipton, 2018).

What are the main risks associated with the use of these technologies?

- **Bias and misrepresentation:** Data visualisation and modality transformation can introduce biases, either intentionally or unintentionally. The choice of data to highlight, the way it is represented, and the algorithms used to transform it can all influence the user's perception. It is crucial to carefully consider potential biases and strive for objectivity and fairness in the design and implementation. Independent audits of the system and its outputs can help identify and mitigate biases.
- **Oversimplification:** Complex issues like ecocide can be difficult to represent in a way that is both accurate and easy to understand. Oversimplification can lead to misinterpretations or a lack of appreciation for the nuances of the problem. It's important to strike a balance between clarity and comprehensiveness, providing enough detail to inform without overwhelming the user.
- **Emotional manipulation:** While emotional engagement can be a powerful tool for raising awareness, it also carries the risk of manipulation. Visualisations that are overly graphic or sensationalised can be distressing or even exploitative. It is important to adhere to ethical guidelines for visual communication and avoid using emotionally charged imagery solely for shock value.
- **Desensitisation:** Repeated exposure to visualisations of ecocide could potentially lead to desensitisation, where users become less responsive to the issue over time. It's important to vary the presentation and provide opportunities for users to take action, such as supporting organisations working to combat food fraud or advocating for policy changes.

S4: Bio-Intelligent Data

Outline. The future of the food system involves diverse pathways and complex data-rich value chains, with vertically integrated industrial agriculture, lab-grown food, and smallholder farming co-existing. Data economies are emerging, with big data seamless integration into the food value chain, while data storage has shifted to decentralised blockchain networks to ensure data permanence and traceability.

Sensing technology, AI, biosensors, and neurotechnology have led to exponential growth in data access and understanding of biological intelligence and the natural world. However, challenges persist, like conflicting information and the need to navigate consumer choices. Researchers are exploring incorporating the human perspective into the food chain by converting biological characteristics into data, addressing persistent issues within the food system and decoding communicative information from the biological body.

Technological trends
This project identified two main technological trends from the application of the DFA method.

- **Data Lakes:** This trend focuses on the evolution of data management within the food supply chain. It highlights the move towards cloud neutrality, open-source data, and increased data accessibility for planning and decision-making. Data lakes are seen as crucial for organising, optimising, and innovating within food supply chains to enhance sustainability. This includes data-driven governance and using digital platforms for better food safety and supply chain oversight.
- **Affective Computing:** This trend revolves around the increasing ability of technology to identify and interpret human physiological and psychological states. This is driven by the desire for personalised health and experiences, extending to understanding interspecies relationships. It involves tools that decode and interpret emotional and mental states to enhance the "personalised" experience, particularly in the context of food sourcing, preparation, and consumption.

These trends are further elaborated through some specific domains and scenarios, which are summarised below for convenience.

Domains include *"Block-Chained Voice and Food System"* (on utilising blockchain to track the lifespan of produce, incorporating biological data at each stage, from planting to consumption);

"NeuroTechnology - Daily Diaries of the ID" (envisioning the use of neurotechnology to decode inner dialogue related to food, storing and interpreting brain signals to increase agency over food choices); and "*A Psychotropic Intelligence"* (on combining psychotropics and neurotechnology for personal and environmental health optimisation. These are exemplified in the following scenarios:

- **Democratised data in diverse decentralised food systems:** Open-source and private data collaborations, along with AI and real-time sensing, enhance transparency and sustainability in decentralised food systems.
- **Democratised data in vertically integrated centralised food systems:** Open-source and private data support the rise of lab-grown and molecular food, raising questions about the marginalisation of traditional agriculture.
- **Private data and data monopolies in decentralised food systems:** Private tech companies control data, leading to a fragmented food system and potentially exacerbating disparities in food access.
- **Private data and data monopolies in vertically integrated centralised food systems:** Private control of data in centralised, lab-grown food production raises concerns about prioritising profit over sustainability and equitable access.

What are the main technological components that can be inferred from this project?

Several related technologies were already identified by the artist to address the various challenges of the project. These are summarised and expanded below.

- **IoT Devices and Sensors** are central for monitoring various stages of food production, storage, and transportation. Specifically, sensors can measure environmental parameters (temperature, humidity, light), soil conditions (moisture, nutrient levels), plant health (growth rate, disease detection), and even the ripeness of produce. IoT devices can also be used in smart packaging to monitor freshness and quality during transit. As per the survey by Atzori et al. (2010), the integration of IoT in agriculture can lead to more efficient resource management and crop yields.
- **AI and Machine Learning** can enable the analysis of large datasets related to dietary habits, health outcomes, and food production. Machine learning algorithms can identify patterns and correlations, enabling personalised dietary recommendations, predictive modelling of crop yields, and optimisation of resource allocation. This aligns with the findings of Kamilaris and Prenafeta-Boldú (2018), who highlight the potential of machine learning in precision agriculture. There are several examples of AI techniques that can be used in this context. For instance, deep learning models can be trained on sensor data and satellite imagery to predict crop yields and optimise irrigation schedules (e.g., Van Klompenburg et al., 2020). Another example is the use of natural language processing (NLP) to extract relevant information from scientific literature and dietary guidelines, facilitating the development of personalised nutrition plans.
- **Data Governance Frameworks and Privacy Regulations** are also central to the overall vision proposition. With the increasing use of personal data in the food system, robust data governance frameworks and privacy regulations are essential. These frameworks should define data ownership, access rights, and usage guidelines,

ensuring that individuals' health data is protected. The General Data Protection Regulation (GDPR) in the European Union provides a strong foundation for data privacy in this context (Voigt & Von dem Bussche, 2017).

- **Blockchain Technology** can enhance transparency and traceability in the food supply chain. By creating an immutable ledger of transactions, it becomes possible to track the origin and journey of food products, ensuring authenticity and preventing fraud. This can be particularly useful for verifying the organic or fair-trade status of products. Related to the vision, Kshetri (2018) discusses the potential of blockchain in strengthening cybersecurity and protecting privacy. For example, a blockchain-based system could enable consumers to scan a QR code on a product and access detailed information about its origin, processing, and transportation, building trust and confidence in the food system.
- **Smart Kitchen Appliances** can provide real-time nutritional analysis and recommendations, integrating with other data sources (e.g., dietary preferences, health goals) to empower individuals to make healthier food choices. For example, a smart refrigerator could track the food items stored inside and suggest recipes based on available ingredients and nutritional needs.
- **Wearables and Health-Tracking Devices** can collect data on individuals' physiological responses to food, such as blood glucose levels, heart rate variability, and sleep patterns. This data can be used to assess the effectiveness of dietary interventions and tailor them to individual needs, leading to more personalised and effective nutrition plans.
- **Affective Computing:** as highlighted in the technological trends, affective computing plays a role in understanding the emotional and psychological aspects of food consumption. Technologies such as facial expression recognition, voice analysis, and physiological sensors can be employed to gauge user responses to food experiences. This information can be used to fine-tune food products, dining environments, and even personalised food recommendations based on emotional states. The review by Picard (1997) provides a comprehensive overview of the principles and applications of affective computing.
- **Neurotechnology:** building on affective computing, neurotechnology offers a more direct way to understand the neural correlates of food preferences, cravings, and satisfaction. Techniques such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) can be used to study brain activity during food-related tasks. While the application of neurotechnology in everyday food contexts is still in its early stages, research by companies such as NeuroFocus has demonstrated its potential in understanding consumer behaviour.

Does this project envision a HM interaction?

The project, in its current form, primarily focuses on the interconnection, regulation, and exploitation of vast and heterogeneous amounts of data. The domains and scenarios described do not explicitly anticipate a human-machine interaction component. Most of the envisioned technologies operate in the background, collecting, processing, and sharing data without direct user input. Therefore, it is challenging to provide guidelines for humanising a component that is not yet foreseen. However, considering the potential evolution of the project and the increasing integration of technology into everyday life, it is reasonable to anticipate that future iterations may involve more direct interactions between users and the envisioned technologies. For example, users might interact with smart kitchen appliances, personalised nutrition dashboards, or even conversational virtual assistants capable of providing dietary recommendations.

If so, how can this technology be made more human?

No explicit HM interaction was envisioned. If future iterations of the project incorporate direct user interaction, principles of human-centred design could be applied to enhance usability and user acceptance. For instance, Norman's (2013) principles of interaction design, such as affordances, signifiers, and feedback, could guide the development of intuitive interfaces for smart kitchen appliances or personalised nutrition platforms.

What are the main risks associated with the use of these technologies?

The project responsibly addresses data governance and ethical considerations, acknowledging the importance of responsible data acquisition and manipulation. However, several potential risks are associated with the use of the envisioned technologies.

The collection and use of sensitive health data raise significant privacy concerns. Robust security measures, including encryption and access controls, are essential to prevent data breaches and unauthorised access. Also, algorithms trained on biased data can perpetuate or amplify existing **societal biases**, potentially leading to discriminatory outcomes in dietary recommendations or access to resources. Careful data curation and algorithmic auditing are necessary to mitigate this risk. Meanwhile, unequal **access** to technology and data could exacerbate existing health disparities. Efforts should be made to ensure that the benefits of these technologies are accessible to all members of society, regardless of socioeconomic status or technological literacy.

The **overreliance on technology** and the potential **psychological impact** are also worth noting. Excessive reliance on technology for dietary guidance could diminish individuals' ability to make informed food choices independently. It is crucial to strike a balance between technological assistance and the development of personal nutritional knowledge and skills. Instead, the constant monitoring and quantification of food intake and physiological data could lead to increased anxiety or obsessive behaviours around food. A mindful approach to data presentation and user feedback is needed to avoid negative psychological consequences.Overall, as neurotechnology and affective computing become more sophisticated, ethical guidelines are also needed to ensure that these technologies are used responsibly and do not infringe on individuals' agency or autonomy.

S5: One Health Recipes

Outline. The project is set in 2033, and envisions a landscape where governance is undergoing a profound transformation. The crisis of confidence in the ability of human authorities to address the environmental crisis is being compounded by technological advancements in artificial intelligence (AI). In response to this paradigm shift, new alliances are emerging between humans and nonhumans, driven by the technological empowerment of both parties. One such union is the EcoMind Alliance, a collaboration between scientists, farmers, indigenous people, activists, and technologists, led by the Artificial Intelligence known as GAIA. Leveraging the capabilities of AI and satellite and sensor networks, the EcoMind Alliance monitors the planet on an unprecedented scale. It collects and interprets environmental data in partnership with local communities, using AI support systems like GAIA-AI. Based on these insights, the EcoMind Alliance devises policies, manages regenerative farms, and implements the rights of nature in jurisdiction, acknowledging the Earth as a community of subjects. Its guiding principle, "One Health," recognizes the interdependence of all earthly beings and aims to foster a harmonious coexistence between human economy and the earth's ecology.

Through the EcoMind Alliance, society is exploring a radical reimagining of governance models. It is a bold experiment in shared governance between humans and nonhumans, seeking to create a sustainable and equitable future for all inhabitants of the Earth.

Technological trends

The artist already identified the following trends as technology enablers.

Earth observation is the gathering of information about the physical, chemical, and biological systems of the planet Earth. It can be performed via **remote-sensing technologies** (satellites) or through direct-contact sensors. The Group on Earth Observations (GEO), which has over 100 member countries and over 100 participating organisations coordinates international efforts to build a Global Earth Observation System of Systems (GEOSS).

Already today, AI is used as decision support in cancer treatments. "By **crossing data** and deploying data analytics, it could be used to **identify patterns** in bureaucratic flux and improve decision-making processes", once the technology advances. In the 70s, the Chilean government implemented a technology-driven decision support system to synchronise and increase the efficiency of their farming produce.

What are the main technological components that can be inferred from this project?

This project envisions a complex interplay of technologies to achieve its goals. The core technological components can be broken down and expanded upon as follows.

- **Earth Observation and Remote Sensing:** This involves the use of satellites and other remote sensing technologies to gather data about the Earth's physical, chemical, and biological systems. As outlined in the project description, the Group on Earth Observations (GEO) is already coordinating international efforts in this area. The Global Earth Observation System of Systems (GEOSS) aims to provide a unified platform for accessing and sharing Earth observation data (GEO, n.d.). In the context of this project, remote sensing can be used to monitor deforestation, land degradation, water quality, and other environmental factors that impact food production. Computer vision techniques will be critical for processing satellite imagery and extracting meaningful information, such as crop health, soil moisture levels, and the presence of pests or diseases.
- **In-Situ Sensors and the Internet of Things (IoT):** Alongside remote sensing, the project envisions the deployment of ground-based sensors to collect data at a more granular level. These sensors, connected through an IoT infrastructure, can measure soil conditions (pH, nutrient levels, moisture), microclimate (temperature, humidity, wind speed), and plant health (growth rate, stress indicators). This data complements the broader view provided by remote sensing, offering a more detailed understanding of local ecosystems. The use of IoT in agriculture is already gaining traction, with numerous studies demonstrating its potential for improving resource management and crop yields (e.g., Elijah et al., 2018).
- **Data Integration, Big Data, and Data Fusion:** A cornerstone of the project is the ability to integrate and analyse vast amounts of data from diverse sources. This requires robust data management systems, capable of handling the volume, velocity, and variety of big data generated by sensors, satellites, and other sources. Data fusion techniques will be needed to combine data from different modalities and resolutions, creating a unified and coherent picture of the environment. This process might involve dealing with conflicting or incomplete data, requiring sophisticated data reconciliation and validation methods (e.g. Castanedo, 2013). For example, data from a soil moisture sensor might be combined with satellite-derived precipitation data and weather forecasts to predict irrigation needs.
- **Data Analysis:** This is where the GAIA-AI system comes into play. Machine learning algorithms can be used to process the integrated data, identify patterns, and contribute novel insights. This includes developing predictive models for crop yields, disease outbreaks, and the impact of climate change on agriculture. As mentioned, AI is already being used in healthcare for decision support, and this project envisions a similar application in the context of food production and environmental management. Machine learning can be used to optimise farming practices, such as fertilisation, irrigation, and pest control, based on real-time data and predictive models (e.g., Benos et al., 2021).
- **Robotics (Service Robots for Nature):** This is a more speculative aspect of the project, but it raises questions about the role of robotics in environmental stewardship. The idea of "Robot Guardians of Nature" suggests a shift from anthropocentric to ecocentric robotics. These robots might be tasked with monitoring ecosystems, collecting data, removing pollutants, or even intervening to protect endangered species. To our best, this area is relatively unexplored in HRI.
- **Wearables and Human-Environment Connection:** The "Sensing the Planet / Eating the Extinct" domain explores the potential of wearables to create a more direct

connection between humans and the environment. This could involve sensors that measure physiological responses to environmental changes or devices that provide haptic feedback based on ecosystem health. While still largely conceptual, this area aligns with research on embodied cognition and the role of sensory experience in shaping our understanding of the world (e.g., see Wilson, 2002). It can include sensor technologies to create a connection between the human body and the planet. For instance, wearables could be used to measure physiological responses to changes in the environment, or provide haptic feedback related to ecosystem health.

Does this project envision a HM interaction?

Similar to "Bio-Intelligent Data", this project, in its current form, does not explicitly envision a direct human-machine interaction component. The focus is on creating an intelligent system (GAIA-AI) that operates autonomously, making decisions based on data analysis. However, there are potential areas where HMI could become relevant:

- **Data Visualisation and Interpretation:** While GAIA-AI might make decisions autonomously, humans (farmers, policymakers, scientists) will likely need to understand the data and the rationale behind those decisions. This could involve interactive dashboards and visualisations that allow users to explore the data, query the system, and understand its reasoning. This is confirmed by element 3 described in the proposal, where GAIA AI is said to generate plans, advice, and experiments by integrating data with knowledge from local farmers, communities, and researchers.
- **Robotics:** If "Robot Guardians of Nature" are deployed, there might be situations where humans need to interact with them, either to provide instructions, override their actions, or collaborate on specific tasks. This would require the development of appropriate communication protocols and interaction modalities.
- **Wearables:** The wearable component inherently involves human interaction, as the devices are designed to be worn and to provide feedback to the user. The nature of this interaction will depend on the specific design and purpose of the wearables.

In addition, the robotics scenario presents unique challenges (outlined below) while not envisaging a particular human-machine interaction. In fact, technology is expected to serve and guard nature instead of humans. As the former is non-human, it is difficult to anticipate how technology should be humanised. Finally, the wearable application shares substantial similarities and overlaps with *P2: Soil Skinships: soil fertility and our reproductive futures* – given the specific goal of connecting humans and soil through wearable technology.

If so, how can this technology be made more human?

While direct HMI is not a primary focus, the principles of human-centred design can still be applied to enhance the overall system:

- **Transparency and Explainability:** Even if GAIA-AI operates autonomously, it is crucial that its decision-making process is transparent and explainable to humans. This is particularly important when the system's actions have significant environmental or societal impact. Techniques from explainable AI (XAI) can be used to provide insights into the system's reasoning (e.g., see Adadi & Berrada, 2018).

- **User Control and Agency:** While the system is designed to be autonomous, humans should retain a sense of control and agency. This could involve the ability to set high-level goals, adjust system parameters, or even override the system's decisions in certain situations.
- **Ethical Considerations:** The design of the system should be guided by ethical principles, ensuring that it aligns with human values and societal norms. This includes considerations of fairness, accountability, and responsibility.

What are the main risks associated with the use of these technologies?

A primary concern is the potential for **overreliance** on GAIA-AI, potentially leading to a gradual **de-skilling of human farmers** and an **erosion of valuable traditional ecological knowledge**. This dependence could be further complicated by the introduction of "Robot Guardians of Nature," whose actions, while intended to serve the environment, might directly conflict with human interests, leading to social friction and resistance. Justifying these robotic actions to the public, particularly when they result in negative consequences for certain individuals or groups, poses a significant communication and ethical challenge.
Furthermore, the autonomous nature of these robots could raise concerns regarding **error and unintended consequences**, necessitating robust mechanisms for human oversight and intervention. The vast amount of data collected and processed by the EcoMind Alliance brings with it inherent risks to **data security and privacy**, demanding adequate safeguards to protect sensitive environmental and personal information. Similarly to other projects and scenarios, the deployment of such advanced technology raises concerns about **equitable access and distribution of benefits**, potentially exacerbating existing inequalities and concentrating power in the hands of a few, while disproportionately burdening marginalised communities with negative consequences.

S6: Holobiont Futures

Outline.Holobiont Gardens envisions a future where urban environments merge with human health and microbiomes. Set in 2035, it explores a thriving microbiome wellness industry amidst a growing global microbial justice movement. Public access to beneficial microorganisms is recognized as a human health right, with accessible microbiome testing and community-based science shaping care plans. Post-industrial urban sites transform into "Holobiont Gardens," guided by Traditional Ecological Knowledge (TEK) and probiotic architecture, serving as hubs for nurturing macro and microbiodiversity, growing medicinal foods, and mapping holobiont health.

Through the elements contributed to this scenario, the authors envision a world where microbiome tracking and microbial justice are central to system design, acknowledging that all entities are holobionts. TEK and technology merge to create equitable resource distribution and comprehensive care systems. Economic systems mimic mycelial networks, fostering collaboration and resource-sharing, mimicking nature's efficiency. Public spaces, ceremonies, and social practices around food as medicine are nurtured, emphasising embodied and emotional experiences as vital for planetary survival and thriving.

Technological trends

The authors identified technologies designed to **map or quantify** the user's microbiome in some form, such as home-testing kits, metabolism monitoring apps or services, and body monitoring products. These products and services aim to provide users with a more intimate, albeit quantified, **knowledge** of their bodies. Notably, there has been a rise in services that enable this monitoring to be conducted domestically.

What are the main technological components that can be inferred from this project?

This project envisions a convergence of several technologies, some explicitly mentioned and others inferred, to create a future centered around microbiome health and environmental justice. The main components are outlined as follows.

- **Microbiome Tracking Technologies** are a central component here, encompassing a range of tools for analysing and understanding the human microbiome. These include: **home-testing kits allowing** individuals to collect samples (e.g., stool, saliva) at home and send them for analysis, providing information about the composition and diversity of their microbiome; **metabolism monitoring apps and services:** as digital tools helping users track dietary intake, physical activity, and other lifestyle factors that influence the microbiome (also with the potential of providing personalised recommendations based on the user's data and goals); and **body monitoring products (wearables),** such as smartwatches, fitness trackers, and other wearable devices that can collect physiological data (e.g., heart rate, sleep patterns, body temperature) that can be correlated with microbiome data to provide a more holistic view of health.
- **Hologenomics Data Portals** provide platforms that serve as centralised repositories for storing, managing, analyzing, and sharing hologenomic data. This includes data from the host genome, the microbiome, and environmental factors. These portals facilitate collaboration among researchers, clinicians, and potentially even citizen scientists. Interoperability and data standardisation efforts are expected to be central for the success of these portals (e.g., see Korpela et al., 2020).
- **Machine learning algorithms** are already used to analyse the complex and high-dimensional data generated from microbiome and hologenomic studies. These can identify patterns, correlations, and potential biomarkers that would be difficult to detect through traditional statistical methods. For example, these algorithms can be used to predict disease risk based on microbiome composition or to develop personalised

dietary interventions (e.g., see Zeevi et al., 2015).

- **Blockchain Technology** here could provide a secure and immutable ledger system for managing hologenomic data. This can help ensure data integrity, prevent tampering, and track data provenance. It can also facilitate secure data sharing among researchers and institutions while protecting individual privacy (e.g., see Angraal et al., 2017).
- **Robotics:** the project suggests a role for robotics in automating tasks related to microbiome research and potentially in interacting with humans to promote microbiome health. This could take the form of **laboratory automation** or **social robots**. In the former, robots can automate repetitive tasks in the lab, such as sample processing, DNA extraction, and sequencing, increasing efficiency and reducing the risk of human error. Instead, social robots could be used to educate the public about the microbiome, promote healthy lifestyle choices, and even guide individuals through microbiome-related practices, such as preparing fermented foods or participating in microbiome-friendly activities. This can take advantage of existing research in social robotics, where robots have been successfully used as educational tools and to promote well-being (e.g., see Luperto et al, 2023, Pu et al., 2019).
- **Traditional Ecological Knowledge (TEK) Integration:** while not a technology in itself, the project emphasises the importance of integrating TEK with technological advancements. This could involve developing databases or platforms that document and share TEK related to food, medicine, and environmental stewardship. It could also involve designing technologies that are informed by TEK principles, such as biomimicry or sustainable resource management practices.

Does this project envision a HM interaction?

While the scenario does not explicitly focus on human-machine interaction, several of the envisioned technologies imply a degree of interaction.

- **Microbiome Tracking Technologies:** Users interact with home-testing kits, metabolism monitoring apps, and wearables to collect and input data about their bodies and lifestyles. They also receive feedback and recommendations from these technologies, creating a feedback loop.
- **Hologenomics Data Portals:** Researchers and clinicians interact with these portals to access, analyse, and share data. The design of the user interface and the data visualization tools significantly impact the usability and effectiveness of the platforms.
- **Social Robots:** If social robots are used to educate and engage the public, this would involve direct and potentially complex social interactions between humans and robots. The design of the robots' appearance, behavior, and communication style would be crucial for creating engaging and effective interactions. More guidelines related to this dimension are given below, as well as in Sections 2 and 3.
- **TEK Integration Platforms:** If platforms are developed to share TEK, users will interact with them to learn, contribute, and potentially collaborate with TEK holders.

If so, how can this technology be made more human?

Given the implied interactions, we identified the following solutions to make these technologies more human-centered:

- **User-Friendly Interfaces:** Home-testing kits, apps, wearables, and data portals should be designed with intuitive and easy-to-use interfaces. This includes clear instructions, simple navigation, and accessible language. This is a foundational aspect of HCI.
- **Personalised Feedback:** The feedback provided by microbiome tracking technologies and AI algorithms should be tailored to the individual user's needs, goals, and level of understanding. Personalisation is a key aspect to improve the effectiveness of the interaction and the adoption of a technology.
- **Data Visualisation:** Complex microbiome and hologenomic data should be presented in a clear, concise, and visually appealing manner. Effective data visualization can help users understand their data and make informed decisions (e.g., see Borkin et al., 2013).
- **Social Robot Design:** If social robots are used, their design should be guided by principles of social robotics, ensuring that they are perceived as trustworthy, engaging, and socially appropriate. Their **non-verbal cues** (e.g. gaze, proxemics), and v**erbal communication** need to be carefully designed to foster positive interactions (e.g. see Leite et al., 2013). The robots' physical appearance should be fitting for the agricultural context and designed to be non-intimidating and approachable, potentially resembling friendly animals, plants, or even abstract representations of natural elements. Effective communication is paramount, requiring robust natural language processing (NLP) capabilities to understand and respond to **human speech**, alongside the ability to express **emotions** through a range of **modalities**, including facial expressions, body language, and dynamic changes in color or light patterns. Beyond basic communication, robots should demonstrate social intelligence, accurately interpreting social cues, adapting their behavior based on the context, and building rapport with users through recognizing and responding to human emotions. To further enhance the human-robot bond, robots could be designed to express **empathy** and cultivate emotional connections, personalising their interactions based on user profiles, past interactions, and individual preferences. Crucially, **transparency** and **explainability** are vital, with robots clearly articulating their capabilities, limitations, and the reasoning behind their actions in a manner easily understood by human users (Tapus, 2007).
- **Cultural Sensitivity:** The design of TEK integration platforms should be culturally sensitive and respectful of Indigenous knowledge systems. This might involve co-designing these platforms with TEK holders and ensuring that they have control over how their knowledge is shared and used.
- **Transparency and Explainability:** machine learning algorithms used to analyse microbiome data should be transparent and explainable, allowing users to understand how recommendations are generated and **build trust** in the technology.
- **Embodied Interaction:** Considering the project's emphasis on embodied experiences, technologies could be designed to encourage physical engagement with the microbiome, such as through gardening, food preparation, or other activities that promote a healthy microbiome.

What are the main risks associated with the use of these technologies?

The collection, storage, and use of sensitive microbiome and genomic data raise significant **privacy concerns**. Robust security measures, including encryption, access controls, and anonymisation techniques, are essential to protect this data from unauthorised access and misuse. Clear guidelines are needed regarding data ownership and control, ensuring that individuals have agency over their own data and can decide how it is used and shared. Furthermore, the ethical use of AI in this context requires careful consideration to prevent **bias and discrimination**. AI algorithms trained on biased data could perpetuate or amplify existing societal inequalities, for example, by providing different recommendations or opportunities based on an individual's microbiome profile. Regular auditing of algorithms and a commitment to fairness and transparency are crucial to mitigate this risk.

The increasing reliance on technology for understanding and managing our health could lead to an **overemphasis on quantification** and a reductionist view of well-being. While data can be valuable, it represents only a partial picture of human health. Qualitative factors, such as emotional well-being, social connections, and a sense of purpose, are equally important but harder to measure. An excessive focus on data could also diminish individuals' ability to make informed decisions about their own health, leading to a dependence on technology and a deskilling of personal health literacy. Moreover, access to microbiome technologies and their benefits might not be evenly distributed, potentially exacerbating existing health disparities. Efforts should be made to ensure equitable access for all, regardless of socioeconomic status, geographic location, or technological literacy.

The project's focus on environmental microbial justice is commendable, but it is crucial to ensure that the pursuit of this goal does not inadvertently harm the environment or specific communities. The introduction of new technologies and practices should be carefully evaluated for their potential ecological impact, and steps should be taken to minimise any negative consequences. The growing microbiome wellness industry also raises concerns about the potential for commercialisation and commodification of the microbiome. This could lead to the exploitation of individuals and the environment, with companies prioritising profit over public health and ecological sustainability. The use of social robots, while promising, also carries risks. Technological **overreliance** on robots for social interaction could potentially lead to social isolation or a decline in human social skills. It is important to ensure that robots are used to enhance, rather than replace, human interaction.

S7: What the World Eats

Outline. This project aims to envision a transformative future paradigm at the intersection of technology, agriculture, and the environment. Rooted in gratitude for the Earth's provisions and committed to planetary health, the project delves into ancestral dimensions of technology and agrologistics, advocating for intergenerational lifespans, uses, and agencies. It explores questions such as whether technology can become compostable for the Earth and serve as an intergenerational nurturing force for non-humans. The project investigates elements like mycelium-based agriculture, animal architectures, environmental sensing apparatuses, and companion plantings, intertwining technology with the symbiotic workings of the Earth. It challenges conventional perspectives by emphasising gratitude for the world's gifts and recognising the need to care for more-than-human lives and the planet's well-being.

A summary of the main elements of the scenario, which is necessary to identify and infer its technological components, is given below. These are elaborated from their proposal.

- **Biocomputing and sensing** investigates the technology's potential to **create life forms modelled after plants, fungi, and bacteria**. These organisms could possess intelligence, sensory capabilities, and the ability to transmit electronic information. This unconventional computing paradigm challenges traditional rock-based hardware and raises questions about senseability and how their sensory abilities could influence our understanding of non-human entities in food cultures.
- **Organic materials**, such as fungi's mycelium networks, offer versatile potential across various sectors. Mycelium networks function as biodegradable binders that digest organic components like agricultural waste, creating **solid structures** applicable in **architecture, textiles, interior design, soft robotics**, and more. These fungal structures are said to have the unique ability to grow, build, and repair themselves and could become computable sensors.
- **Biodiversity and Traditional Ecological Knowledges (TEK)** shares parallels with P6: Holobiont Futures and is inspired by the role indigenous communities play as environmental custodians, preserving 80% of the remaining biodiversity on Earth. TEK goes beyond modern technology by utilising **soft, symbiotic living systems** to harness environmental energy. It is rooted in spiritual and social fabric, transmitting ecocultural wisdom across generations. It encompasses concepts like kinship with nature, reciprocity, and gratitude toward ecosystems and their inhabitants.
- **Variability and invasive friendships:** as the planet changes and global warming alters landscapes, ecosystems and societies face heightened pressures. Food can help societies adapt to variability and create affirmative cultures. By embracing "invasive" species through culinary adaptation, this can promote biodiversity, resilience, and cross-cultural experimentation.
- **Cultural thinking** suggests that everything is interconnected. Birds, cows, and soil have artistic and environmental potential. All objects, technologies, places, beings, and environments are alive, expressive, and **connected through time**. Meals align with nature, singing resonates in the landscape, and pigeon towers mimic the wind.
- **Non-Human architectures** can implement agricultural landscapes resembling multispecies cities, with small towns for swallows and pigeons, villages of beehives, and cities of caves for compost-making crustaceans. The fields accommodate a diversity of species, some providing space for one another, like beans using corn as a climbing rod in the Mexican milpa. Self-repairing structures built with senseable mycelium architectures offer shade for grazing animals.

What are the main technological components that can be inferred from this project?

This scenario envisions a future where technology and nature are deeply intertwined, with a focus on sustainability,biodiversity, and a renewed respect for ancestral knowledge. Several key technological components can be inferred from the project description:

- **Biorobotics and soft robotics:** This is arguably the most central technological component, directly linked to the "Bio Computing and Sensing" element. The scenario imagines creating "life forms modelled after plants, fungi, and bacteria" with "intelligence, sensory capabilities, and the ability to transmit electronic information." **Soft robotics** could leverage materials like mycelium (as mentioned in "Organic Materials") to create robots that can mimic the growth, movement, and adaptability of natural organisms. This aligns with the growing field of soft robotics, which draws inspiration from biological systems to create more flexible and adaptable robots (Rus & Tolley, 2015). Another potential direction is **biorobotics**, which relies on Integrating biological components with robotic systems. This could involve using living cells or tissues to create actuators, sensors, or even processing units. For example, research is exploring the use of engineered microorganisms to create living sensors for environmental monitoring or to power micro-robots (Shivalkar et al., 2023). Finally, to design and test these biorobotic systems, advanced computational models will be needed. These models will need to simulate the complex behaviour of biological materials and their interactions with the environment (Lipson, 2014).
- **Mixed Reality (MR) for interaction and education:** While not explicitly stated, MR technology is strongly implied as a means to experience and understand the concepts presented in the scenario. For example, MR could **visualise and Interact with Bio-Robotic Systems**, or **create immersive learning environments**. Users could indeed interact with virtual representations of the plant, fungi, and bacteria-inspired life forms. They could observe their behaviour, manipulate their environment, and even "experience" the world through their simulated senses. Alternatively, MR can recreate ecosystems that showcase biodiversity and traditional ecological knowledge (TEK). Users could virtually visit indigenous communities, learn about their sustainable practices, and understand the interconnectedness of nature in a highly engaging way. For example, educational MR applications in cultural heritage are becoming more common, showcasing great usability (Bekele et al., 2018)
- **Biofabrication and material science:** The "Organic Materials" element highlights the use of mycelium networks for various applications. This implies the use of biofabrication techniques, which involve growing materials from living cells, such as mycelium, into desired shapes and structures. This is recognised as an active area of research with potential applications in sustainable architecture, product design, and even food production (Karana et al., 2018). Understanding the properties of mycelium-based materials, such as their strength, flexibility, and biodegradability, also require advanced material characterisation techniques.
- **Sensor networks and environmental monitoring:** The concepts of "Environmental Sensing Apparatuses" and understanding the sensory abilities of bio-robotic organisms suggest the need for **advanced sensor technologies,** including, for example, bio-sensors that mimic the sensory capabilities of natural organisms, as well as

traditional sensors for monitoring environmental parameters like temperature,humidity, and soil composition; but also **data analysis and interpretation** technologies**,** using computational models to analyse and interpret this data to understand ecosystem health and the impact of human activities.

Does this project envision a HM interaction?

This scenario does *not* explicitly envision a highly structured or task-oriented human-machine interaction in the traditional sense. However, **implicit** forms of human-machine interaction are present and crucial to the scenario's vision.

- **Experiential Interaction through Mixed Reality:** MR provides a powerful medium for users to interact with the concepts of the scenario. This interaction is less about direct control and more about observation, exploration, and gaining a deeper understanding of the interconnectedness of technology and nature.
- **Interaction with biorobotic systems:** While the scenario does not detail specific interactions, we can expect that humans would interact with the bio-robotic life forms. This could involve: *monitoring and guiding growth***,** to guide the development of mycelium structures or influencing the behaviour of bio-robotic organisms through environmental cues; or *collaborative activities***,** where humans and bio-robotic systems work together in agricultural or environmental restoration tasks.

If so, how can this technology be made more human?

The key to humanising the interaction in this scenario lies in fostering a sense of connection, respect, and understanding between humans and the envisioned technologies. This can be achieved by considering the following directions.

- **Embodied Interaction in MR:**
  - **Natural Interaction modalities:** MR interfaces should leverage natural human interaction modalities like gesture, gaze, and voice control to make the experience intuitive and immersive (Billinghurst et al., 2015).
  - **Embodied cognition:** Design interactions that consider how our bodies and physical experiences shape our understanding of the world. For example, users could physically move through a virtual ecosystem or use their hands to interact with virtual plants and organisms.
- **Bio-Inspired design principles:**
  - **Biomimicry:** Design the behaviour and appearance of bio-robotic systems to be inspired by natural organisms. This can make them appear less alien and more relatable to humans (Lepora et al., 2013).
  - **Transparency and explainability:** While the inner workings of complex bio-robotic systems might be difficult to fully understand, providing users with some level of transparency about their behaviour and decision-making processes can build trust.
- **Focus on education and reflection:**

- **Narrative and storytelling:** Use MR experiences to tell compelling stories about the interconnectedness of nature and technology, highlighting the importance of sustainability and traditional ecological knowledge.
- **Promoting reflection:** Design interactions that encourage users to reflect on their own relationship with nature and technology and consider the ethical implications of the scenario's vision.

What are the main risks associated with the use of these technologies?

The implementation of the envisioned technologies carry several inherent risks, primarily stemming from the introduction of novel bio-robotic and bio-fabricated entities into natural environments. A key concern is the potential for **unintended ecological consequences**, as introducing artificial life forms, even those designed to be beneficial, could disrupt existing ecosystems, impact biodiversity, and create unforeseen imbalances. **Controlling and containing these bio-robotic systems** poses another substantial challenge, as ensuring they remain within designated areas and do not proliferate uncontrollably may prove difficult. The very act of creating artificial life raises ethical concerns about **"playing God"** and the potential for unforeseen ramifications, particularly regarding the **commodification of natural processes** through biofabrication and related technologies. Furthermore, an **over-reliance on these advanced technological solutions** could lead to a **loss of traditional ecological knowledge** and create a **dependence that makes society vulnerable** to system failures or disruptions. Finally, **unequal access** to these potentially transformative technologies could exacerbate existing social and economic inequalities.

S8: Patterns that persist

Outline. In a world where biodiversity becomes the benchmark for healthy human food systems, a journalist named Max embarks on a journey through Europe in 2033 to explore the impact of the radical legislation, "Maximising Biodiversity," approved by the European Commission in 2028. As Max interacts with various stakeholders, from traditional farmers struggling to adapt to the new requirements to regenerative farmers and food producers working to heal agricultural landscapes, he discovers that technology plays a crucial role in monitoring and optimising biodiversity. In particular, Max encounters a technician in Portugal who designs monitoring tech for food forests, such as AI-enabled audio ecology devices and an online platform that connects producers with eaters. This technology aids in tracking the health and biodiversity of food forests, thus promoting sustainable agricultural practices and empowering communities to become active participants in the biodiversity movement.

In this scenario 4 persona and 2 events, the element that envisages a technological presence is the Inês persona. Inês is a drone technician and pioneer farmer who inherited a neglected plot of land and decided to use technology to transform it. Combining traditional wisdom, modern technology, and community involvement, she aimed to boost the biodiversity of our local food system. Using **drones**, she took **multi-spectral images** to assess the landscape's health and developed an **algorithm to assist** with planting and harvesting in our food forest. Today, the land thrives with 200 species adapted to the changing climate. She has built bespoke technologies to measure ecosystem services, including **sensors** for soil, water, and carbon storage. Additionally, an **AI-enabled audio ecology monitoring system** tracks biodiversity. The data collected helps me qualify for financial incentives, allowing me to hire local workers for delicate harvesting tasks that **robots** cannot perform. Through this innovative approach, she is creating a sustainable and thriving food forest that benefits both the environment and the community.

Among the trends, the authors of the scenario acknowledge current advancements in technology bringing new instruments, tools, and epistemologies that enable more accurate measurements. These include AI models for **bird sound recognition** and **remote sensing** and **monitoring** tools. Optimization and efficiency technologies, including robots, algorithms, AI, and labs, are being utilized to enhance food production processes. These can manifest as alternative proteins, lab-grown meat, vertical farms, and automated growing or milking operations, potentially displacing the role of human farmers.

What are the main technological components that can be inferred from this project?

The main technological components of this scenario are outlined below.

- **Audio Monitoring Systems** can enable the assessment of biodiversity. The use of AI-enabled audio technologies for ecological monitoring is well-documented. For example, Stowell et al. (2019) provide a comprehensive overview of automatic acoustic detection of birds through machine learning, highlighting various feature extraction techniques and classification algorithms suitable for this task. The system could leverage deep learning models, such as Convolutional Neural Networks (CNNs), trained on extensive datasets of bird vocalisations. These models can achieve high accuracy in identifying different species even in noisy environments. Similar techniques can be applied to insect sounds, which are also important indicators of ecosystem health (Riede, 1998).
- **Online Platforms for Connecting Producers and Consumers:** These platforms facilitate direct interaction and knowledge exchange, fostering a sense of community and transparency. Effective visualisation of biodiversity data is crucial for communicating complex information to a non-expert audience. Techniques such as interactive maps, charts, and infographics can be employed to present data on species richness, population trends, and the impact of farming practices (Pousman et al., 2007). Furthermore, integrating e-commerce functionality allows consumers to directly support biodiversity-friendly farming. Blockchain technology can enhance traceability, allowing consumers to track the origin and journey of their food, ensuring transparency and

building trust (Kshetri, 2018).

- **Drones for Multi-spectral Imaging and Precision Agriculture** are revolutionising agriculture by providing detailed aerial insights. As mentioned in the scenario, multi-spectral cameras on drones can capture data beyond the visible spectrum, providing information about plant health, soil conditions, and water stress (Mulla, 2013, Hino et al, 2018). This data can be used to create detailed vegetation indices, such as the Normalised Difference Vegetation Index (NDVI), which are strong indicators of plant health. Also, the algorithms developed by Inês could guide autonomous drones or other robotic systems for precision planting and harvesting. This minimises soil disturbance, optimises resource use, and reduces the need for manual labour in certain tasks (Zhang & Kovacs, 2012). For example,this could inform and guide a swarm of agricultural robots, which are used to minimise the impact on the environment while improving the efficiency of operation (e.g. harvesting, seeding) and reducing the need for large fields (Shamshiri et al., 2018).
- **Sensors for Soil, Water, and Carbon Storage** provide real-time data on crucial environmental parameters. Soil Sensors can measure parameters like moisture, nutrient levels (NPK), pH, and temperature. This data can inform irrigation and fertilisation strategies, optimising resource use and minimising environmental impact (Padhiary et al., 2024). Water quality sensors can monitor parameters like dissolved oxygen, turbidity, and the presence of pollutants, providing insights into the health of water bodies within the food forest (Bhardwaj et al., 2022). Similarly, accurate measurement of carbon sequestration in soil and biomass is essential for quantifying the environmental benefits of food forests. Techniques like eddy covariance and soil carbon sampling can be employed (Arias-Navarro et al., 2021).

Does this project envision a HM interaction?

While the scenario doesn't explicitly detail direct user interfaces for these technologies, it implies several points of human-machine interaction:

- **Farmers (like Inês) interacting with:**
  - Drone control interfaces for flight planning and data acquisition.
  - Data analysis dashboards to interpret sensor data and multi-spectral imagery.
  - Interfaces for programming and managing the audio monitoring system.
  - The online platform to manage their profile, interact with consumers, and access market information.
- **Consumers interacting with:**
  - The online platform to learn about biodiversity, browse products, place orders, and potentially track the journey of their food.

Therefore, there is an **implicit** HM interaction component that, while not the primary focus, is essential for the successful implementation of these technologies.

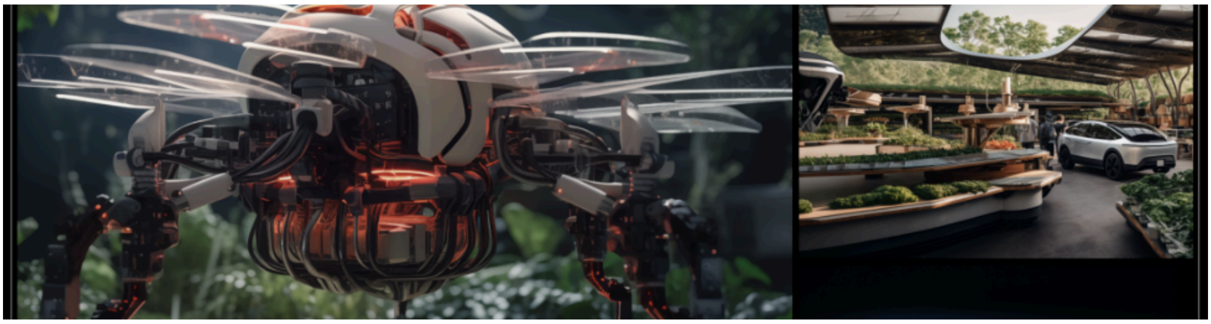
If so, how can this technology be made more human?
Although the scenario primarily focuses on environmental monitoring, we can enhance the interaction component by considering the following guidelines.

- **User-Centred Design for Farmers:**
    - **Intuitive Interfaces:** Drone control interfaces and data dashboards should be designed with simplicity and ease of use in mind, considering the potential varying levels of technical expertise among farmers (Rasmussen, 1983).
    - **Personalisation:** The systems should allow farmers to tailor the information displayed and the level of automation to their specific needs and preferences.
    - **Feedback and Control:** Provide clear feedback on system status, data interpretation, and the results of actions taken (e.g., changes in planting strategies based on sensor data).
- **Engaging and Informative Platform for Consumers:**
    - **Storytelling and Transparency:** The platform should go beyond simple e-commerce and use storytelling to connect consumers with the farmers and the ecological benefits of their practices. Visualisations, farmer profiles, and narratives about the food forest can create a compelling experience.
    - **Education and Gamification:** Incorporate educational content about biodiversity and sustainable agriculture. Gamification elements, such as badges, rewards, or challenges, can further engage consumers and encourage them to make informed choices (Deterding et al., 2011).

What are the main risks associated with the use of these technologies?

The extensive use of technology in this scenario presents risks related to data privacy, algorithmic bias, and technological dependence. Firstly, the vast collection of sensitive environmental and agricultural data, including farm locations and operational details, raises significant **privacy concerns**. Unauthorised access or misuse of this data could allow malicious actors to track farmers, compromise operations, or commit sabotage. Secondly, reliance on AI algorithms for critical tasks like species identification and ecosystem assessment introduces the risk of **algorithmic bias**. Biased or incomplete training data could lead to inaccurate assessments and flawed decision-support tools, potentially harming biodiversity and impacting farmers unfairly. Finally, increasing dependence on technology creates a vulnerability to **technological failures**. System malfunctions, outages, or obsolescence could severely disrupt farm operations, leading to economic losses and jeopardizing food security. This dependence highlights the need for backup systems, contingency plans, and ongoing training.

S9: From Farm to Table in a Hyperconnected World



Outline. The authors envision a near-future scenario where a pioneering agroforestry initiative emerges on the outskirts of rapidly expanding urban areas. Led by B-Corp, a forward-thinking organisation, this initiative challenges the prevailing ethos of relentless growth and financial gains. Inspired by Kate Raworth's "Doughnut Economics," B-Corp's philosophy integrates ecology and economy, managing resources meticulously and prioritising societal and planetary boundaries. New global and local policies support this transformative approach, including Extended Producer Responsibility (EPR), non-edible plastic taxes, and a nascent United Nations Global Treaty. These policies address issues like artificially priced plastic and carbon credits, emphasising stakeholder liability and shared responsibility for environmental preservation.

Amidst these changes, communities respond with a "**Manifesto for Un-Stuffing**" aiming to reclaim lives from consumerism and challenging digital giants like Amazon and Alibaba. B-Corp intensifies cybersecurity measures to counter automated systems and AI designed for crop and ecosystem management, as these technologies disrupt the delicate balance of the ecosystem. The "Manifesto for Un-Stuffing" and disruptive AI forces underscore the complexities of navigating a future where ecological balance, responsible business practices, and societal values intersect.

In the scenario, **BioHarvest Haven** emerges as a groundbreaking blend of technology and sustainable agriculture. These urban hubs seamlessly merge with cityscapes, dismantling barriers between urban and natural spaces. At the core is an intricate agroforestry network, utilizing pixel farming and remote sensing. Interspersed trees double as crop supports and wildlife habitats, accessible to bio-mechanical harvesting robots and AI-controlled CyberCrows. AI orchestrates these havens, fostering harmony among humans, animals, plants, and soil micro-organisms. Intelligent checkpoints manage visitor access, ensuring minimal human interference. AI-controlled robots monitor crops, combat pests, and execute precise harvesting, exemplifying regenerative responsibility and ecological equilibrium.

Among these technological advancements, **CyberCrows** stand out as a remarkable AI-controlled agroforestry swarm system. They seamlessly merge with nature, sampling in-vivo cells and injecting natural agro-microbials to promote crop-microbe synergy for increased growth. As a collective intelligence, CyberCrows ensure interspecies communication, environmental control, and pest prevention with non-toxic methods like sound waves and lasers. Additionally, they offer immersive art experiences, aligning with AI ethics and providing a unique, interconnected journey through their perspective.

The overarching scenario envisions an innovative hybrid encompassing traditional agriculture, agroforestry, and lab-grown food products. This sustainable symbiosis is powered by a diverse array of cutting-edge technologies, including AI, IoT, robotics, and remote sensing. The integration of these technologies is **humanised** through communal experiences enriched by **immersive art and gamification**, ensuring data transparency, compliance with AI ethical standards, and fostering a sense of community.
As the scenario transitions from macro to mezzo and micro levels, novel features emerge, such as edible electronics and soft robotics, pushing the boundaries of culinary experiences. A distinctive highlight is the introduction of **personalised augmented sensory dining**

experiences intricately woven with **personal data**. This approach not only allows for the incorporation of the individual into the culinary process but also addresses the complexities of data ownership in a hyperconnected, post-globalised world characterised by both centralised and decentralized influences, impacting every facet of our in-real-life (IRL) and online (URL) existence.

In this narrative, the coexistence of natural and digital ecologies is paramount, presenting a holistic vision where technology and nature seamlessly intertwine to shape the future of our food experiences, promoting sustainability, well-being, and inclusivity.

Technological trends

Among the technological trends identified by this scenario we find: **ChatGPT**, and more broadly Generative AI, which is anticipated to be a groundbreaking solution for robotics as well; **Robotics manipulation**, in particular looking at methods for hybrid hierarchical learning that are capable to solving complex sequential tasks such as ROMAN (Triantafyllidis et al, 2023), and robot scarecrows implemented by the Akita Prefectural University; **Interspecies communication through AI**, which is said to potentially create a new ecology of sustainable competitions (e.g. attract natural predators ad hoc to solve a pest); **IoT and data-driven agriculture**, where robots can leverage remote sensing and use fairness trained optimisation algorithms enabling a new era of renewed co-existence; **Big data** and hidden patterns, which are detected by computational methods and help farmers and non-human agents to make better predictions/decision in a decentralised networkers ecosystem with a holistic perspective; **Gamification**, to incentivise community building.

Among the elements for this review is the "Technological Advancements", envisioning technologically advanced and interconnected agroforestry hubs. Cutting-edge innovations support sustainable agriculture. Drones equipped with artificial intelligence analyse soil health, providing valuable insights. Nanobots enhance plant growth by delivering precise doses of tailored nutrients. The fusion of biotechnology and AI has given rise to "EcoTech-AIs." These sentient AI systems are designed to coexist harmoniously with nature, working symbiotically to optimize agricultural practices and ensure ecosystem longevity.

What are the main technological components that can be inferred from this project?

Overall, this scenario is very rich in terms of technological components and related challenges. It also shares vision and challenges with other projects.

- **Gamification** techniques can be employed to incentivise community building and engagement in sustainable agriculture practices. By integrating gamified elements such as rewards, challenges, and progress tracking, individuals can be encouraged to participate in activities that contribute to the well-being of the agroforestry ecosystem. This could include tasks such as monitoring crop health, identifying pests, and sharing knowledge and experiences with others. Gamification can help foster a sense of community and collective responsibility for the success of BioHarvest Haven, while also making the learning process more engaging.

- **Robotics** is a core technological component in this scenario. Bio-mechanical harvesting robots navigate the agroforestry network with agility and precision, harvesting crops with minimal damage to the environment. These robots are equipped with advanced sensors and algorithms, allowing them to differentiate between ripe and unripe crops, ensuring selective harvesting to prevent wastage. AI-controlled CyberCrows, on the other hand, seamlessly blend with nature, acting as guardians of the agroforestry ecosystem.
- **Internet of Things** (IoT) weaves a seamless web of connectivity across BioHarvest Haven, linking various devices and sensors throughout the agroforestry network. This complements the robots' sensing capabilities discussed before. Soil moisture sensors, temperature gauges, and nutrient monitors gather real-time data, providing AI systems with a constant stream of information. This data is then analysed and utilised to make informed decisions about irrigation, fertilization, and pest control, ensuring optimal growing conditions for crops. Additionally, IoT devices enable remote monitoring and control of agricultural processes. Farmers can access real-time data and manage their crops from anywhere, using their smartphones or tablets. This level of connectivity allows for quick responses to changing conditions, minimizing losses and maximising yields.
- **Artificial Intelligence** methods could implement the machine intelligence backbone of BioHarvest Haven, harmoniously orchestrating the interactions between humans, animals, plants, and soil micro-organisms based on the gamification strategy set. The use of AI also extends to the robots' sensing capabilities, monitoring crop growth, detecting and combat pests in real-time, and executing precision harvesting. This ensures regenerative responsibility and maintains ecological equilibrium.
- **Remote Sensing** sensing technologies, such as drones equipped with advanced cameras and sensors, can also play a crucial role in monitoring crop health and soil conditions. These drones fly over the agroforestry network, collecting valuable data that is then analysed by AI systems. This information helps farmers identify areas of stress or disease in their crops, enabling targeted interventions to prevent the spread of pests and diseases.
- **Blockchain** technology provides a secure and transparent foundation for BioHarvest Haven. All agricultural data, including crop yields, soil conditions, and pest management strategies, are recorded on the blockchain, ensuring data transparency and compliance with AI ethical standards. This fosters a sense of community and trust among all stakeholders, from farmers to consumers.

Does this project envision a HM interaction?

In this envisioned future of farming, humans and robot manipulators form a symbiotic partnership, fundamentally challenging agricultural practices. Through extensive use of sensory devices and advanced machine learning algorithms to process such multimodal information, robot manipulators will act as tireless assistants, monitoring crop growth, detecting and eliminating pests, and executing harvesting with unmatched precision. This collaboration will enable farmers to optimise crop yields while minimising resource usage and reducing environmental impact. To design this system, we can envision human-robot interaction as a collaborative partnership where humans provide high-level guidance, setting goals and making decisions, while robots handle repetitive, complex, and potentially hazardous tasks. This division of labor will allow farmers to focus on strategic decision-making, innovation, and value-added activities.

To enhance the interaction between humans and robot manipulators, elements of NLP and affective computing can be incorporated. This will allow robots to understand and respond to human emotions, making the interaction more intuitive and engaging. Additionally, robots can be designed with user-friendly interfaces and intuitive control mechanisms, allowing farmers with varying levels of technical expertise to interact with them easily.

If so, how can this technology be made more human?

To foster a deeper sense of connection and trust between humans and robot manipulators, the integration of social robotics should also be considered. As detailed in Section 2, robots can be designed with human-like features and behaviors, such as facial expressions and body language, to make them more relatable and approachable. This has the potential to enhance the sense of collaboration and mutual understanding, making the human-robot partnership more harmonious and productive.

What are the main risks associated with the use of these technologies?

The main risks associated with the use of technologies include the potential disruption of the delicate balance of the ecosystem. While autonomous agents are designed to work in harmony with nature, their advanced capabilities could inadvertently harm the environment if not properly managed. Additionally, the integration of AI and IoT devices raises concerns about **data privacy and security**. The collection and analysis of vast amounts of agricultural data could create opportunities for unauthorised access and misuse, potentially compromising sensitive information and disrupting the operations of BioHarvest Haven. It is crucial for the project's developers to address these risks by implementing robust security measures, ensuring transparent data governance, and engaging in ethical decision-making processes to mitigate potential negative consequences.

S10: The Cooking Ape Institute

Outline. In a society heavily reliant on digital technology, the importance of sensory activities for human well-being is often overlooked. Despite the human brain being wired for a pre-digital era, the senses work in unison to enable the perception of the world. In the culinary realm, multi-sensory experiences are particularly prominent, with various senses contributing to a shared experience. To address this, there is a growing interest in "food as medicine" and personalised nutrition. However, looking beyond nutrition itself, considering the broader context of food preparation reveals even greater potential. The preparation of food is linked to the development of fine motor skills, technologies, and material handling. While food preparation was once arduous and driven by automation, contemporary Western society presents an opportunity for food preparation to take on new significance for mental well-being. Technologies such as brain wave analysis, AI-driven recipe development, and microbiome sequencing can help achieve this vision. Opportunities exist for companies to offer personalised nutrition solutions, AI-driven recipe development, and innovations in technology-enhanced kitchen appliances. By aligning with the scenario's emphasis on health-optimized meals and stress reduction, companies can foster innovation and drive advancements in holistic, technology-enhanced food preparation.

What are the main technological components that can be inferred from this project?

This scenario highlights the intersection of technology and culinary experiences, focusing on well-being. Key technological components include the pointers below.

- **Brain Wave Analysis (EEG):** As described, EEG is used to measure and interpret brain activity, providing insights into cognitive states, emotions, and arousal levels. This technology could be integrated into wearable devices or kitchen appliances to monitor users' mental states during food preparation and consumption. Relevant HRI literature includes Chanel et al. (2009) on using EEG for emotion recognition and Mühl et al. (2014) on brain-computer interfaces in real-world settings.
- **AI-Driven Recipe Development:** AI algorithms analyse user data (dietary needs, preferences, brain states) to generate personalised recipes. This could involve natural language processing for understanding user input and machine learning for recipe generation. Elsweiler et al. (2017) explore personalised recipe recommendations, while Goel & Bagler (2022) delve into data-driven applications in gastronomy. The user

interaction component is also very relevant, and for instance, the work by Shneiderman on direct manipulation interfaces (Shneiderman, 1983) can help to design this type of technology.

- **Microbiome Sequencing:** DNA sequencing analyses the gut microbiome to provide insights into individual health and inform personalised nutrition recommendations. This technology could be integrated with AI-driven recipe development to tailor meals for optimal gut health.
- **Smart Kitchen Appliances:** The scenario implicitly suggests the development of smart appliances that integrate with brain wave analysis and AI-driven recipe systems. These appliances could adjust cooking parameters (e.g., temperature, time) based on user's mental state and recipe requirements. For example, an oven could automatically adjust its temperature based on a user's stress levels, detected through brain wave analysis, to promote relaxation during cooking. This area relates to the broader field of the Internet of Things (IoT) and ambient intelligence (Aarts & De Ruyter, 2009). Norman's work on the design of everyday things also informs the development of kitchen appliances to support the users (Norman, 1988).

Does this project envision a HM interaction?

The project strongly envisions human-machine interaction, particularly between users and AI-driven systems, smart kitchen appliances, and data-driven feedback mechanisms. The goal is to create a seamless and intuitive experience where technology supports and enhances the human experience of food preparation and consumption for well-being.

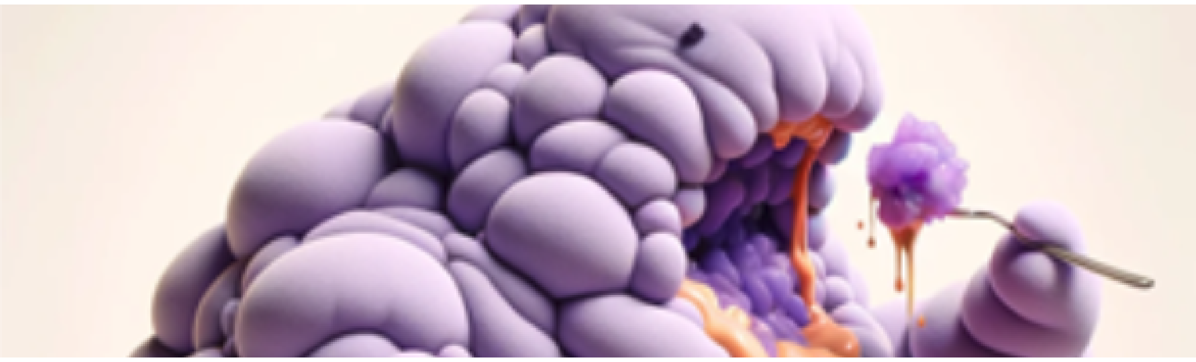
If so, how can this technology be made more human?

- **Personalisation:** Tailoring recipes, cooking guidance, and environmental adjustments (e.g., lighting, music) to individual users' needs, preferences, and real-time emotional states can increase the adoption of these technologies. Personalisation and service robots can further this vision (de Berardinis et al., 2020).
- **Explainable AI (XAI)** methods can provide transparent explanations for their recipe recommendations and cooking adjustments. Users should understand why a particular ingredient or technique is suggested, fostering trust and engagement (Miller, 2019).
- **Affective computing** principles can be integrated to enable technology to recognise and respond to user emotions while cooking. For instance, a system could detect frustration and offer simplified instructions or calming music (Picard, 1997, Coutinho et al., 2021).
- **Multimodal interaction**, such as voice control, gesture recognition, and visual feedback, can create a more natural and engaging experience (Oviatt, 2003). For example, users could verbally request recipe modifications, use hand gestures to control appliances, and receive visual feedback on their states through lighting.
- **Gamification:** as seen in the previous scenario, incorporating game-like elements (e.g., challenges, rewards) can motivate users to engage in healthy cooking practices and explore new recipes (Deterding et al., 2011).

What are the main risks associated with the use of these technologies?

The collection and analysis of highly sensitive data, such as brain waves and microbiome information, raise **data privacy and security** concerns, necessitating robust security measures and transparent data handling practices. Secondly, **algorithmic bias** within AI systems trained on non-representative datasets could perpetuate or exacerbate existing health disparities, requiring careful attention to data diversity and algorithm fairness during development. There is also a risk of fostering **over-reliance on technology**, potentially diminishing users' own culinary skills and intuition as they become overly dependent on automated guidance. Finally, the advanced nature of these technologies raises concerns about **accessibility and equity**, as they might not be affordable or available to everyone, potentially creating a divide between those who can benefit from them and those who cannot.

S11: Poetry of Nutrition



Outline. What are our true priorities? Is nutrition the most extensive field of destructive consumerism or a noble means of survival? Poetry of Nutrition is a realistic dystopian industrial saga with an optimistic and brave revolutionary twist. Let’s imagine the future we really want to have in spite of everything.

By 2030, a global health crisis, both mental and physical, triggers widespread societal unrest and government overhauls. A new Nutritional Health System emerges, blending technology and psychotherapy. Soft robots, designed with empathetic, visually engaging behaviors, become central to this system, bridging generational divides and teaching people to control food production and the market. These robots, far more effective than previous health warnings, motivate genuine lifestyle changes. Art, humanities, medicine, and science converge in this new paradigm.

Industry adapts, offering health-focused products like food therapy apps and pesticide monitoring drones. Outside the formal system, communities strengthen ties with local farmers, shifting from global brands to trusted, local food sources. A chain of practical empathy develops, rediscovering the meaning of community and collective health.

Key technological trends underpinning this future include the development of edible robots, the use of robots as clinicians, AI-generated soft robots for rapid creation and durability, automation of kitchens with a focus on improving the standard of life and using robots as utilities, companions and pets rather than replacing workers in the food industry, the creation of self-healing and liquid robots, and biomimicry (imitating nature for sustainable design).

Elements of the Scenario

- The Food Taster soft robot: A central figure, this soft robot is a kitchen utility, pet, and companion experiencing an existential crisis yet deeply caring for humans. It embodies the advancements in soft robotics that enable therapeutic interactions.
- Technological advancement of robotics: Sophisticated soft and rigid robotics facilitate beneficial interactions and revolutionize food production.

What are the main technological components that can be inferred from this project?

This scenario envisions a future where technology plays a crucial role in a new "Nutritional Health System" aimed at improving public health. Key technological components include:

- **Soft Robotics** as a core technology, with an emphasis on edible, biomimetic, and AI-generated soft robots.These robots are envisioned as companions, kitchen assistants, and therapeutic tools. **Edible robots** made from materials like gelatin, potentially for therapeutic purposes or to redefine the concept of food. This area draws on material science and bioengineering. Relevant research includes work on edible electronics (Floreano et al., 2024, Irimia-Vladu, 2014) and biodegradable materials for robotics (Laschi et al.,2012). **Biomimetic robots** are designed based on biological organisms, particularly octopuses, for their dexterity and adaptability. This leverages principles of biomimicry to create robots with fluid movement and potentially, a more organic appearance, as highlighted in the work by Kim et al. (2013) and Cianchetti et al.,(2018). Also, robots can be designed and potentially fabricated using AI methods, enabling rapid prototyping and adaptation. This could involve generative design and machine learning for optimising robot form and function. Lipson & Kurman (2016) provide insights into "fab labs" and self-replicating machines. Finally, another trend is that of **self-healing and liquid robots –** soft robots with self-healing capabilities, and liquid robots with shape-shifting abilities. This area intersects with materials science and research on autonomous systems. The work by Terryn et al. (2021) is particularly relevant here.
- **Robot clinicians** are used in therapeutic settings, building on existing research on robots for weight loss, dementia care, and elderly companionship. This involves integrating AI for personalised interaction and potentially, emotional intelligence. Broadbent et al. (2009) provide a review of robots in healthcare.
- **Food therapy apps** are mobile applications that provide personalised nutritional guidance, potentially integrated with data from soft robots and other sensors. This requires expertise in user interface design, data visualisation, and potentially, behaviour change techniques.
- **Pesticide monitoring drones:** Drones equipped with sensors to monitor pesticide levels in agricultural settings,supporting the shift towards local and sustainable food sources. This combines drone technology with environmental sensing.
- **Statistical dishes:** This concept is less clearly defined but could refer to smart kitchenware that analyses food composition and provides nutritional feedback to users. This involves integrating sensors and data analysis into everyday objects.

- **Educational and therapeutic games:** Computer games designed to promote healthy eating habits and potentially address mental health issues related to food. This draws on principles of game design, persuasive technology, and potentially, cognitive behavioural therapy.

Does this project envision a HM interaction?

The project envisions extensive HMI through interactions with soft robots ("*The Food Taster*") that serve as companions, therapists, and kitchen assistants. The scenario also implies interactions with food therapy apps, smart kitchenware, and potentially, virtual environments within therapeutic games.

If so, how can this technology be made more human?

- **Empathy and emotional Intelligence:** Programming robots with empathetic responses and the ability to recognise and respond to human emotions is crucial. This involves research in affective computing and social robotics (Breazeal, 2003).
- **Aesthetic design:** Creating robots with "somatosensory and visually opulent behaviour" can enhance their appeal and acceptance. This requires collaboration between engineers, designers, and artists.
- **Personalisation:** Tailoring robot behaviour, appearance, and interactions to individual user preferences and needs can foster stronger bonds and improve therapeutic outcomes.
- **Transparency and explainability:** Users should understand the robot's actions and motivations, especially in a therapeutic context. This relates to the field of XAI.
- **Focus on shared activities:** Designing robots to participate in shared activities, such as cooking, eating, or playing games, can strengthen HR relationships.
- **Integration with social networks:** Connecting users with local farmers and food producers through technology can foster a sense of community and belonging.

What are the main risks associated with the use of these technologies?

The envisioned project presents several risks, including the potential for **over-reliance on robots** for social and emotional needs, potentially hindering human connection. **Deskilling** in areas like cooking is possible as automation increases. Ethical dilemmas arise concerning the use of **robots as therapists**, raising questions about authenticity and potential manipulation within the therapeutic relationship. **Data privacy and security** are major concerns given the sensitive nature of personal information collected by these systems. Furthermore, **social inequalities could be exacerbated** if access to these technologies is not equitable. Finally, the use of **edible robots** introduces potential food safety, consumer acceptance, and ecological concerns.

S12: Healthy Food Protocols

Outline. The deep political, economic and social crisis has seen Serbia of 2034 as a country of the poor, leaving almost every seventh resident below the minimum survival income. The "Right to Food" protocol has been adopted to enable a sustainable, social and united economy of healthy food chains in big cities by operating within community urban farms.

The scenario envisions innovative community tech and AI-managed farms to enhance food security, nutritional value, and personalized consumption. Technology facilitates information gathering, improves regenerative agriculture, and optimises supply chains. Key elements include urban planning that prioritises experimental gardens and larger urban farms, alongside an augmented reality game to engage citizens in the planning process. An online platform will integrate the digital, physical, and social aspects of the farm, fostering a sharing economy and incorporating traditional knowledge. An educational centre will offer learning in agriculture, robotics, and AI, featuring immersive mixed-reality experiences. Farms are designed for self-sufficiency, inspired by Palmanova's historical layout, with a focus on supporting the elderly through a "produce + sell + consume" model and food deliveries. Collaborative robots will compensate for labour shortages, assisting in tasks from growing vegetables to contactless delivery. A "brace" prototype will collect health data, enabling remote digital food control and direct food deliveries to those in need. Repurposing smartphones as building "bricks" will allow citizens to contribute data to the farm's structure, fostering real-time communication within the community. The overall philosophy aims to rebuild faith in communities based on ecological, cultural, and humanist values, strengthening ties between humans, non-humans, and AI.

What are the main technological components that can be inferred from this project?

This scenario envisions a future where technology is deeply integrated into urban farming and community building to address food insecurity and social inequality. Key technological components include and intersect with the following directions.

- **AI-Driven Farm Management** can provide algorithms to optimise farm operations, including resource allocation, crop management, and yield prediction. This involves machine learning models trained on data from various sources (sensors, weather patterns, historical yields) to enhance decision-making processes. Relevant research includes Liakos et al. (2018) on machine learning in agriculture. Its use can also support decision-making processes that maintain food security, increase the nutritional value of food, secure the most personalised food consumption model and therefore improve the health and the overall human condition.

- **Collaborative Robots (Cobots)** working alongside humans in various farm tasks, such as planting,harvesting, sorting, and food preparation. These robots are designed for safe and efficient human-robot collaboration, potentially incorporating advanced sensing, dexterity, and AI for adaptability. This area is covered by Cherubini et al. (2016) on collaborative manufacturing with physical human-robot interaction, and by Ravichandar (2020) in the context of machine learning for control.
- **Sensor Networks (IoT)** throughout the farm and in wearable devices (e.g., the "brace") to collect data on environmental conditions, plant health, human health metrics, and food consumption patterns.This data feeds into AI systems and provides real-time insights for farm management and personalised nutrition.The work by Tzounis et al. (2017) is particularly relevant in this context.
- **Blockchain Technology** can be potentially used for supply chain management, ensuring transparency and traceability of food from farm to table. It could also facilitate a sharing economy model for surplus produce. This is a less central technology in the scenario but aligns with the broader trend of using blockchain in food systems (Caro et al., 2018).
- **Augmented Reality (AR) and Virtual Reality (VR)** technologies are used for educational purposes, and would allow visitors to experience immersive learning about farming techniques, plant growth, and the overall ecosystem of the urban farm. This leverages the potential of AR/VR for experiential learning and engagement (Billinghurst et al., 2015).
- **Generative AI** can also be integrated in a data-driven infrastructure to enhance the ecological performance of the urban farm. The use of generative design tools can help to incorporate traditional knowledge into the design and operation of the farm.
- **Online Cloud Platform ("The Right to Food"):** A digital platform for community engagement, resource sharing,knowledge exchange, and data analysis. This platform integrates data from various sources (sensors, user inputs,etc.) and uses algorithms to generate insights and facilitate communication.
- **"Community Gadgets" (e.g., "Brick"):** Innovative use of personal devices, such as smartphones, as building components in the farm's infrastructure, enabling data collection and real-time communication within the community. This explores the convergence of personal technology, architecture, and community participation.

Does this project envision a HM interaction?

The project envisions a high degree of HMI. Humans interact with:

- Collaborative robots, working alongside robots in farming and food-related tasks;
- AI Systems, receiving personalised recommendations and insights from AI-driven systems based on sensor data and user inputs;
- AR/VR environments, engaging in immersive educational experiences;
- Online Platform, participating in community forums, sharing resources, and accessing information;
- "Community Gadgets", contributing data and interacting with the built environment through personal devices.

If so, how can this technology be made more human?

- Focus on **human-robot collaboration** to design robots and intelligent systems to work collaboratively with humans, augmenting human capabilities rather than fully automating them (Semeraro et al., 2023).
- User-centred design principles can support the creation of intuitive, user-friendly, and accessible interfaces for the various technologies in this scenario, ensuring accessibility for diverse users, including the elderly and those with disabilities.
- Transparency and explainability mechanisms can make AI decision-making processes transparent and understandable to users, fostering trust and engagement.
- Community ownership should be incentivised to shape the design, implementation, and use of technology, ensuring it aligns with their values and needs.
- Emphasis on social Interaction through technology, to facilitate social connections and community building, both online and offline. The "brace", for instance, can provide valuable feedback to the user, and this can be integrated with strategies to increase human-human interaction.
- Integration of traditional knowledge should be considered, thereby incorporating traditional farming practices and local knowledge into AI systems and educational programs. This can be achieved through Semantic Web technologies and (neuro-)symbolic approaches to achieve both interoperability and explainability.
- Aesthetic and emotional considerations should also be considered to design robots and virtual environments that are not only functional but also aesthetically pleasing and emotionally engaging.

What are the main risks associated with the use of these technologies?

The reliance on advanced technologies also introduces potential risks. **Data privacy and security** are primary concerns, given the vast amounts of personal information collected, necessitating robust security and strict data governance. **Algorithmic bias** could perpetuate or exacerbate existing inequalities if AI algorithms are trained on biased data, impacting resource allocation and personalised recommendations. **Technological dependence** poses a threat, as over-reliance on these systems makes them vulnerable to technical failures or cyberattacks, potentially disrupting food production and community management. The potential for **exacerbation of social divisions** exists if access to technology or digital literacy is unevenly distributed, widening the gap between socioeconomic groups. **Ethical concerns** arise from using AI in decision-making, particularly regarding resource allocation and individual health, raising questions about autonomy, fairness, and accountability. Finally, the extensive use of sensors and data collection creates a risk of **potential for surveillance**, which could be misused, eroding individual freedoms and privacy.

Outline of identified technologies

Across the 12 scenarios, a diverse array of technologies is envisioned to support the envisioned futures of food, sustainability, and community well-being. **Generative AI** emerges as a prominent tool, employed for tasks ranging from crafting novel food products and recipes (S1, S10, S11) to designing robots (S7, S11) and optimising farm layouts (S12). **Conversational AI** is primarily featured in scenarios focusing on education, training, and persuasion (S1), where it can facilitate personalised learning and promote the adoption of new practices through tailored interactions. **Mixed Reality (MR)**, including Augmented and Virtual Reality, is frequently highlighted for its potential in education (S7, S12), offering immersive experiences that connect users with nature (S8), traditional ecological knowledge, and the intricacies of food production. **Wearables** and **haptic technologies** are proposed to bridge the gap between humans and their environment (S2, S6), providing sensory feedback on soil health (S2) or the impact of food choices (S6). Data, in general, plays a crucial role in most scenarios. This includes **data transformation** and **signal processing** for tasks like converting soil data into actionable insights (S2, S3) or visualising complex ecological relationships (S3). **Data mining** techniques, often powered by **Big Data** analytics, are envisioned for tasks like identifying food fraud (S3), optimising agricultural practices (S4, S12), and personalising nutrition (S4, S10, S11). **Blockchain** technology is suggested for enhancing transparency and traceability in the food supply chain (S3, S4, S6, S9, S12), as well as for managing data provenance (S6).

The **Internet of Things (IoT)** is a recurring theme, enabling the creation of interconnected networks of sensors in farms (S9, S12), kitchens (S10), and even on the human body (S2, S6). These sensor networks, often including **drones** (S8, S11,S12) and other **audio computing** devices (S8, S12), generate vast amounts of data that are analysed using AI and machine learning. The use of **computer vision** is also envisioned for analysing such data. **Robotics** is envisioned both in the form of autonomous agricultural robots for tasks like harvesting and monitoring (S5, S9, S11, S12) and in the more experimental form of soft robots for therapeutic human-machine interaction (S11). **Gamification** is proposed as a tool to encourage engagement and behaviour change, particularly in the context of community participation and education (S9,S10, S11, S12).

Several common threads emerge regarding technology use across the scenarios. There is a strong emphasis on using technology to promote sustainability, enhance human well-being, and foster a more harmonious relationship between humans and nature. Data-driven decision-making, often powered by AI and machine learning, is seen as crucial for optimising resource use, improving food production, and personalising nutrition. Human-machine interaction is a key consideration, with many scenarios envisioning collaborative partnerships between humans and robots or AI systems. The importance of user-friendly interfaces, personalised feedback, and transparent AI algorithms is highlighted throughout. Moreover, many scenarios emphasise the need to integrate technology with traditional ecological knowledge and community values. Overall, we can see the emphasis on using data to inform decisions across scenarios.

Technology	MUSAE projects											
	1	2	3	4	5	6	7	8	9	10	11	12
Big data												
Generative AI												
Conversational AI												
AR/VR												
Wearables												
Haptic technologies												
Data transformation												
Signal processing												
Data analysis												
Blockchain												
Internet of Things (IoT)												
Robotics												
Computer vision												
Drones												
Audio Computing												
Gamification												
Affective Computing												
Neurotechnology												

2) Overview of interaction guidelines

Building on the technological review of the MUSAE scenarios, we now focus on human-machine interaction (HMI), particularly human-robot interaction (HRI), within those scenarios featuring interactive robotic systems. This section presents **guidelines for designing these interactions**, ensuring they are intuitive, engaging, and ethically sound. Drawing from established HCI and HRI principles, with an emphasis on multimodal interaction, these guidelines cover key aspects such as **robot appearance**, **behaviour**, **communication**, **collaboration**, and **ethical considerations**. While broadly applicable, they are tailored to the MUSAE context, where technology aims to enhance our relationship with food, promote sustainability, and foster community. The following sections detail these guidelines, illustrated with examples from the scenarios, culminating in a dedicated section on multimodal interaction and a framework for evaluating HRI effectiveness within the project. They are intended to be adaptable to the specific context of each scenario.

Robot Appearance and Embodiment

Guideline: Carefully consider the robot's appearance and form factor, aligning it with the intended function, interaction context, and user expectations. The robot's appearance significantly impacts human perception, trust, and willingness to interact.

A robot's form should match its function. A robot designed for industrial tasks may prioritise a robust and efficient design, while a social robot might benefit from a more approachable and friendly appearance. Consider the user's cultural background and prior experiences with robots, as these can influence their expectations and reactions.

Relevant literature

- **DiSalvo et al. (2002)** explore how different design features of robot heads influence human perception, highlighting the importance of considering the specific context and desired interaction when designing a robot's appearance. They emphasise that a "one-size-fits-all" approach to robot design is not effective.
- **Goetz et al. (2003)** demonstrate that aligning a robot's appearance with its behaviour leads to improved cooperation and task performance in human-robot teams. It suggests that a robot's appearance sets up expectations about its capabilities, and when these expectations are met, interaction becomes more natural and efficient.

Scenario Examples

- In **S11 (Poetry of Nutrition)**, soft robots serving as therapeutic companions might benefit from an aesthetically pleasing, organic, and perhaps biomimetic design. This could involve soft, rounded shapes, warm colors, and textures that invite touch. Edible robots in this context add another layer of complexity, requiring a balance between visual appeal, food safety, and palatability.
- In **S5 (One Health Recipes)**, "Robot Guardians of Nature" should have a non-threatening appearance that blends with the environment. This might involve camouflage, natural colors, and designs inspired by animals or plants. The goal is to minimise disturbance to wildlife while still being recognisable as a technological artifact.
- In **S7 (What the World Eats)**, biorobotics used in food handling should prioritize a hygienic appearance, suggesting cleanliness and safety. Functionality and ease of cleaning are paramount here, potentially leading to a more industrial or clinical aesthetic.
- In **S9 (From Farm to Table)**, bio-mechanical harvesting robots could have a utilitarian, robust design that conveys strength and efficiency. The CyberCrows, however, present a unique challenge, needing to balance a bird-like appearance with the need to avoid being perceived as a threat by either humans or other animals.

Guideline: Strive for a balance between *anthropomorphism* and *functionality*. While some level of human-likeness can facilitate social interaction, overly realistic robots can fall into the "uncanny valley," evoking negative reactions.

Anthropomorphism can be a powerful tool for creating engaging social robots, but it is a double-edged sword: robots that are too human-like but not perfectly so can trigger a sense of unease or revulsion. The "uncanny valley" hypothesis suggests that finding the right level of abstraction is key.

Relevant literature

- **Mori (1970)** introduced the concept of the uncanny valley, a phenomenon where almost-human-like entities elicit negative emotional responses. While originally proposed for humanoids, the concept has been applied more broadly to other forms of artificial agents. The uncanny valley remains a crucial consideration in robot design, particularly when aiming for social interaction.

Scenario Example: In **S6 (Holobiont Futures)**, social robots designed to educate people about the microbiome should avoid being overly realistic. A stylised, friendly appearance, perhaps with exaggerated features or cartoonish proportions, might be more effective in creating a positive and engaging interaction.

Robot Behaviour and Movement

Guideline: Design robot movements to be predictable, legible, and safe, especially in shared workspaces.

When robots and humans share a physical space, it's crucial that the robot's actions are easily understandable and anticipated. Predictable movements allow humans to react appropriately and avoid collisions or other unsafe situations. Legibility refers to the ability of an observer to infer the robot's intentions from its movements.

Relevant literature

- **Dragan et al. (2013)** provide a formal framework for understanding and designing legible robot motion. They argue that legible motion allows observers to quickly and accurately infer the robot's goal, while predictable motion allows them to anticipate the robot's future trajectory. Applying these principles in shared workspaces is essential for safety and efficient collaboration.

Scenario Examples

- In **S12 (Healthy Food Protocols)**, collaborative robots (cobots) working alongside humans in urban farms must have clear movement patterns. They should avoid sudden changes in direction or speed and use clear signals (e.g., lights, sounds) to indicate their

intentions. This allows human co-workers to anticipate the robot's actions and work safely alongside them.
- In **S9 (From Farm to Table)**, the bio-mechanical harvesting robots should move in a way that is predictable to both humans and animals in the agroforestry environment. This might involve following predefined paths, using consistent speeds, and signaling any changes in direction or activity.

Guideline: Adapt robot behavior to the specific task and context.

Robots should be able to adjust their behavior based on the situation. This requires a degree of autonomy and the ability to sense and interpret the environment. Interactive autonomy involves finding the right balance between autonomous behavior and human control.

Relevant literature

- **Hoffman (2012)** explores how robots can blend autonomous behaviors with responsiveness to human input, enabling flexible and adaptive interaction across a range of tasks and environments. The concept is particularly relevant when robots need to adapt to dynamic situations or work closely with humans.

Scenario Examples

- In **S5 (One Health Recipes)**, a robot guardian's behavior might change depending on the situation. During routine monitoring, it might move slowly and deliberately to avoid disturbing wildlife. However, if it detects a threat to an endangered species, it might need to move quickly and assertively to intervene.
- In **S11 (Poetry of Nutrition)**, a robot chef might use precise, efficient movements when chopping vegetables but adopt more expressive, gentle movements when interacting with a user in a therapeutic setting. The robot's behavior should reflect the emotional context of the interaction.

Communication and Social Interaction

Guideline: Employ multimodal communication that combines verbal and non-verbal cues, tailored to the interaction context.

Humans communicate through a variety of **channels**, including **speech**, **facial expressions**, **gestures**, and **body language**. Robots that can both understand and generate these multimodal signals can interact more naturally and effectively with humans. The specific combination of modalities should be chosen based on the task, environment, and user preferences.

Relevant literature

- **Breazeal (2002)** provides a comprehensive overview of the principles and challenges of designing robots that can engage in natural and effective social interaction with humans.

It emphasizes the importance of multimodal communication, including facial expressions, body language, and speech, in creating believable and engaging social robots. The principles outlined in this work are highly relevant to scenarios involving social robots, such as S6 and S11.

Scenario Examples

- In **S6 (Holobiont Futures)**, social robots educating about the microbiome could use speech to explain complex concepts, facial expressions to convey enthusiasm or concern, gestures to point out relevant information, and even changes in color or texture to represent different types of microbes. For example, a robot might smile and use an upbeat tone of voice when discussing beneficial bacteria, while adopting a more serious expression and tone when explaining the risks of harmful pathogens. They need to communicate effectively using both verbal and nonverbal cues.
- In **S12 (Healthy Food Protocols)**, a cobot might use indicator lights to signal its intentions (e.g., "moving left," "picking up object") and simple sounds to acknowledge human instructions. For instance, a green light might indicate that it is safe for a human to approach, while a red light and a beeping sound might signal a warning.

Guideline: Develop social robots with appropriate social intelligence, enabling them to understand and respond to social cues, adapt to different personalities, and build rapport.

Social intelligence involves the ability to **perceive**, **interpret**, and **respond** appropriately to social signals. This includes understanding social norms, recognising emotions, and adapting one's behavior to different social contexts. For robots designed for social interaction, developing a degree of social intelligence is crucial for creating engaging and effective interactions.

Relevant literature

- **Fong et al. (2003)** provide a broad overview of the field of socially interactive robotics, covering various aspects such as robot appearance, behavior, and social intelligence. They highlight different approaches to endowing robots with social skills and discuss the challenges involved in creating robots that can interact naturally and effectively with humans in various social contexts.
- **Leite et al. (2013)** contributed a survey that focuses specifically on the challenges of creating social robots that can maintain engaging interactions with users over extended periods. They emphasize the need for robots to be adaptive, learn from their interactions, and develop a model of the user's personality and preferences to sustain long-term engagement. These considerations are particularly relevant for scenarios like S11, where robots are envisioned as long-term therapeutic companions.

Scenario Example

In **S11 (Poetry of Nutrition)**, robot therapists need a high degree of social intelligence to engage in meaningful therapeutic interactions. This requires advanced emotion recognition capabilities, allowing them to detect subtle changes in a user's facial expressions, tone of voice, and body language. They also need to be able to adapt their communication style and therapeutic approach based on the user's personality and emotional state, demonstrating empathy and building a strong therapeutic relationship over time.

Guideline: Ensure transparency and explainability in robot communication, particularly when AI is involved in decision-making.

Users are more likely to trust and accept robots if they understand how they make decisions, especially when those decisions impact the user directly. Explainable AI (XAI) aims to make the reasoning behind AI algorithms more transparent and understandable to humans. This can involve providing explanations for specific actions, visualizing the decision-making process, or allowing users to query the system.

Relevant literature

- **Miller (2019)** argues that explanations should be tailored to the audience and the specific context, drawing on principles from social sciences. They suggest that explanations should be contrastive (explaining why one decision was made over another), selective (focusing on the most important factors), and social (presented in a way that is understandable and relatable to the user). These insights can inform the design of robot communication strategies, particularly when robots need to justify their actions or recommendations.

Scenario Example

If a robot in **S10 (The Cooking Ape Institute)** suggests a recipe change based on brainwave analysis, it should be able to provide a simple, understandable explanation for its recommendation. For example, it might say, "I'm suggesting adding more carbohydrates because your brain activity suggests you might need an energy boost." This explanation is contrastive (adding carbs vs. not adding them), selective (focusing on brain activity and energy), and social (using relatable language).

Human-Robot Collaboration

Guideline: Design for intuitive and efficient collaboration, clearly defining roles and responsibilities for humans and robots.

Successful human-robot collaboration requires a clear understanding of who does what. This involves carefully considering the strengths and weaknesses of both humans and robots and allocating tasks accordingly. Humans excel at tasks requiring creativity, adaptability, and complex decision-making, while robots are well-suited for repetitive, physically demanding, or precision-oriented tasks.

Relevant literature

- **Goodrich & Schultz (2007)** provide a comprehensive overview of the field of HRI, including various aspects of human-robot collaboration. They discuss different interaction paradigms, such as supervisory control, peer-to-peer interaction, and shared control, and highlight the importance of designing for clear roles, responsibilities, and communication in collaborative tasks. The principles outlined in this survey are applicable to a wide range of collaborative scenarios.

- **Cherubini et al. (2016)** focus specifically on human-robot collaboration in industrial settings, where robots and humans work together in close proximity to perform manufacturing tasks. They discuss various aspects of physical human-robot interaction, such as collision avoidance, force control, and shared workspace management, which are highly relevant to scenarios like S12, where cobots are used in urban farming.
- **Semeraro et al. (2023)** performed a systematic review on the most common approaches based on machine learning techniques in human-robot collaboration. They are used to either gather high-level information from the robot's workspace or to directly compute the high-level actions that the robot needs to execute to progress in the collaboration with the human. The work categorizes scientific works based on type of collaborative tasks, cognitive variables modeled, type of machine learning used and sensing modalities employed.

Scenario Examples

- In **S9 (From Farm to Table)**, farmers and bio-mechanical harvesting robots might have a clear division of labor. Humans could focus on higher-level tasks like planning, monitoring crop health, and making strategic decisions, while robots handle repetitive and physically demanding harvesting tasks. This leverages the robot's ability to work tirelessly and with precision, while allowing humans to apply their expertise and judgment.
- In **S12 (Healthy Food Protocols)**, humans and cobots might work together in an urban farm. Humans could handle delicate tasks like seeding, transplanting, and tending to fragile plants, while robots assist with heavier tasks like lifting, transporting materials, and performing repetitive tasks like weeding or pruning. Clear communication and coordination protocols are essential to ensure that humans and robots can work together safely and efficiently.

Guideline: Provide appropriate interfaces for controlling and monitoring robots, considering user expertise and the complexity of the task.

The way humans interact with robots is crucial for effective collaboration. Interfaces should be designed to be **intuitive**, **easy to use**, and **tailored** to the specific task and user group. This might involve graphical user interfaces (GUIs), voice control, gesture recognition, or even brain-computer interfaces, depending on the context. The complexity of the interface should match the user's level of expertise and the demands of the task.

Relevant literature

- **Nielsen (1993)** provides a comprehensive guide to designing user-friendly interfaces, emphasizing the importance of understanding user needs, conducting user testing, and iterating on designs based on feedback. The principles of usability engineering are broadly applicable to the design of robot control interfaces, ensuring that they are efficient, effective, and satisfying to use.

- **Shneiderman (1983)** introduced the concept of direct manipulation interfaces, where users interact with digital objects in a way that mimics real-world interactions. This approach can be applied to robot control, allowing users to directly manipulate virtual representations of robots or use gestures to control their movements. Direct manipulation can make robot control more intuitive and easier to learn.

Scenario Examples

- In **S5 (One Health Recipes)**, an interface for remotely monitoring robot guardians might use maps, visualizations, and alerts to provide a clear overview of the robots' status and the ecosystem's health. The interface should be designed to be accessible to users with varying levels of technical expertise, allowing both scientists and members of the public to understand the data being collected.
- In **S9 (From Farm to Table)**, farmers might use a tablet or smartphone app to control and monitor drones and other robots. The app should have intuitive controls for tasks like setting waypoints, adjusting camera angles, and initiating specific actions. Real-time feedback from the robots, such as live video feeds and sensor readings, should be clearly displayed.

Guideline: Foster trust through reliable performance, predictable behavior, and clear communication of the robot's capabilities and limitations.

Trust is essential for effective human-robot collaboration. Users need to be able to rely on robots to perform their tasks safely and effectively. This requires robots to be **reliable**, **predictable**, and **transparent** about their capabilities and limitations. Clear **communication** about what the robot is doing, why it's doing it, and what it can and cannot do is crucial for building and maintaining trust.

Relevant literature

- **Hancock et al. (2011)** contributed a meta-analysis that identifies key factors that influence trust in HRI, including robot performance (reliability, predictability), robot attributes (appearance, communication style), and human factors (user's personality, prior experience with robots). The findings emphasise the importance of designing robots that are not only technically capable but also perceived as trustworthy by users. This is particularly important in scenarios where robots are entrusted with important tasks, such as handling food or providing therapy.
- **Freedy et al. (2007)** explore different methods for measuring trust in HRI, including subjective questionnaires, behavioral measures, and physiological indicators. They highlight the multidimensional nature of trust and suggest that a combination of measures is often necessary to capture its complexity. Understanding how trust is formed and maintained is crucial for designing effective human-robot collaborative systems.

Scenario Example: In any scenario involving close human-robot collaboration, such as **S12 (Healthy Food Protocols)**, consistent and safe robot behavior is paramount. If a cobot is designed to lift heavy objects, it must do so reliably without dropping them or causing injury. Predictable behavior is also key; the robot should move and act in a way that humans can anticipate, avoiding sudden or unexpected actions. Transparent communication about any uncertainties or errors is also crucial.

Multimodal Human-Robot Interaction

Multimodal HRI refers to interactions that involve multiple communication channels, such as speech, gestures, facial expressions, touch, and even physiological signals. Integrating these modalities can create more natural, intuitive, and engaging interactions, particularly in social and collaborative contexts. These guidelines focus on leveraging multiple modalities effectively in the MUSAE scenarios. The following guidelines are particularly relevant for scenarios such as S6, S7, S10, and S11.

Guideline: Choose modalities that are appropriate for the task, context, and user preferences.

The best combination of modalities depends on the specific situation. Consider the strengths and weaknesses of each modality and how they can complement each other. For example, speech is good for conveying complex information, while gestures are useful for providing spatial cues or demonstrating actions. Touch can be powerful for conveying emotion or providing feedback, but it also raises important ethical and safety considerations. Consider also the user's abilities and preferences; for example, some users may be more comfortable with voice control, while others might prefer touch or gesture-based interfaces.

Relevant literature

- **Oviatt (2003)** provides a foundational understanding of multimodal interface design, highlighting the benefits of combining different input modalities to create more robust and user-friendly systems. They emphasise the importance of considering the cognitive load associated with different modalities and designing interfaces that minimize user effort. This is relevant to make robots more accessible.
- **Su et al., (2023)** contributed a more recent comprehensive overview of the field of multimodal HRI, covering a wide range of modalities and interaction scenarios. It discusses the challenges and opportunities associated with designing, implementing, and evaluating multimodal HRI systems, providing valuable guidance for researchers and practitioners.

Scenario Examples

- In **S6 (Holobiont Futures)**, a social robot educating about the microbiome might primarily use speech and facial expressions, but also incorporate gestures to point out features on a visual display or use changes in its external texture or color to represent different types of microbes.

- In **S10 (The Cooking Ape Institute)**, a smart kitchen system could combine voice control for hands-free operation with visual feedback on a screen and tactile feedback through haptic devices to guide the user through a recipe.
- In **S11 (Poetry of Nutrition)**, a robot therapist might use a combination of speech, touch, and physiological sensing to interact with users. For example, the robot might offer a comforting touch while speaking in a soothing voice and monitoring the user's heart rate to assess their emotional state.

Guideline: Ensure seamless and coherent integration of modalities.

Avoid treating each modality as an isolated channel. Instead, strive for a cohesive and integrated experience where the different modalities work together synergistically to convey meaning and facilitate interaction. For example, a robot's speech should be synchronised with its lip movements (if it has a face) and gestures. The timing and coordination of different modalities are crucial for creating a natural and intuitive interaction.

Relevant literature

- **Bolt (1980)** seminal work demonstrated the power of combining speech and gesture for interacting with computer systems. While focused on human-computer interaction, the principles of multimodal integration outlined in this paper are highly relevant to HRI, particularly for scenarios involving direct manipulation or spatial tasks.
- **Cohn et al. (2016)** offer a theoretical framework for understanding the complexities of multimodal communication, particularly relevant to visual narratives like comics, which extends beyond the scope of traditional multimodal theories. While traditional theories often focus on interactions where only one modality utilizes combinatorial structure (like syntax in language), Cohn's framework, building on Jackendoff's (2002) parallel architecture, addresses situations where multiple modalities can employ complex grammatical sequences. It is like a blueprint for understanding interactions where speech, gestures, and visual sequences can all carry intricate meanings, similar to how different input modalities in HRI, as discussed by Oviatt (2003) and Su et al. (2023), must be integrated to minimise cognitive load and create a natural user experience.

Scenario Examples

- In **S7 (What the World Eats)**, if a robot is explaining how it handles food, its verbal explanation should be accompanied by corresponding movements or visual demonstrations.
- In **S11 (Poetry of Nutrition)**, a robot therapist's comforting words should be synchronized with appropriate facial expressions and a gentle tone of voice. If the robot offers a physical touch, it should be timed appropriately with the verbal and emotional context.

Guideline: Design for redundancy and complementarity.

Use multiple modalities to reinforce important information or to provide alternative ways of interacting. This can improve robustness (if one modality fails, others can compensate) and accessibility (users can choose the modality that best suits their needs and preferences). For example, a robot could provide both spoken and visual instructions, or it could accept both voice commands and touch input. Complementary modalities work together to enhance the overall interaction, such as using gestures to clarify spoken instructions or providing haptic feedback to reinforce visual cues.

Relevant literature

- **Turk et al., (2014)** provides a review that highlights the importance of redundancy and complementarity in multimodal interface design. It discusses how different modalities can be used to reinforce each other, compensate for each other's weaknesses, or provide alternative interaction pathways. These principles are directly applicable to the design of multimodal HRI systems.

Scenario Examples

- In **S6 (Holobiont Futures)**, a social robot could provide information about the microbiome both verbally and visually, using diagrams or animations to reinforce the spoken explanation.
- In **S10 (The Cooking Ape Institute)**, a smart kitchen system could accept both voice commands and touch input, allowing users to choose their preferred mode of interaction. The system could also provide feedback through multiple modalities, such as displaying information on a screen, speaking aloud, and providing haptic feedback through a vibrating countertop.

Guideline: Provide appropriate feedback across modalities.

Feedback is crucial for letting users know that their input has been received and understood, and for guiding them through the interaction. Multimodal feedback can be more informative and engaging than feedback delivered through a single channel. For example, a robot could provide visual feedback (e.g., a change in its facial expression or a light signal), auditory feedback (e.g., a confirmation sound or a spoken response), and tactile feedback (e.g., a vibration or a gentle touch) to acknowledge a user's command.

Relevant literature

- **Haptic Feedback:** Various works on haptic feedback, such as those by Jones & Sarter (2008) and others, provide insights into how tactile feedback can be used to enhance user interfaces and improve task performance. This is particularly relevant for scenarios involving physical interaction with robots, such as S11 and S12.
- **Visual and Auditory Feedback:** Research on visual and auditory feedback in HCI, such as that by Brewster et al. (2003) and others, provides guidance on how to design effective feedback mechanisms using these modalities. This is relevant to all scenarios involving multimodal interaction.

Scenario Examples

- In **S9 (From Farm to Table)**, a drone could provide feedback to the farmer through visual displays on a control panel, auditory alerts, and even haptic feedback through a vibrating controller, indicating, for example, that it has successfully identified a target area or that its battery is low.
- In **S11 (Poetry of Nutrition)**, a robot therapist could provide feedback through a combination of modalities. For example, it might nod its head and say "I understand" to acknowledge a user's statement, while also displaying a calming color on its body and gently touching the user's arm (if appropriate).

Guideline: Consider the cognitive load associated with different modalities and combinations.

Processing information from multiple modalities can be cognitively demanding. It is recommended to avoid overloading the user with too much information or too many complex interactions. The cognitive load should be appropriate for the task and the user's capabilities. For example, a simple task might only require simple unimodal feedback, while a more complex task might benefit from more elaborate multimodal feedback – but only if it does not overwhelm the user.

Relevant literature

- **Sweller (1988)** introduced the concept of cognitive load theory, which has had a significant impact on the design of instructional materials and user interfaces. The theory suggests that working memory has limited capacity, and that instructional design should aim to minimise extraneous cognitive load to facilitate learning and performance. These principles can be applied to the design of multimodal HRI, ensuring that the interaction doesn't overwhelm the user's cognitive resources.
- **Mayer & Moreno (2003)** provide specific guidelines for reducing cognitive load in multimedia learning environments, based on cognitive load theory. Many of these guidelines, such as the modality principle (presenting words as audio narration rather than as visual text) and the redundancy principle (avoiding unnecessary repetition of information across modalities), are also relevant to the design of multimodal HRI.

Scenario Examples

- In **S10 (The Cooking Ape Institute)**, a smart kitchen system should avoid bombarding the user with too much information at once. Instructions should be presented in a clear and concise manner, and the system should avoid unnecessary interruptions or distractions.
- In **S6 (Holobiont Futures)**, a social robot teaching about the microbiome should carefully manage the amount of information it provides at any given time, using a combination of modalities that is engaging but not overwhelming.

3) Evaluation Metrics for Human-Robot Interaction

Evaluating the effectiveness of human-robot interaction (HRI) is essential to ensure that the robotic systems developed within the MUSAE project are not only technologically advanced but also user-friendly, engaging, and truly beneficial to individuals and communities. This section outlines key performance metrics for evaluating HRI, categorised for clarity, and explained in a way that is accessible to a broad audience. Each metric is contextualised within the MUSAE scenarios to illustrate its relevance.

Task Performance Metrics

These metrics assess how well the human-robot team performs specific tasks. They provide objective measures of efficiency and effectiveness.

Efficiency

Completion Time: This metric measures the time it takes to complete a given task, either by the robot working alone or by the human and robot working together. It is like a stopwatch measuring how fast a certain task is accomplished.

- In **S9 (From Farm to Table)**, we might measure how long it takes a bio-mechanical harvesting robot to harvest a field of crops. A shorter time generally means the robot is more efficient.
- In **S12 (Healthy Food Protocols)**, we could measure the time it takes for a human-robot team to plant a section of an urban farm. If the team is faster than a human working alone, it suggests the robot is effectively assisting the human.
- In **S7 (What the World Eats)** we can measure the time it takes for robots to complete tasks related to food processing, such as sorting, packaging, or preparing ingredients.

Faster completion times generally indicate higher efficiency. However, speed should always be balanced with safety and accuracy. We would not want a robot to work so fast that it makes mistakes or puts people at risk. It can also be useful to assess whether robots in **S6 (Holobiont Futures)** and **S11 (Poetry of Nutrition)** correctly interpret a user's requests.

Resource Utilisation: This metric quantifies the resources used during task execution, such as energy, materials, or consumables. It is like checking the robot's fuel gauge or how much material it uses to do its job. Lower resource utilisation generally indicates higher efficiency and sustainability.

- In **S5 (One Health Recipes)**, we might measure how much energy a "Robot Guardian of Nature" uses while patrolling an ecosystem. A robot that can patrol for longer periods on a single charge is more efficient.
- In **S12 (Healthy Food Protocols)** we can measure the amount of water used by a robotic system for precision irrigation in an urban farm.
- In **S11 (Poetry of Nutrition)**, we could look at how much material an edible robot is made of or how much energy a robot chef uses during food preparation.

Accuracy

Error Rate: This metric measures the frequency or severity of errors made by the robot while performing a task. It is like counting the number of mistakes the robot makes.

- In **S7 (What the World Eats)**, we might measure the percentage of produce that gets damaged by a soft robotic food handling system. A lower percentage means the robot is handling the food more carefully.
- In **S12 (Healthy Food Protocols)**, we could measure how often a cobot deviates from a predefined planting pattern in an urban farm.
- In **S11 (Poetry of Nutrition)**, we can use this metric to evaluate the ability of robots to correctly follow a recipe when used in the kitchen, or to follow instructions in a therapeutic setting.

Lower error rates are generally better, especially when robots are handling delicate items like food, or when they are involved in tasks where precision is crucial, such as in **S6 (Holobiont Futures)** to assess whether social robots understand instructions and requests.

Precision: This metric assesses how consistent and repeatable the robot's actions are. It is like checking if the robot can do the same thing the same way multiple times.

- In **S9 (From Farm to Table)**, we might measure how consistently a robotic planting system spaces seeds and plants them at the correct depth. Consistent spacing and depth are important for optimal plant growth. It can also be used to evaluate drones' ability to deliver targeted treatments, such as fertilizers or pesticides, to specific plants or areas within the farm.
- In **S7 (What the World Eats)** we can measure how consistently robots can identify and sort different types of produce based on size, shape, color, or other characteristics.

High precision is important for tasks that require uniformity, like planting seeds or assembling products. It ensures that the robot's actions are reliable and predictable.

Safety Metrics

These metrics focus on the safety of the interaction between humans and robots. Safety is crucial in all scenarios, but it is especially important when robots and humans are expected to work closely together.

Collision Rate

Frequency of Collisions measures the number of times the robot bumps into humans or other objects in its environment. It is like counting the number of accidents or near misses.

In **S12 (Healthy Food Protocols)**, where cobots work alongside humans in urban farms, this metric is critical. We want to make sure that the robots can move around safely without bumping into people or damaging plants. A lower collision rate means the interaction is safer.

The same applies when considering robots used in therapy in **S11 (Poetry of Nutrition)** or social robots in **S6 (Holobiont Futures)**.

A lower collision rate indicates a safer system, as we want to minimise (or remove) the risk of robots causing harm to people or damaging property.

Safety System Activation

Frequency of Safety Stops: This metric measures how often the robot's safety mechanisms are triggered. These mechanisms are designed to prevent accidents, like an emergency stop button or a sensor that detects when a human is too close.

Frequent safety stops might mean that the robot's control system is too sensitive or that the robot's movements are not well-adapted to the environment. This is particularly important for cobots in **S12 (Healthy Food Protocols)**, where robots and humans are working in close proximity, and for robots used in therapy in **S11 (Poetry of Nutrition)**.

While safety stops are essential for preventing accidents, frequent activations can disrupt workflow. The goal is to find a balance between safety and efficiency.

Human-Robot Interaction Quality Metrics

These metrics assess the quality of the interaction from the human perspective. They focus on subjective factors like how much a person trusts a robot, how difficult it is to work with the robot, and how satisfied they are with the overall experience.

Trust

Level of Trust in the Robot: This measures how much a person trusts the robot to perform its tasks correctly, safely, and reliably. Intuitively, it is like gauging someone's confidence in the robot's abilities. High levels of trust are important in all scenarios. For example, in **S11 (Poetry of Nutrition)**, patients need to trust that the robot therapist is providing appropriate guidance and support. In **S5 (One Health Recipes)**, people need to trust that the robot guardians are effectively protecting the environment. Farmers in **S9 (From Farm to Table)** need to trust robots to perform agricultural tasks correctly. Overall, trust is crucial for the acceptance and adoption of robotic technology. If people do not trust robots, they are less likely to use them or rely on them.

Workload

Perceived Mental and Physical Workload: This measures how much mental and physical effort a person feels is required to interact with the robot. The idea is assessing how hard someone feels they are working, both mentally and physically. Lower perceived workload is generally better. We want robots to make tasks easier and less demanding for humans, not more difficult. In **S9 (From Farm to Table)**, a well-designed interface for controlling and monitoring multiple robots should make the farmer's job easier, not harder. The goal is to reduce the mental workload associated with managing a complex agricultural operation. Similarly, in **S12 (Healthy Food Protocols)**, cobots should reduce the physical workload of farmers by handling strenuous or repetitive tasks.

Usability

Ease of Use and Learnability: This measures how easy it is for people to learn how to use the robot and its interface, and how efficiently they can interact with it. Intuitively, it is like assessing how user-friendly the robot is. Good usability is crucial for user acceptance and adoption. If a robot is difficult to use or understand, people are less likely to use it, even if it's technologically advanced. In **S10 (The Cooking Ape Institute)**, the interface for interacting with AI-driven recipe systems and smart kitchen appliances should be intuitive and easy to learn. Even people who are not tech-savvy should be able to use the system effectively. User interfaces for controlling and programming robots in **S9 (From Farm to Table)** should be designed to be user-friendly and require minimal training.

Social Acceptance

Perceived Social Presence: This measures the extent to which people perceive the robot as a social being, rather than just a machine. Put simply, it is like assessing how much the robot feels like a companion or a collaborator, rather than just a tool. This is particularly important for social robots, like those in **S6 (Holobiont Futures)**, which are designed to educate and engage with people. To be effective, these robots need to be perceived as more than just machines; they need to have a degree of social presence. Similarly, robot therapists in **S11 (Poetry of Nutrition)** need to establish a social connection with users to build rapport and facilitate therapeutic interactions. Higher perceived social presence can lead to more natural and engaging interactions, especially for robots designed for social interaction.

User Comfort and Satisfaction: This measures how comfortable and satisfied people feel with the overall interaction. Positive user experiences are essential for the long-term adoption and success of robotic technology. High levels of comfort and satisfaction are important in all scenarios. For example, if people are uncomfortable working alongside cobots in **S12 (Healthy Food Protocols)**, they are less likely to accept them in the workplace. In **S11 (Poetry of Nutrition)**, user satisfaction with robot therapists is crucial for the success of the therapy.

Context-Specific Metrics

These metrics are tailored to the specific goals and context of individual MUSAE scenarios. They help assess the effectiveness of robots in achieving specific outcomes related to education, therapy, environmental impact, or community engagement.

<u>Educational Impact</u> (S6, S10, S11)

Knowledge Gain: This measures how much a person's knowledge about a particular topic increases after interacting with a robot. Intuitively, it is like giving someone a test before and after interacting with the robot to see how much they have learned. This is a key metric for **S6**

(Holobiont Futures), where social robots are used as educational tools to teach people about the microbiome. It's also relevant to **S10 (The Cooking Ape Institute)**, where users learn about healthy cooking through smart kitchen appliances and AI-driven recipe systems. **S11 (Poetry of Nutrition)** can also use this metric to evaluate how users learn from educational games. Demonstrating knowledge gain is crucial for validating the effectiveness of robots as educational tools.

Therapeutic Effectiveness (S11):

Improvement in Well-being: This measures changes in a person's emotional state, stress levels, or other relevant health indicators after interacting with a robot. Intuitively, it is like tracking someone's mood or anxiety levels to see if the robot is having a positive impact. This is the central metric for **S11 (Poetry of Nutrition)**, where soft robots are used as therapeutic companions. Demonstrating improvements in well-being is essential for validating the use of robots in therapeutic settings.

Environmental Impact (S5, S7, S8, S9, S12):

Ecosystem Health Indicators: This measures changes in various environmental parameters, such as biodiversity, soil health, water quality, or other relevant environmental parameters. It is like taking the pulse of the environment to see if it's getting healthier. This is crucial for **S5 (One Health Recipes)**, where robots are used to monitor and protect ecosystems. It's also relevant to scenarios involving sustainable agriculture, such as **S9 (From Farm to Table)**, **S7 (What the World Eats)**, **S8 (Patterns that Persist)** and **S12 (Healthy Food Protocols)**. Overall, demonstrating positive environmental impacts is essential for validating the use of robots in promoting ecological sustainability.

Importance: Community Engagement (S12):

Participation Rate: This measures the level of community involvement in activities facilitated by robots, such as urban farming initiatives. It's like counting how many people are getting involved in community projects. This is a key metric for **S12 (Healthy Food Protocols)**, which emphasizes community building and shared responsibility for food production. Higher participation rates suggest that the technology is effectively engaging the community and fostering a sense of collective ownership.

Together, these metrics provide a simple and intuitive framework for evaluating the success of HRI within the MUSAE project. By carefully selecting and applying these metrics, developers can gain valuable insights into the effectiveness of their robotic systems, identify areas for improvement, and ensure that the technologies developed are truly beneficial to users and aligned with the project's overarching vision.

It is important to note that the specific methods for measuring these metrics will vary depending on the context and available resources. Some metrics might be measured through questionnaires and interviews, asking people about their experiences and opinions. Others might be measured using sensors, tracking physiological data like heart rate or brain activity. Behavioral observation, where researchers watch and record how people interact with robots, can also be a valuable tool. Finally, automated data logging, where the robots themselves record data about their performance and interactions, can provide objective insights. The choice of metrics should be driven by the research questions and the specific goals of each scenario. By combining different measurement methods, we can gain a comprehensive understanding of the complex interplay between humans and robots in the applications of the envisioned scenarios.

Conclusions

This deliverable provided an intuitive and accessible framework for designing and evaluating human-machine interaction (HMI) within the MUSAE project, with a particular focus on human-robot interaction (HRI). By conducting a thorough technological review of the 12 MUSAE scenarios, we have identified a diverse array of technologies that underpin the project's vision for the future of food, including generative AI, conversational AI, mixed reality (MR), wearables, haptic technologies, data analytics, blockchain, Internet of Things (IoT), robotics, computer vision, drones, audio computing, gamification, affective computing, and neurotechnology. These technologies, often integrated and interconnected, are envisioned to play a crucial role in promoting sustainability, enhancing human well-being, and fostering a more harmonious relationship between humans, technology, and the environment.

Our analysis has revealed a strong emphasis on **data-driven decision-making** across the scenarios, with AI and machine learning being employed to optimise resource use, improve food production, personalise nutrition, and even identify potential risks like food fraud. The integration of technology with traditional ecological knowledge and community values is another recurring theme, highlighting the importance of a holistic approach that respects both technological advancements and cultural heritage.

Recognising the centrality of HMI in realizing the projects' vision, we have provided a set of detailed **interaction guidelines**, drawing upon established HCI and HRI principles. These guidelines address key aspects of robot design, including appearance and embodiment, behavior and movement, communication and social interaction, and human-robot collaboration, with a dedicated section on multimodal interaction. By emphasising principles such as user-centered design, personalisation, transparency, explainability, and ethical considerations, these guidelines aim to ensure that the robotic systems developed are not only effective but also intuitive, engaging, accessible, and aligned with human values.

To evaluate the effectiveness of HRI within the project, we have anticipated a comprehensive set of **metrics**, encompassing task performance, safety, interaction quality, and context-specific indicators. These metrics, contextualised within the various scenarios, provide a framework for assessing the impact of robotic systems on efficiency, safety, user experience, education, therapy, environmental sustainability, and community engagement. By carefully selecting and applying these metrics, developers can gain valuable insights into the strengths and weaknesses of their designs, iterate on their implementations, and ultimately ensure that the technologies developed are truly beneficial to users.

References

Rasmussen, J. (1983). Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models. IEEE transactions on systems, man, and cybernetics, (3), 257-266.

Fong, T., Nourbakhsh, I., & Dautenhahn, K. (2003). A survey of socially interactive robots. Robotics and autonomous systems, 42(3-4), 143-166.

Bolt, R. A. (1980, July). “Put-that-there” Voice and gesture at the graphics interface. In Proceedings of the 7th annual conference on Computer graphics and interactive techniques (pp. 262-270).

Brewster, S., Lumsden, J., Bell, M., Hall, M., & Tasker, S. (2003, April). Multimodal 'eyes-free' interaction techniques for wearable devices. In Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 473-480).

Cohn, N. (2016). A multimodal parallel architecture: A cognitive framework for multimodal interactions. Cognition, 146, 304-323.

Hoffman, G. (2012). Embodied cognition for autonomous interactive robots. Topics in cognitive science, 4(4), 759-772.

Dragan, A. D., Lee, K. C., & Srinivasa, S. S. (2013, March). Legibility and predictability of robot motion. In 2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 301-308). IEEE.

Goodrich, M. A., & Schultz, A. C. (2008). Human–robot interaction: a survey. Foundations and Trends® in Human–Computer Interaction, 1(3), 203-275.

Goetz, J., Kiesler, S., & Powers, A. (2003, November). Matching robot appearance and behavior to tasks to improve human-robot cooperation. In The 12th IEEE International Workshop on Robot and Human Interactive Communication, 2003. Proceedings. ROMAN 2003. (pp. 55-60).

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y., De Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. Human factors, 53(5), 517-527.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011, September). From game design elements to gamefulness: defining" gamification". In Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments (pp. 9-15).

Wu, L., Alqasemi, R., & Dubey, R. (2020). Development of smartphone-based human-robot interfaces for individuals with disabilities. IEEE Robotics and Automation Letters, 5(4), 5835-5841.

Su, H., Qi, W., Chen, J., Yang, C., Sandoval, J., & Laribi, M. A. (2023). Recent advancements in multimodal human–robot interaction. Frontiers in Neurorobotics, 17, 1084000.

Triantafyllidis, E., Acero, F., Liu, Z. et al. Hybrid hierarchical learning for solving complex sequential tasks using the robotic manipulation network ROMAN. Nat Mach Intell 5, 991–1005 (2023). https://doi.org/10.1038/s42256-023-00709-2

Baldauf, M., Dustdar, S., & Rosenberg, F. (2007). A survey on context-aware systems. *International Journal of Ad Hoc and Ubiquitous Computing*, *2*(4), 263-277.

Chanel, G., Kierkels, J. J., Soleymani, M., & Pun, T. (2011). Short-term emotion assessment in a recall paradigm. *International Journal of Human-Computer Studies*, *69*(10), 607-627.

de Berardinis, J., Pizzuto, G., Lanza, F., Chella, A., Meira, J., & Cangelosi, A. (2020, November). At your service: Coffee beans recommendation from a robot assistant. In Proceedings of the 8th international conference on human-agent interaction (pp. 257-259).

Cherubini, A., Passama, R., Crosnier, A., Lasnier, A., & Fraisse, P. (2016). Collaborative manufacturing with physical human–robot interaction. Robotics and Computer-Integrated Manufacturing, 40, 1-13.

Pousman, Z., Stasko, J., & Mateas, M. (2007). Casual information visualization: Depictions of data in everyday life. IEEE transactions on visualization and computer graphics, 13(6), 1145-1152.

Culbertson, H., Schorr, S. B., & Okamura, A. M. (2018). Haptics: The present and future of artificial touch sensation. Annual review of control, robotics, and autonomous systems, 1(1), 385-409.

DiSalvo, C., Sengers, P., & Brynjarsdóttir, H. (2010). Mapping the landscape of sustainable HCI. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*[1] (pp. 1975-1984).

DiSalvo, C. (2002). All Robots Are Not Created Equal: The Design and Perception of Humanoid Robot Heads. Human Computer Interaction Institute and school of Design, Carnegie Mellon University.

Freedy, A., DeVisser, E., Weltman, G., & Coeyman, N. (2007, May). Measurement of trust in human-robot collaboration. In 2007 International symposium on collaborative technologies and systems (pp. 106-114).

Luperto, M., Monroy, J., Renoux, J. et al. Integrating Social Assistive Robots, IoT, Virtual Communities and Smart Objects to Assist at-Home Independently Living Elders: the MoveCare Project. Int J of Soc Robotics 15, 517–545 (2023). https://doi.org/10.1007/s12369-021-00843-0

Coutinho, E., Alshukri, A., de Berardinis, J., & Dowrick, C. (2021, September). POLYHYMNIA Mood–Empowering people to cope with depression through music listening. In 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 (pp. 188-193).

Felzmann, H., Villaronga, E. F., Lutz, C., & Tamò-Larrieux, A. (2019). Transparency you can trust: Transparency requirements for artificial intelligence between legal norms and contextual concerns. Big Data & Society, 6(1), 2053951719860542.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. Advances in neural information processing systems, 27.

Tzounis, A., Katsoulas, N., Bartzanas, T., & Kittas, C. (2017). Internet of Things in agriculture, recent advances and future challenges. Biosystems engineering, 164, 31-48.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.
Caro, M. P., Ali, M. S., Vecchio, M., & Giaffreda, R. (2018, May). Blockchain-based traceability in Agri-Food supply chain management: A practical implementation. In 2018 IoT Vertical and Topical Summit on Agriculture-Tuscany (IOT Tuscany) (pp. 1-4). IEEE.

Ravichandar, H., Polydoros, A. S., Chernova, S., & Billard, A. (2020). Recent advances in robot learning from demonstration. Annual review of control, robotics, and autonomous systems, 3(1), 297-330.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, *267*, 1-38.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2), 2053951716679679.

Nielsen, J. (1993). *Usability engineering*. Academic Press.

Sacha, D., Senaratne, H., Kwon, B. C., Ellis, G., & Keim, D. A. (2017). The role of uncertainty, awareness, and trust in visual analytics. *IEEE transactions on visualization and computer graphics*, *23*(1), 240-249.

Spence, C., & Driver, J. (Eds.). (2004). *Crossmodal space and crossmodal attention*. Oxford University Press.

Riede, K. (1998). Acoustic monitoring of Orthoptera and its potential for conservation. Journal of insect conservation, 2(3), 217-223.

Stowell, D., Wood, M. D., Pamuła, H., Stylianou, Y., & Glotin, H. (2019). Automatic acoustic detection of birds through deep learning: the first bird audio detection challenge. Methods in Ecology and Evolution, 10(3), 368-380.

Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. ACM computing surveys (CSUR), 41(3), 1-58.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering, 114(4), 358-371.

Shamshiri, R. R., Weltzien, C., Hameed, I. A., Yule, I. J., Grift, T. E., Balasundram, S. K., ... & Chowdhary, G. (2018). Research and development in agricultural robotics: A perspective of digital farming. International Journal of Agricultural and Biological Engineering, 11(4), 1-14.

Zhang, C., & Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: a review. Precision Agriculture, 13(6), 693-712.

Hermann, T., Hunt, A., & Neuhoff, J. G. (Eds.). (2011). *The sonification handbook*. Logos Verlag Berlin GmbH & Co. KG.

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on* [1] *Computer Vision and Pattern Recognition* [2] *(CVPR)*(pp. 10684-10695).

Keim, D. A., Mansmann, F., Schneidewind, J., Thomas, J., & Ziegler, H. (2008). Visual analytics: Scope and challenges (pp. 76-90). Springer Berlin Heidelberg.

Kingma, D. P., & Welling, M. (2013). Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*.

Lipton, Z. C. (2018). The mythos of model interpretability. *Communications of the ACM*, *61*(10), 36-43.

Norman, D. A. (1988). The psychology of everyday things. Basic Books. Norman, D. A. (2013). *The design of everyday things: Revised and expanded edition*. Basic books.

Norman, D. A., & Draper, S. W. (1986). User centered system design; new perspectives on human-computer interaction. L. Erlbaum Associates Inc..

Segel, E., & Heer, J. (2010). Narrative visualization: Telling stories with data. *IEEE transactions on visualization and computer graphics*, *16*(6), 1139-1148.

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). IEEE access, 6, 52138-52160.

Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. Sensors, 21(11), 3758.

Castanedo, F. (2013). A review of data fusion techniques. The scientific world journal, 2013(1), 704504.

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. N. (2018). An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet of Things Journal*, *5*(5), 3758-3773.

GEO (n.d.). The Group on Earth Observations. Retrieved from https://www.earthobservations.org/

Wilson, M. (2002). Six views of embodied cognition. Psychonomic bulletin & review, 9, 625-636.

Bhardwaj, A., Dagar, V., Khan, M. O., Aggarwal, A., Alvarado, R., Kumar, M., ... & Proshad, R. (2022). Smart IoT and machine learning-based framework for water quality assessment and device component monitoring. Environmental Science and Pollution Research, 29(30), 46018-46036.

Padhiary, M., Saha, D., Kumar, R., Sethi, L. N., & Kumar, A. (2024). Enhancing Precision Agriculture: A Comprehensive Review of Machine Learning and AI Vision Applications in All-Terrain Vehicle for Farm Automation. Smart Agricultural Technology, 100483.

Arias-Navarro, C., Diaz-Pines, E., Klatt, S., Brandt, P., Rufino, M. C., Butterbach-Bahl, K., & Verchot, L. V. (2021). Spatial variability of soil N2O and CO2 fluxes in different land-use types in the highlands of Kenya. Nutrient Cycling in Agroecosystems, 119(1), 5-27.

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. *Computer networks*, *54*(15), 2787-2805.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, *147*, 70-90.

Kshetri, N. (2018). Blockchain's roles in strengthening cybersecurity and protecting privacy. *Telecommunications Policy*, *41*(10), 823-838.

Van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. Computers and electronics in agriculture, 177, 105709.

Voigt, P., & Von dem Bussche, A. (2017). *The EU general data protection regulation (GDPR): A practical guide*. Springer International Publishing.

Angraal, S., Krumholz, H. M., & Schulz, W. L. (2017). Blockchain technology: Applications in health care. *Circulation: Cardiovascular Quality and Outcomes*, *10*(9), e003800. https://doi.org/10.1161/CIRCOUTCOMES.117.003800

Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., & Pfister, H. (2013). What makes a visualization memorable?. IEEE transactions on visualization and computer graphics, 19(12), 2306-2315.

Aagaard, K., Petrosino, J., Keitel, W., Watson, M., Katancik, J., Garcia, N., ... & Versalovic, J. (2013). The Human Microbiome Project strategy for comprehensive sampling of the human microbiome and why it matters. The FASEB Journal, 27(3), 1012.

Leite, I., Martinho, C., & Paiva, A. (2013). Social robots for long-term interaction: a survey. International Journal of Social Robotics, 5, 291-308.

Leite, I., Pereira, A., Mascarenhas, S., Martinho, C., Prada, R., & Paiva, A. (2014). The influence of empathy in human–robot relations. *International Journal of Human-Computer Studies*, *71*(3), 250-260.

Mori, M., MacDorman, K. F., & Kageki, N. (2012). The uncanny valley [from the field]. *IEEE Robotics & Automation Magazine*, *19*(2), 98-100.

Pu, L., Moyle, W., Jones, C., & Todorovic, M. (2019). The effectiveness of social robots for older adults: a systematic review and meta-analysis of randomized controlled studies. The Gerontologist, 59(1), e37-e51.

Tapus, A., Maja, M., & Scassellatti, B. (2007). The grand challenges in socially assistive robotics. IEEE Robotics and Automation Magazine, 14(1), N-A.

Zeevi, D., Korem, T., Zmora, N., Israeli, D., Rothschild, D., Weinberger, A., ... & Segal, E. (2015). Personalized nutrition by prediction of glycemic responses. Cell, 163(5), 1079-1094.

Shivalkar, S., Chowdhary, P., Afshan, T., Chaudhary, S., Roy, A., Samanta, S. K., & Sahoo, A. K. (2023). Nanoengineering of biohybrid micro/nanobots for programmed biomedical applications. Colloids and Surfaces B: Biointerfaces, 222, 113054.

Bekele, M. K., Pierdicca, R., Frontoni, E., Malinverni, E. S., & Gain, J. (2018). A survey of augmented, virtual, and mixed reality for cultural heritage. Journal on Computing and Cultural Heritage (JOCCH), 11(2), 1-36.

Billinghurst, M., Clark, A., & Lee, G. (2015). A survey of augmented reality. Foundations and Trends® in Human–Computer Interaction, 8(2-3), 73-272.

Karana, E., Blauwhoff, D., Hultink, E. J., & Camere, S. (2018). When the material grows: A case study on designing (with) mycelium-based materials. International Journal of Design, 12(2).

Hino, M., Benami, E., & Brooks, N. (2018). Machine learning for environmental monitoring. Nature Sustainability, 1(10), 583-588.

Lepora, N. F., Verschure, P., & Prescott, T. J. (2013). The state of the art in biomimetics. Bioinspiration & biomimetics, 8(1), 013001.

Lipson, H. (2014). Challenges and opportunities for design, simulation, and fabrication of soft robots. Soft Robotics, 1(1), 21-27.

Rus, D., & Tolley, M. T. (2015). Design, fabrication and control of soft robots. Nature, 521(7553), 467-475.

Aarts, E., & De Ruyter, B. (2009). New research perspectives on ambient intelligence. Journal of Ambient Intelligence and Smart Environments, 1(1), 5-14.

Goel, M., & Bagler, G. (2022). Computational gastronomy: A data science approach to food. Journal of Biosciences, 47(1), 12.

Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. Educational psychologist, 38(1), 43-52.

Chanel, G., Kronegg, J., Grandjean, D., & Pun, T. (2006, September). Emotion assessment: Arousal evaluation using EEG's and peripheral physiological signals. In International workshop on multimedia content representation, classification and security (pp. 530-537). Berlin, Heidelberg: Springer Berlin Heidelberg.

Mühl, C., Allison, B., Nijholt, A., & Chanel, G. (2014). A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges. *Brain-computer interfaces*, *1*(2), 66-84.

Elsweiler, D., Trattner, C., & Harvey, M. (2017, August). Exploiting food choice biases for healthier recipe recommendation. In Proceedings of the 40th international ACM SIGIR conference on research and development in information retrieval (pp. 575-584).

Oviatt, S. (2003). Multimodal interfaces. In *The human-computer interaction handbook: Fundamentals, evolving technologies, and emerging applications* (pp. 286-304). L. Erlbaum Associates Inc..

Picard, R. W. (1997). *Affective computing*. MIT press.

Shneiderman, B. (1983). Direct manipulation: A step beyond programming languages. Computer, 16(08), 57-69.

Breazeal, C. (2003). Toward sociable robots. Robotics and autonomous systems, 42(3-4), 167-175.

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. International journal of social robotics, 1, 319-330.

Cianchetti, M., Laschi, C., Menciassi, A., & Dario, P. (2018). Biomedical applications of soft robotics. Nature Reviews Materials, 3(6), 143-153.

Irimia-Vladu, M. (2014). “Green” electronics: biodegradable and biocompatible materials and devices for sustainable electronics. *Chemical Society Reviews*, *43*(2), 588-610.

Floreano, D., Kwak, B., Pankhurst, M., Shintake, J., Caironi, M., Annese, V. F., ... & Boom, R. M. (2024). Towards edible robots and robotic food. Nature Reviews Materials, 1-11.

Kim, S., Laschi, C., & Trimmer, B. (2013). Soft robotics: a bioinspired evolution in robotics. Trends in biotechnology, 31(5), 287-294.

Laschi, C., Cianchetti, M., Mazzolai, B., Margheri, L., Follador, M., & Dario, P. (2012). Soft robot arm inspired by the octopus. Advanced robotics, 26(7), 709-727.

Lipson, H., & Kurman, M. (2016). *Fabricated: The new world of 3D printing*. John Wiley & Sons.

Terryn, S., Langenbach, J., Roels, E., Brancart, J., Bakkali-Hassani, C., Poutrel, Q. A., ... & Vanderborght, B. (2021). A review on self-healing polymers for soft robotics. Materials Today, 47, 187-205.

Semeraro, F., Griffiths, A., & Cangelosi, A. (2023). Human–robot collaboration and machine learning: A systematic review of recent research. Robotics and Computer-Integrated Manufacturing, 79, 102432.

Turk, M. (2014). Multimodal interaction: A review. Pattern recognition letters, 36, 189-195.

Jones, L. A., & Sarter, N. B. (2008). Tactile displays: Guidance for their design and application. Human factors, 50(1), 90-111.

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. Learning and instruction, 4(4), 295-312.