Recuisine

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DIGSIM
Designing for Growing Systems in the Home

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

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Introduction

This report covers the process of the Recuisine project, carried out within the Designing for Growing Systems in the Home (DIGSIM) squad at the faculty of Industrial Design Eindhoven. The project contributes towards the design challenge Human-AI Collaborative Experience. This challenge entails designing for the collaboration between humans and Artificial Intelligence (AI) within the domain of the smart home of 2030. After initial research and exploration, our group narrowed the scope of the project down to facilitate this collaboration in tackling the challenges emerging from the transition towards a more healthy and sustainable society within the context of the future kitchen.

A semester of elaborating and iterating over this resulted in the family of products we call Recuisine. This system of 3 products works together to support households of the future in making substantiated decisions towards developing their desired cuisine. This report covers our process and the design decisions we made along the way.

Design process

The design process of this project consists of five different iterations, spread over fifteen weeks (see figure 1). In each iteration, we went through different phases of the Reflective Transformative Design Process (Hummels & Frens, 2009). Reflection took place during the whole process, but especially during the start of each iteration. In this project report, each iteration is elaborated by explaining the decisions made during the iteration and the rationale behind these decisions.

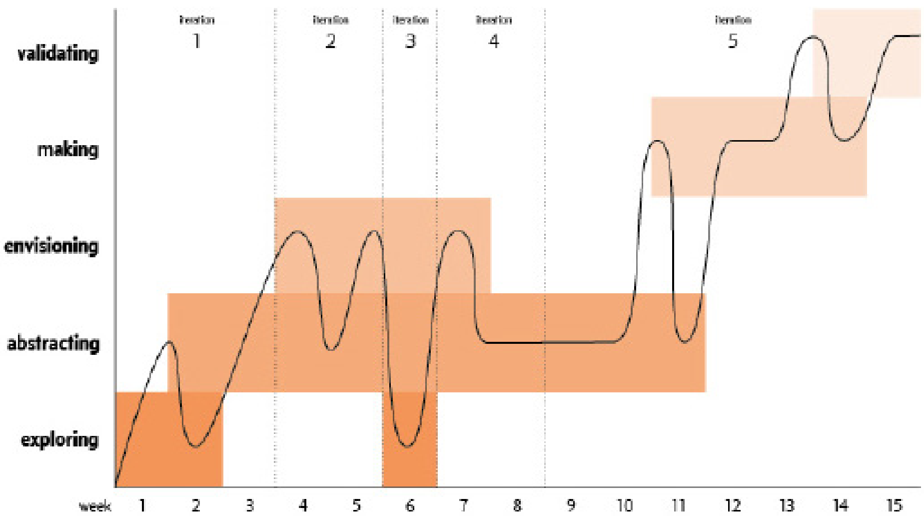

Figure 1: A visualization of our design process. The phases on the left side are retrieved from the Reflective Transformative Design Process (Hummels & Frens, 2009).

Exploration and ideation

Iteration 1 - designing for the kitchen of 2030

Our group first went into an exploration phase to discover the possibilities of AI in the future home context and to define a vision for our project based on the group members' individual visions and competencies. To better grasp what setting we had to design for and what the opportunities for AI would be, mind mapping was used, and the result was an overview of several relevant areas within the future home context, centered around lifestyle.

We then framed the desired interaction between the AI and the human household. For this, the so-called IoT-Sandbox (Frens et al., 2018) was used, a digital tool in the shape of a scale model house inhabited by a fictional family, the Gorré family. Both the IoT sandbox and the Gorré family's personas have been used as an ideation tool throughout the project, and have been at the basis of scenarios and collaboration within the squad. In this given context, we then defined the potential role of AI and its role in the household. By creating short scenarios (Rosson & Carroll, 2012), a spectrum was observed between the AI as an extra person in the house and the AI as an agent for automation. We concluded that both the inhabitants and the AI should perform tasks that they are good at. Three interest areas were predominantly present and particularly interesting to us from these several ideation sessions: lifestyle, calm computing (Weiser & Brown, 1997), and home maintenance. We defined possible concept directions for each of these areas, and eventually, we chose to further explore calm computing and using AI for the regulation of IoT devices to stimulate peace of mind.

Attention-seeking acts of household devices were listed using scenarios based on the Gorré family, and by doing so, we discovered possible intervention areas. Starting from our previous conclusion that AI should only take on tasks that it is better at than humans, such as doing calculations and analysing data rather than e.g. making decisions. Based on this, a list of requirements was made. This stimulated us to further explore the role our AI could and should be having, and we made an overview of its strengths and weaknesses. At this point, we realized that for the purpose of internal communication, we needed to create a glossary of what terms we would use for what concepts. As data and AI can be interpreted quite broadly, communicating ideas sometimes proved to be challenging. This list was updated throughout the project and can be found in appendix A.

Using mind mapping, all our exploration up to this point concerning our vision, possible concept directions, areas of interest, and tools we wanted to use, was laid-out. An overview of this ideation can be found in appendix B. Based on this mind map, individual design proposals were written, based on the opportunities found and the mixing up of combinations of tools, visions, trends, and concept directions. By going through these design proposals together several trends and ideas were identified. We found that the kitchen was the main intersection of our proposals, so we decided to focus our efforts in this context and see how we could design for human-AI collaboration in the kitchen of 2030.

Iteration 2 - exploring the kitchen setting

After deciding on the kitchen context, literature reviews and market analysis were conducted to define trends in the kitchen of 2030. Based on this, a vision mind map was made in which sign values and design opportunities were highlighted (see appendix C). It was found that health and sustainability will play an important role in the kitchen of 2030. The mind map was used to decide which design opportunity to focus on and to define the design goal. This goal was formulated as *"supporting the (creative) process of home cooking by taking into account health factors (through health in the home/design for the quantified self) and mental wellbeing (through stimulating creativity/cooking as a rich activity)".*

The goal was used as a starting point for a brainstorm about concrete ways to reach the goal through a product. For this brainstorm, we used the 6-3-5 brainwriting method (Rohrbach, 1969). Examples of the products that we thought of are an ingredient pair advisor and kitchen tools that teach new cooking techniques to its user.

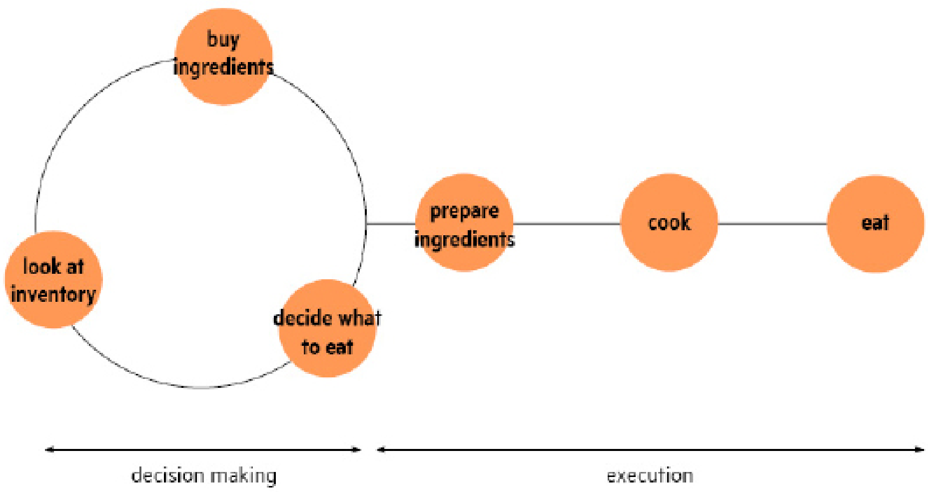

Figure 2: The user journey map.

To better understand the different phases of the cooking process, a user journey map (Nenonen, Rasila, Junnonen & Kärnä, 2008) was made (see figure 2). Using the user journey map and keeping our design goal in mind, we looked at where in the cooking process we could make a difference. It was found that the decision making process was most interesting to us, since this process can be influenced. After this, we started ideating about what type of products could enhance the cooking process. For this ideation session, we used the forced association method (Kokotovich, 2004) combined with sketching. After that, the ideas were categorized based on specific roles that our system of products could have (e.g., support learning new things, recipe recommendation).

It was decided to focus on the idea to suggest spices based on their related use. This direction was chosen since it fits the design goal well and has potential for integrating AI. The idea was elaborated by making a WWWWH map (Buzan & Buzan, 2006). This map can be found in appendix D. Next to that, sketches were made to visualize different outputs that the system could use for its recommendations (see figure 3).

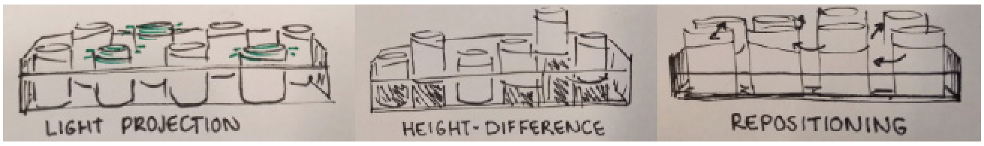

Figure 3: Sketch of different outputs that the spice suggestion product could use.

Iteration 3 - creativity in the kitchen

The third iteration started with reflecting on the first design concept idea and the reasoning behind it. Since the formulation of the project vision was still a bit too broad, it was decided to take a step back and define an improved project vision. This vision can be summarized as *"facilitating healthy and sustainable cooking choices by adding creative elements to the cooking process and enhancing the cooking process as a mindful activity"*.

To understand the role of creativity in the kitchen, a literature review was conducted. From this review, it was found that problem-solving activities stimulate creativity and learning (Surgenor, McMahon &

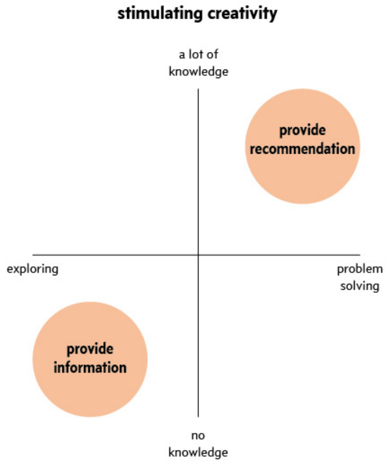

Figure 4: A diagram that was made while ideating about different ways to stimulate creativity.

Beattie, Burns & Hollywood, 2016). Next to that, exploration is an important part of the creative cooking process (Horng & Hu, 2008). A diagram was made as an exploration of different ways of stimulating creativity (see figure 4).

With this new information in mind, we decided on designing a system that provides both information and recommendation to stimulate creativity in the kitchen. Another ideation sketching session was done with these functionalities in mind, which resulted in the second design concept idea: a cutting board that provides information about ingredients and recommends ingredient pairings. Two video prototypes were made to further explain the idea. These videos can be found here.

Iteration 4 - sustainability in the kitchen using AI

To further clarify the problem statement and project vision, a new version focused on sustainability was written (see appendix E). Based on this, the design concept was further defined as a family of products that facilitates Human-AI collaboration to support the decision making of and give insight in what ingredients are consumed. To support this description, scenarios within the Gorré family were formulated of potential problems that our system could help out with (see appendix F).

Several possible products and functions of these products were elaborated on, related to the level of automation the system would have. The functionality that we decided to focus on was to give recommendations for what products to buy. This can be done by giving general information about the sustainability of products (little automation), giving suggestions for products to buy that are sustainable and can be combined with products that are already at home (more automation) or giving suggestions for a full grocery shopping list of sustainable ingredients that correspond with the users behavior and taste (fully automated). It was decided to go for the second option in which the computer narrows the selection down to a few. This is automation level 3 of the ten Levels of Automation by Mackeprang, Müller-Birn and Stauss (2019). To elaborate on this, the concrete roles that the AI and humans would take were defined (see appendix G).

After making the clear framing for the family of products, a more concrete product was developed. This product is a screen that can be placed in the kitchen and gives information about the food purchases of the household (see figure 5). Next to that, several other products were thought of that could be connected to the first product to create a family of products, such as a tangible interaction interface and a connected family cookbook. The concept direction was presented during the mid-term presentation. The video that was shown during this presentation can be found here.

Figure 5: A cardboard prototype of the mid-term design concept.

Conceptualization

Through the feedback from our coaches during the mid-term, we concluded that we had to develop a clearer vision and description for the family of products, to be able to better communicate what we were designing. Although we had a strong background, it had been a while since we reflected on this from our system's perspective, and we could sense the need for a more clear and concise explanation on the part of the functionality as well. We also determined that the proposed 'family cookbook' was an interesting design opportunity, so we decided to investigate this direction further.

With our concept direction established, the first steps into conceptualization could be made. Although the final concept's functionality was not fully determined at this point, we knew we would be needing a lot of data on products and recipes. We therefore started with creating a database of recipes that use only a few ingredients, and a database with the combined ingredients from the recipes database. These databases can be found on Github (appendix H).

To fully determine our family of products' functionality, we used programming flowcharts (Lynch, 2020). Although usually used to make the coding process of software more efficient, our group used it as a communication and ideation tool as well. Creating these flowcharts gave us an overview of our already imagined functionality, while it also made it easier to think about the role of a 'family cookbook' within the system. It facilitated us with the possibility to establish new functions and interactions without losing track on how the small decisions would influence the whole. The final flowcharts can be seen in appendix I.

To make the intended functionality of our system more concrete, we made a product description for each of our family's products, with its goal, functionalities, inputs, output, intended use on the long-, medium-, and short-term, and connected stakeholders. A use cycle for each product was made as well, and together, they facilitated a clear foundation to work from (see appendix J). This meant we could create the first full system concept. Using bodystorming (Oulasvirta et al., 2003), a basis for this was laid.

The result was Recuisine, a family of concept that consists out of three products:

1. An insight interface that can be used to analyze habits and set intentions in a household's food consumption patterns.
2. A paper family cookbook that holds the household's favorite recipes.
3. A digital 'tryout'-module with a built-in projector that communicates the intentions set in the (digital) insight interface to the (physical) family cookbook.

For the insight interface, we decided on using a (touch)screen for the data visualization because it allows us to show a lot of data at the same time. This data would consist of images of products that were recently bought from the supermarket, grouped into categories. These were based on the 'Schijf van Vijf' (Voedingscentrum Nederland, 2020), a way to (a.o.) categorize food which was popularized by the Dutch Nutrition Center. In the interface, intentions can be made clear through intention filters. These filters provide extra information about the products, based on a certain intention criterion, e.g. 'eating more plant-based products'. The user can then use these filters to reflect on their food consumption behavior, and use this to gain insight in these habits. At the same time, the interface makes it easy for the user to communicate their intentions. By selecting an ingredient, alternative ingredients that comply with the chosen intention filter will be recommended and shown on the screen (e.g. 'tofu' will be shown when the 'fish, legumes, meat, egg, nuts, dairy' category is selected with the 'eat more plant-based' filter active). Users can then drag a product they want to try out over to the tryout module to communicate their intent to use this ingredient in the near future.

The cookbook is a highly personalized paper booklet that can be fully designed by the family. The family can use a web interface to add recipes, which will be sent to them on paper through the mail or they can print it themselves. By continuously adding these pages to the Recuisine cookbook, a family cuisine slowly takes shape. We defined this as "the style and range of food in cooking that is characteristic for a particular family", as can be seen in the glossary (appendix A). In the first place, we wanted to make the cookbook authentic in its experience. The goal was to make it an artifact that is appropriated as a family, and perceived as the materialization of both their culinary habits, fitting to their home environment. For this reason, an authentic paper cookbook was chosen as the form, contrary to a digital version. This allows family members to add notes to recipes, use bookmarks, and make it fitting to their liking in whatever way they can imagine. The cookbook is used as the day-to-day implementation of the family cuisine, together with the tryout module.

The tryout module is the bridge between the digital insight interface and the paper cookbook. When attached to the family cookbook, the tryout module will recognize what recipe is currently opened. It will then use AI technology to suggest recommendations based on the tryout ingredients that are currently added to the tryout module, and fit in this particular recipe. These suggestions will be projected onto a dedicated area in the cookbook, and the family can use the recommendations to cook more in line with their intentions, and to further develop their family cuisine.

To specify the AI for this family of products, we used the program flowcharts we created and discussed the options for a Machine Learning (ML) model to use with our coaches. An artificial neural network (ANN) seemed to be suitable for the specific role and functionality that we had in mind, and we made an outline for how we should approach working on this ML algorithm.

Realization

During the realization phase, three different aspects of Recuisine were realized in parallel. Firstly, the screens of the insight interface and physical cookbook were designed. Next to that, an interactive web app was made to demonstrate the functionality of Recuisine and the connection between the different products. Lastly, the AI was developed to be able to make the interactive web-app completely functional.

Interactions with insight interface & cookbook

To get a better understanding of the user flow of the insight interface, a mock-up was made using Adobe Illustrator and MarvelApp. By doing this, we could further define the interaction possibilities & present the concept to others. Several iterations of the interface were made to improve the understandability of the visual language (see figure 6.1 - 6.3). In the final version, each product is shown with an image in a circle. A dark circle indicates that a product is a family favorite. The products are spatially divided in their 'Schijf van Vijf' clusters. On the left side, you can switch to the family favorites by clicking on the tab with the star. At the bottom are buttons to select intention filters. The mock-up of the final insight interface can be found here.

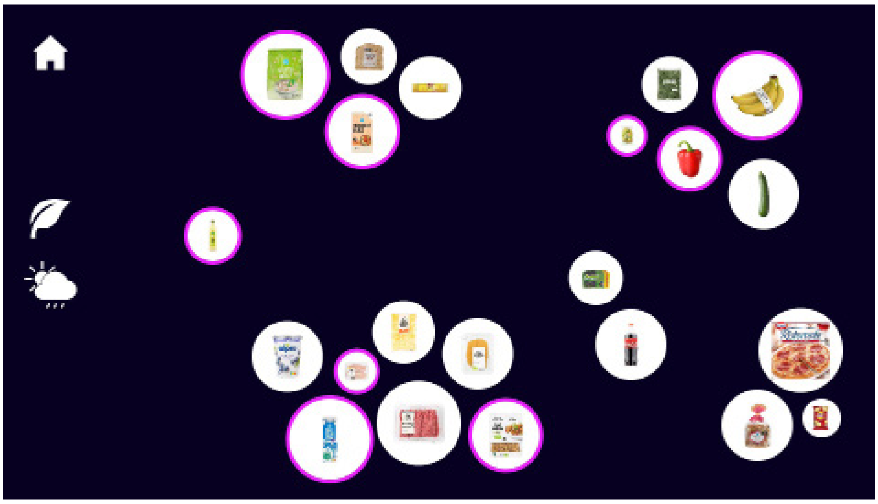

Figure 6.1: First version

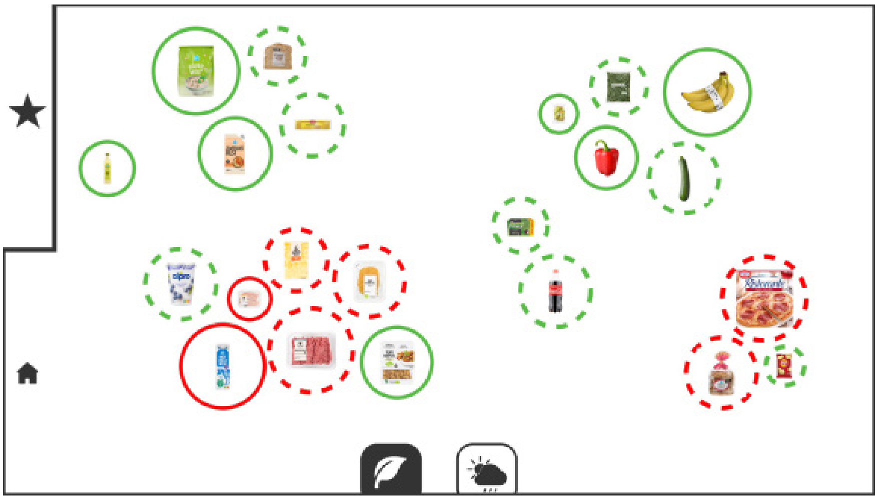

Figure 6.2: Second version

Figure 6.3: Final version

During the realization phase, the focus was on the AI and the interactions with the insight interface. However, it was also important to us to make every part of the system physical, so that they could be used to explain the concept, for example with a video. Therefore, the cookbook was made using easily available materials like a binder with insert sleeves. Next to that, the cookbook stand and tryout module were made from beak wood using the laser cutter.

Interactive web-app

We felt that it was important for the communication of our family of products to have an experience explaining the general functionality as well as the AI functionality in an interactive way. Therefore, we decided to work towards an interactive web application. This web application features the different elements of Recuisine in a simplified way, with various explanatory and exploratory qualities. In the application, users are free to explore the functionality and interactivity in the system of products. To give users a peek behind the curtain, a separate console-like feature was integrated. Here, users find the AI 'agent' explaining its reasoning process, and get feedback on system use. In return, users are able to give their feedback on the resulting score given by the AI, which later could be used for validation.

The web app also gave us the opportunity to interactively showcase the emergent functionalities which resulted from the collaboration with other groups within the squad.The web app (see figure 7) can be visited here. The website source has been publicly published on GitHub for reference, the link to the GitHub can be found in appendix H. The website has been coded in HTML, CSS, and JavaScript. The

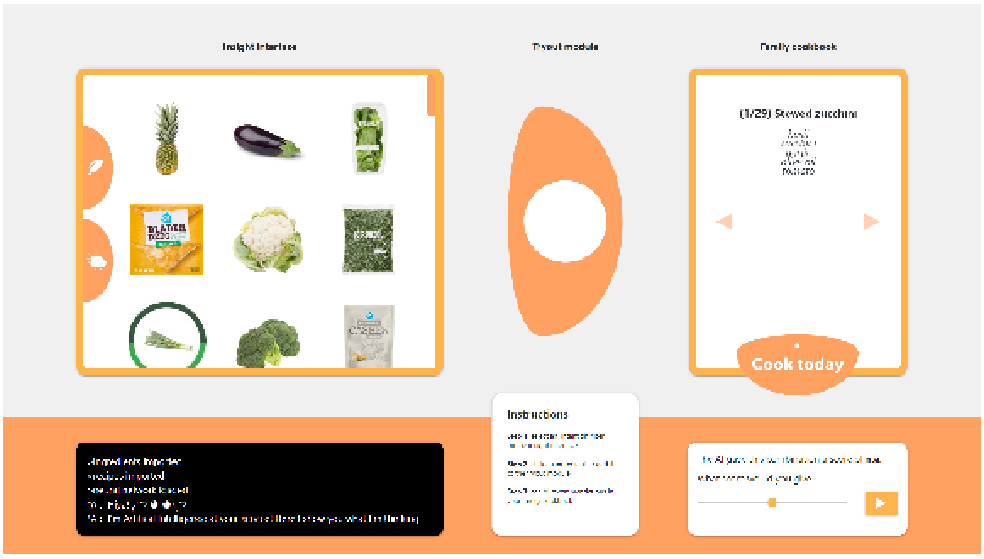

Figure 7: Recuisine web app homepage

score feedback is stored to Data Foundry (Funk et al., 2019), the ANN was trained and leveraged using the ml5.js API (ML5js, n.d.), and the connection with other squad projects was established via OOCSI (Funk, 2019).

AI implementation

We identified the assistance in daily implementation of intentions in the family cuisine as a very suitable task for AI. The system would know which ingredients a household wants to try out and why, and an ML model could help in how these ingredients could be tried out in a convenient way. A good way to do this is for the tryout ingredient to be included in one of the recipes the household already likes, and replace an ingredient in that recipe which didn't align with the household's intention. This would allow households to act on their intentions without disrupting their current cuisine too much. So in essence we wanted a program which would identify a 'bad' ingredient in a household's favourite recipes, swap it with a 'good' ingredient the household wants to try out, and assess if it's a good swap. A ML model would be responsible for this assessment, and look at the new combination of ingredients to give it a score. If this score meets a set threshold value, the swap would be recommended by the tryout module in the specific recipe.

We worked out a proposition for the implementation of a ML model and the full dataflow of the system, which was validated with our expert and coach Janet Huang. After some minor adjustments we had a clear plan. We would work on developing an ANN with a regression task which would output a compatibility score. Its input would be a x amount of ingredients in the form of an array, and its output would be a score between 0 and 1.

We needed two different databases for this to work. A database with different ingredients and their properties, and one with the recipe and corresponding ingredient array. Next to this, a training dataset would be needed in order to train the ANN.

We made the two databases in Google Sheets, as it was both easy to directly connect the databases with the web application or locally export and save them. First, a recipe database was created with 29 recipes retrieved from Allerhande (Albert Heijn, 2020), their name, ingredients and number of ingredients (see appendix K). This database represents the favourite recipes of the household. After this, an ingredient database of 60 ingredients was made using the recipe ingredients plus some extra for recommendations. Additional information such as ingredient category, when an ingredient is in season, and whether it is plantbased was also saved. This information was retrieved from Voedingscentrum Nederland (2020).

Finally, an ingredient array was included for each recipe in the recipe database. This is a binary array consisting of 60 numbers, where each number represents the presence of an ingredient. If the array contains a 1 at position 23, the ingredient from the ingredient database at position 23 would be in the recipe. If it contained a 0, the ingredient at position 23 wouldn't be in there. These arrays provided us with a fast way of communicating recipes and their ingredients within the system, and were especially useful for the ANN input.

Next, we would need to fill a dataset with training data to train the ANN with. It was clear to us we would need a lot of data to even get close to an accurate model. Not only would we need a lot of data, we would also need great variety in who this data came from, since the model would otherwise maybe only fit the taste of our group members. To be able to get a great variety of data we made a data collection application using Processing, and to be able to get a lot of it we made it very simple. For this application a Processing example provided in the course DBM180 Designing with Advanced Artificial Intelligence was used as a starting point. The final data collection tool (see figure 8) can be found in the DataCollectionTool folder on the GitHub page. This application takes a recipe out of the recipe database, swaps an ingredient for another ingredient within the same category, presents the new combination, and asks whether they fit together. Users only have to click yes/no to give their opinion, which is directly stored in a Data Foundry dataset. It stores the ingredient array together with a 1 when ingredients fit together and a 0 when they don't according to the user. After distributing this among students via a form with consent indication, we ultimately gathered 1468 data instances from 21 unique participants.

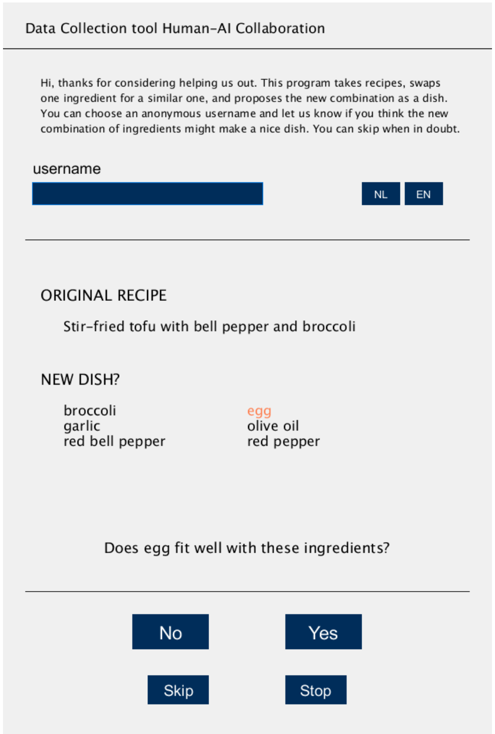

Figure 8: A screenshot of the data collection interface.

This application takes a recipe out of the recipe database, swaps an ingredient for another ingredient within the same category, presents the new combination, and asks whether they fit together. Users only have to click yes/no to give their opinion, which is directly stored in a Data Foundry dataset. It stores the ingredient array together with a 1 when ingredients fit together and a 0 when they don't according to the user. After distributing this among students via a form with consent indication, we ultimately gathered 1468 data instances from 21 unique participants.

After doing some preprocessing using a Processing sketch (which can also be found on the GitHub page), we could use this training dataset to start training and testing on different ANN settings. This was done with the Weka Explorer. Initial testing resulted in a very low accuracy of around 87% error when using training data as test data as well. This turned out to be due to identical ingredient combinations having different scores in the dataset. To fix this, we calculated the mean score for identical combinations (if 2 people liked an ingredient combination and 1 didn't, the score would now be 0.67 instead of 2 times 1 and 1 time 0). This greatly improved the accuracy and we continued looking for the optimal settings. In figure 9 the most important results of this can be found. Here the different layer and node configurations are shown against the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The datasets and exact settings can also be found in the DataAnalysis folder on GitHub to reproduce these tests. Based on these results, we chose for our ANN to have 2 layers, one with 30 nodes and another with 15

Layers & nodes	**MAE** More data (936)	Less data (336)	**RMSE** More data (936)	Less data (336)
30	0,371	0,3764	0,512	0,5185
60	0,3627	0,3933	0,5119	0,5596
30,15	0,2555	0,3545	0,4285	0,4988
30, 30	0,2799	0,3609	0,4508	0,5124
60, 15	0,2697	0,3516	0,4249	0,5024
60, 30	0,2789	0,3553	0,4343	0,4905
60, 60	0,3521	0,4251	0,4612	0,5432
60, 30, 15	0,2537	0,3319	0,4328	0,4903
60, 30, 30	0,2599	0,3468	0,4326	0,4993

Figure 9: Testing results for different configurations.

nodes. Although the 60-30-15 configuration showed better results, we were worried it would be more prone to overfitting and unnecessarily use more computational power.

Later, we additionally removed all data instances of which the ingredient combination only occurred once in our dataset. Although this decreased our amount of data significantly, it increased the validity of the data since every ingredient combination in there was reviewed by at least 2 people. This was ultimately used to train the ANN in the web application, where its resulting scores were converted to a percentage of 0-100% representing the compatibility of the new ingredient combination. Within the system of products this score would dictate if a suggestion gets shown by the tryout module. It would need to match a predetermined threshold, say 70%, before it would get recommended to a household.

Collaboration within the IoT sandbox

Collaboration between projects was a central goal in designing within the IoT-centered DIGSIM squad. Throughout the project, To inspire each others' work and align our concepts from a functionality point of view, we have regularly kept each other updated on our progress. This also prevented us from interfering with each other's work. We have been working together with:

4. Tala: an interactive system that helps to make optimal use of the solar panel energy.

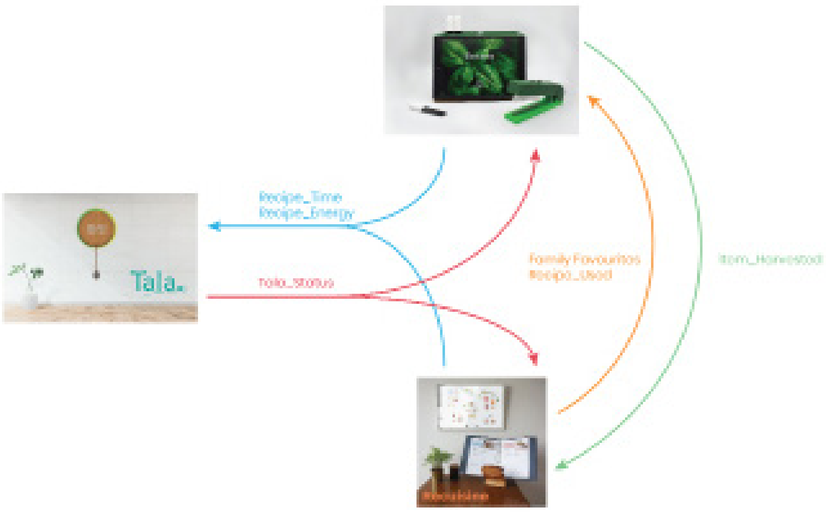

Figure 10: An overview of the data that is shared between the different products.

5. Botano: an all-around system to take care of your plants and find inspiration for recipes to cook with them.

Using OOCSI, data was shared between the IoT-enabled devices to improve each other's functionality. In figure 10, the shared data can be seen. The data sharing was fully functionally implemented in our web demo.

Validation

We wanted to validate Two aspects of our design. The first is the experience of the concept in general. The goal of this validation was to gain insights in what people think and how they feel about Recuisine. Next to that, a plan was made for validation of the ANN. With the validation for the implemented AI, we wanted to test the quality of the suggestions that the AI provided.

Concept validation

The experience validation was done through an online questionnaire. This was the most feasible option to validate the experience with the COVID-19 lockdown restrictions in mind. The questionnaire consists of three parts. The first part is an explanation of our concept. In this part, an explanatory text and a supporting video are provided to inform the participant about our design concept. In the second part, open questions about their first impression are asked. The third part is the User Experience Questionnaire (Laugwitz, Held & Schrepp, 2008). This questionnaire consists of 26 contradicting words on a scale from 1-7. Participants are asked to rate our design concept on these scales. This way, both qualitative and quantitative insights are gathered. The full questionnaire can be found in the appendix L.

The questionnaire was filled in by 8 participants, of which 6 female and 2 male. Most participants were aged 18-24, while one was aged 25-34 and two 55-64. All participants scored themselves between 6-10 for interest in sustainable living. The qualitative data were analyzed using affinity diagramming (Naylor, 2019), while the quantitative data was analyzed by calculating the mean.

The first impression of all participants was positive. Several participants used the terms innovative, interesting, valuable and creative to describe Recuisine. The participants liked the informative aspect of the design. Next to that, it was found through the User Experience Questionnaire that the participants believed that Recuisine is very understandable (6.1/7), supportive (6.2/7) and motivating (6.5/7).

Several participants did not like the physicality of the cookbook. They mentioned that it takes up a lot of space, is not easy to take with you to the supermarket (for when you want to decide last-minute what to buy) and is not very environmental friendly, since recipes have to be printed. Next to that, one participant mentioned that the system consists of too many different components.

AI validation

In the web-app, a slider was integrated with which users could give their own rating. This rating together with the original rating from the AI was sent and saved in a dataset on Data Foundry. This way, we could get quantitative insights in the success of the ML model.

Calculating the absolute difference between the score given by the AI and the score given by a user, would give us the percentage the AI was supposedly off by. Doing this for every instance, and calculating the average of this, would give us the Mean Absolute Error. This could be used as an indication for the true accuracy of the model, as long as it is based on enough instances. However, we did not receive enough instances to meaningfully do this. Optimally, the data would also be accompanied by some qualitative data to put individual instances in perspective. This would help explain where the difference in score came from. After also considering the initial validity of our data, we decided not to actively collect more data on it. This will be elaborated on further in the discussion.

Discussion

This project has used ML to facilitate families in developing their family cuisine in line with their intentions. In this paragraph, we want to reflect on our process and discuss the possible improvements and future works.

During the first four iterations, we took a lot of time for exploration and ideation, to ensure the quality of our vision and design motivation. Although this provided us with a strong background, it also meant that we had less time for iteration in the conceptualization and realization phases. Because of this, some of our decisions could have been better validated to make them more substantiated, either academically and empirically. We tried to compensate for this by including possible means of validation in the future work section below. An example of this is the family cookbook. The assumption was made that an analogue form factor would be better for appropriating the cookbook, but this assumption was not empirically tested and was rejected during our concept validations. THis could have been prevented, had we tested it earlier. Another example is the assumption that exploring and reflecting on consumption behavior using filters should facilitate insight in these habits. Because of this, the interaction with the insight interface has not been tested in a way that allowed us to use the results to improve our concept.

Another point of discussion is the data collection method for the training data of the ANN. When using the AI within the web app, we noticed that some swaps that were suggested were quite illogical. After reviewing this, our hypothesis is that this has to do with the way in which the data was collected. In the data collection interface, the ingredient that would be replaced would not be visible on the screen. This meant that participants would only have the other ingredients of the original recipe to decide if they match well. We deliberately decided to do the data collection in this way to allow for creativity and more flexible matches. But if we would have included the ingredient that was removed as well, the suggestions of our ML model would likely be more accurate as a swap for a specific ingredient.

As some combinations of ingredients in the training data set were only reviewed by up to 3 people, the resulting mean scores are less accurate than if they were to be reviewed by a lot more people. We still used this data to train our models, as collecting huge amounts of data was difficult. However, it would probably be better to collect more data in order to get a more accurate depiction of the true average opinion of people.

The validation of the trained ML model was done in the web app, but due to its non-central place in the web app, no one has completed the entire interaction with the system, and we received no feedback in this way. On the other hand, because the data collection for training was already flawed, the validation would not result in any sensible revelations. This is why we decided to refrain from actively trying to collect more data using this platform.

Future work

We see ample opportunity for future work on this project. A large share of this would revolve around the optimization of the AI implementation and leveraging of generated data.

It became clear to us that not just a huge amount of data is needed for an accurate ML model, specifically a huge amount of accurate data is needed. By keeping collecting a lot of data from a big variety of people this should become better, as the same ingredient combinations get reviewed by multiple different people. The data collection could also be changed so that instead of a yes or no a score could be given out of a range from 0-1 for example.

Further looking at the AI implementation, there is also opportunity for creating more interaction between the AI and the user. A way for the AI to explain itself may be investigated, in the form of embodiment or in a digital form. A way for the user to give the AI feedback, e.g. why they did or didn’t like a certain recipe or ingredient, could also provide to be valuable for the system. This could improve learning accuracy, personalization of the system, and general satisfaction of use.

If in future scenarios multiple households would use the system for a prolonged period, this would generate a lot of data. This data could be used to improve the system between the households, add new interesting features in general, and opens up interesting opportunities for collaboration with external parties.

Right now the compatibility score from the ML model needs to reach a certain threshold before the tryout module will suggest a new combination. This threshold value is currently predetermined and static. This may not be preferable in the future, since it greatly affects what recommendations get shown to a household. A program may be devised to personalize this threshold, such as a learning algorithm. One might even think of a 'surprise me' feature. Some households may be more culinary adventurous than others, and this might be a nice opportunity to accommodate to their preferences.

Another opportunity for personalization could be for the insight interface to suggest ingredients to try out based on households with a similar cuisine. This can be used to expand a household's cuisine while still staying close to their own preferences. This data on overlap could also be leveraged around recipes, and recommending new recipes from similar cuisines to households.

When the ingredient database would be greatly extended to realistically represent the availability of ingredients out there, third parties might be very interested in interoperability or another form of collaboration with the Recuisine platform. Especially organizations operating in and around the food industry might be interested, such as supermarkets or a service such as HelloFresh. This could include new functionalities or integration of their service. One very customizable function for example is the use of intention filters. In general these could be extended to include filtering on vegetarian ingredients, healthy ingredients, or ingredients fitting particular allergies. Then in the context of a filter supplied by business, this could entail something like Albert Heijn supplying a filter for the ingredients they also have on sale or show a personal discount.

If the Recuisine family of products were to be developed in the direction of a service or product line, it would be important to validate the product forms further. Especially the cookbook, as we saw in our validation that some users had some concerns about the cookbook being a physical. It is important consumers are willing for Recuisine to take a long term place in their home, and thus the optimal form of the system should be carefully investigated.

These are only a couple of the directions the project could be taken further into. We think the project is pretty versatile and can be developed further in many directions to be truly integrated in one's everyday life.

Conclusion

This project report describes the design process of Recuisine, a family of products that provides households of the future with insight and support towards the transition and conservation of a healthy and sustainable family cuisine using machine learning technology. By doing this, it aims to support its users to face the (health and sustainability) challenges in the kitchen of 2030. The first product of the family of products is the insight interface that provides insight in the food usage behavior of a household and concrete information to incorporate intentions in their diet. The second product is the cookbook in which family favorite recipes are stored and recommendations are shown. The third product is the tryout module which connects the tryout ingredients from the insight interface to the cookbook.

Several iterations were conducted starting with the definition and exploration of the design context. After that, the family of products within this context was designed. Physical prototypes of the cookbook and tryout module, an insight interface mock-up and an interactive web-app using an artificial neural network were made for demonstration and validation purposes. Lastly, several opportunities for the improvement and further development of Recuisine in the future are proposed.

Acknowledgements

We would like to thank Janet Huang, Mathias Funk, and Joep Frens for their valuable feedback and coaching over the course of this project. We also thank other DIGSIM squad coaches for the feedback and advice we received from them.

Individual contributions

Looking back at our process, we can say that most activities were executed together and with equal personal effort. During the first four iterations, work was mostly done on a communal basis due to the nature of the work. By meeting each other frequently, it was easy to switch between individual work and having group discussions. We would often have prepared work individually which was discussed at the start of the meetings. After this, we made new decisions and formulated new action points from the conclusions. These were divided equally as preparation for the next meeting.

After the mid-term the work became more individual and we were able to divide what had to be done based on expertise and desired development of the group members. In this phase, Lars mainly focused on setting up the data collection, preprocessing, and storage applications. Next to this, he focused on development and testing of the ML model, and back-end development for the web application. Iris' focus during this phase was mainly on the creation of the ingredient & recipe database, the creation of the insight interface mock-up and the set-up and analysis of the concept validation. Jorrit has mainly been working on the web app in the latter part of the project, including setting up a development environment, implementing the ml5.js library and creating the visuals. He has also been responsible for the low- and high-fidelity demonstrators, and editing the report.

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Appendices

Appendix A - Glossary

Family Cuisine: *the style and range of food in cooking that is characteristic for a particular family/household, which includes ingredients as well as recipes*

Current Cuisine: *the style and range of food in cooking that a particular family/household currently has*

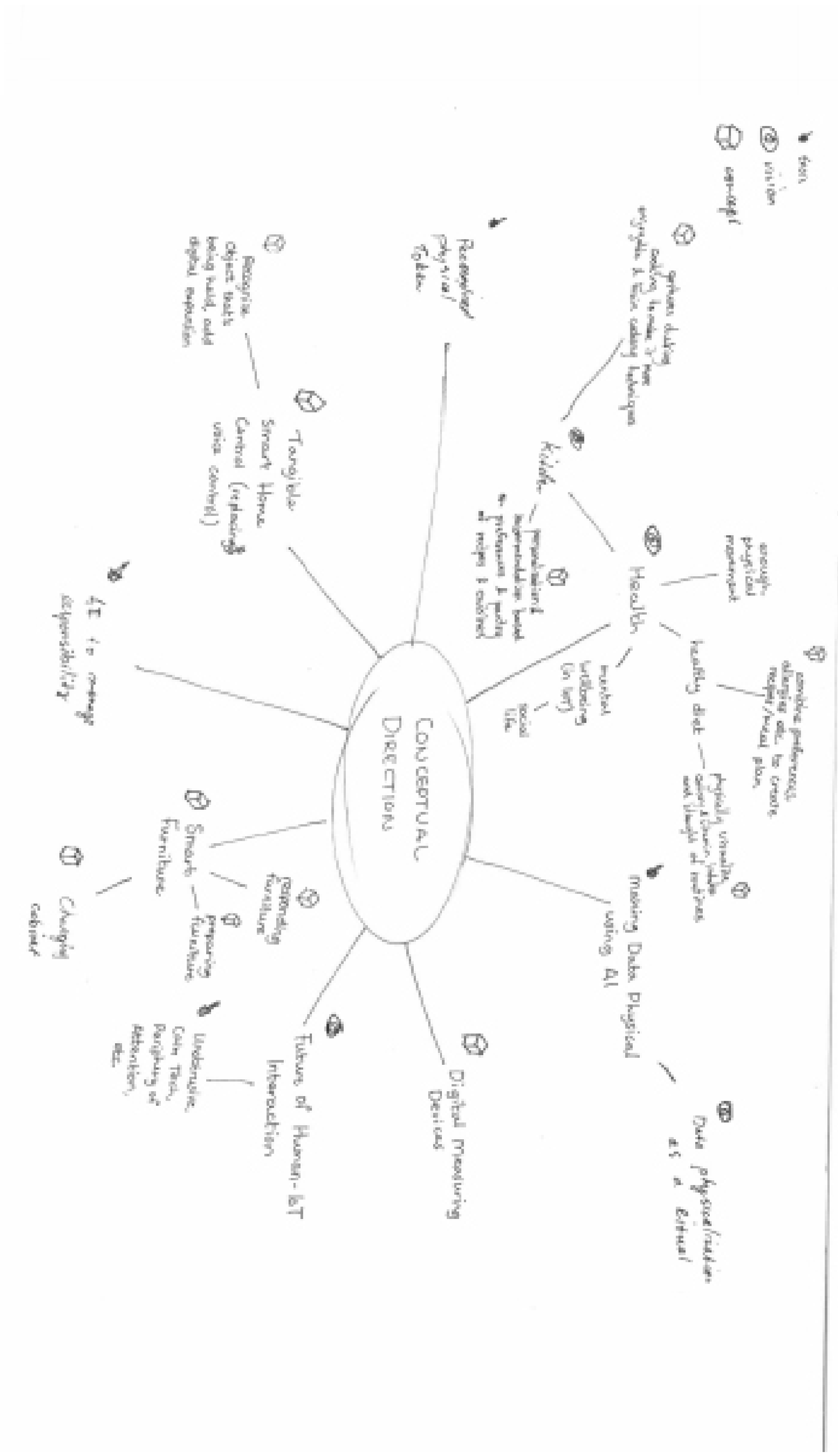
Intended Cuisine: *the style and range of food in cooking that a particular family/household intends to have*

Intention: *an aim or plan, based on the values a family holds*

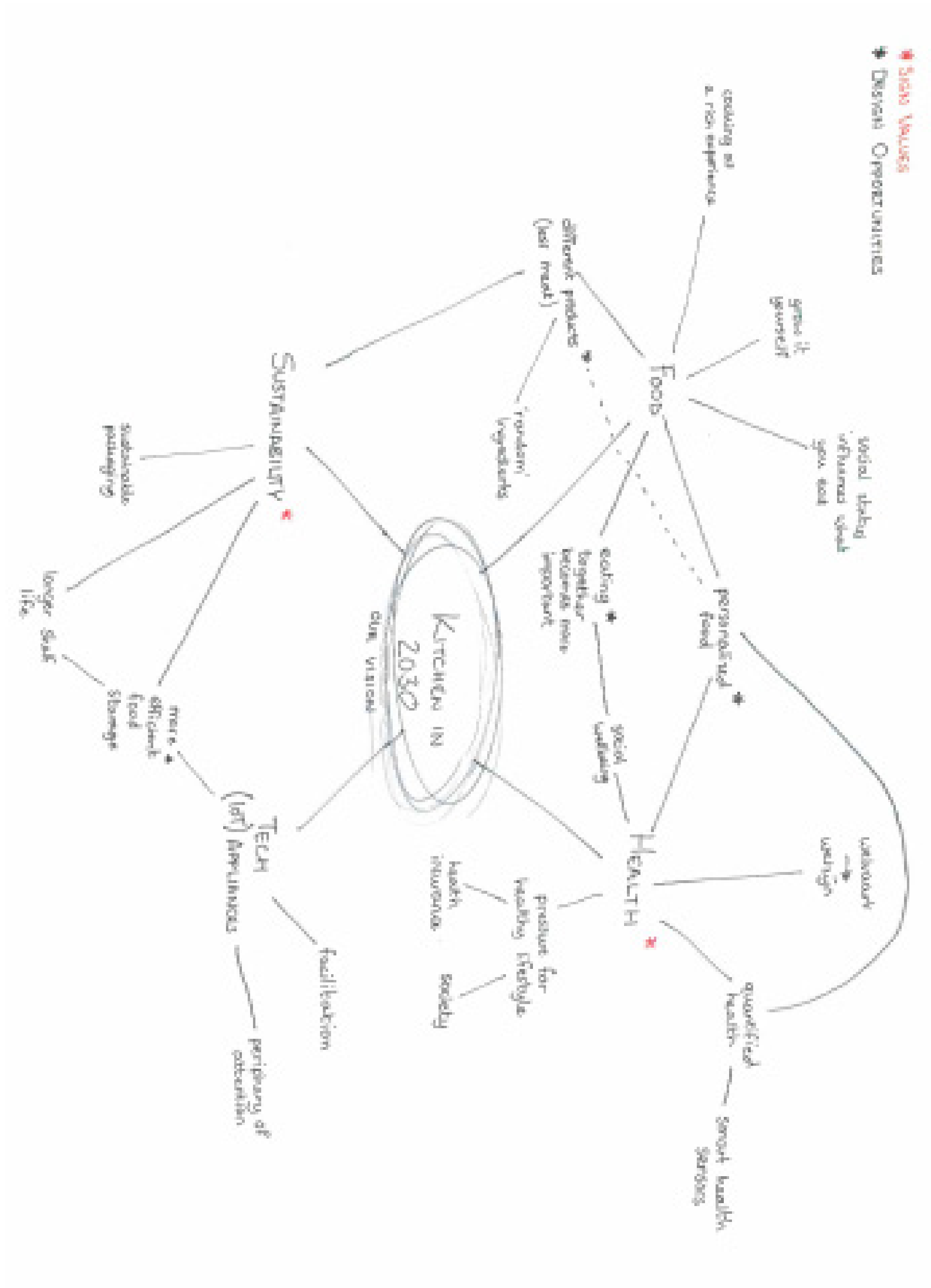
Artificial Intelligence: *a series of systems, methods and technologies that display intelligent behavior by analyzing their environments and taking actions - with some degree of autonomy- toward achieving pre-specified outcomes (Saberi & Menes, 2020).*

Distinction AI and ML: *AI is a bigger concept to create intelligent machines that can simulate human thinking capability and behavior, whereas machine learning is an application or subset of AI that allows machines to learn from data without being programmed explicitly.*

Appendix B - Summarizing ideation mindmap



Appendix C - Kitchen of 2030 vision map



Appendix D - WWWWWH map

Who	Users: Members of the household, with different preferences and expertise levels. People who are not living in the household but who cook in it for whatever reason. Possible other stakeholders: other households globally, (local) producers, VerticalFarm

What	Spice rack that uses rich interaction to recommend spice combinations to inspire new tastes in the creative cooking process and facilitate inter-culture inspired cooking. The spice combinations are based on:
	- what ingredients are being used
	    - VerticalFarm inventory → Check when an item is removed using sensors
	    - User communicates ingredient choice
	    - Detecting which ingredients are in a smart kitchen appliance (oven, pan)
	- What other spices are being used in the dish already
	- What spices are normally used by other members of the household when preparing similar ingredients
	- What spices are normally used by other users of the smart spice rack when preparing similar ingredients (possibly other cultures)
	- What spices are in the spice rack → can be detected through...

When	While preparing ingredients and during cooking.
Where	In the kitchen, the heart of the home and a tech free sanctuary / mindful activity epicentrum. The spice rack will be placed on the counter top.
Why	To enhance the cooking experience by facilitating the exploration of new tastes and new cultures. The spice rack also makes it possible to cook for multiple people while taking into account their flavor preferences, as well as facilitate the user to learn from the inhabitants of the house.
How	By suggesting spices/ingredients/cuisines/flavors based on related use E.g. change position of the spices, change height of the spices, light up spices.

Appendix E - Final project vision & problem statement

Future vision

Sustainable resource management becomes a necessity in the food industry of 2030, as a reaction on the terrible consequences of climate change becoming increasingly visible.

As a result, it is likely there will be an increased public interest in and awareness of sustainable living, a trend we already see emerging in contemporary society.

We call this vision of a sustainably conscious society the *Sustainable Food Society*

Trends and problems that emerge in the SFS are:

- Less meat consumption because of its detrimental effect on the climate
- Less import due to increased export to Africa, an increased global living standard and high carbon emissions for transport
- More interest in local produce and kitchen gardens

Problems in the Sustainable Food Society

People will have limited variety and choice of ingredients available as a result of the societal and environmental changes described in the 'Background' section. Therefore, they will have to re-think the choices they make while shopping for food and while planning meals.

Appendix F - Use scenarios

1. Shivani wants to cook a recipe containing Brussels sprouts, but it is July and she does not want to use imported products.
2. Leo wants to start a vegan diet but he is not sure what he can use as a replacement for a spicy dish using beef, that will provide him with similar nutritional values.
3. Because Shivani cares about the environment she wants to use more local produce in her cooking, but she is unsure what is available and how she can best reach local producers.
4. Ashna makes an omelet for lunch with some random left-overs in the fridge. In the evening, she finds out that there was a bell pepper in the vertical garden that should be eaten as soon as possible. If she had known, she could have added it to the omelet.
5. Neils wants to cook a chicken curry, but Priya bought the groceries and did not bring chicken. So Neils has to think of an alternative.

Appendix G - Roles Human & AI

Role humans	**Role AI**
- Being aware of context	- Identify viable recipe or combination of ingredients
- Tasting (preferences)	- Have an overview of the ingredients @ home
- Cooking	- Analyze people's skills
- Interpret insights from AI	- Analyze possibilities
- Make final decisions	

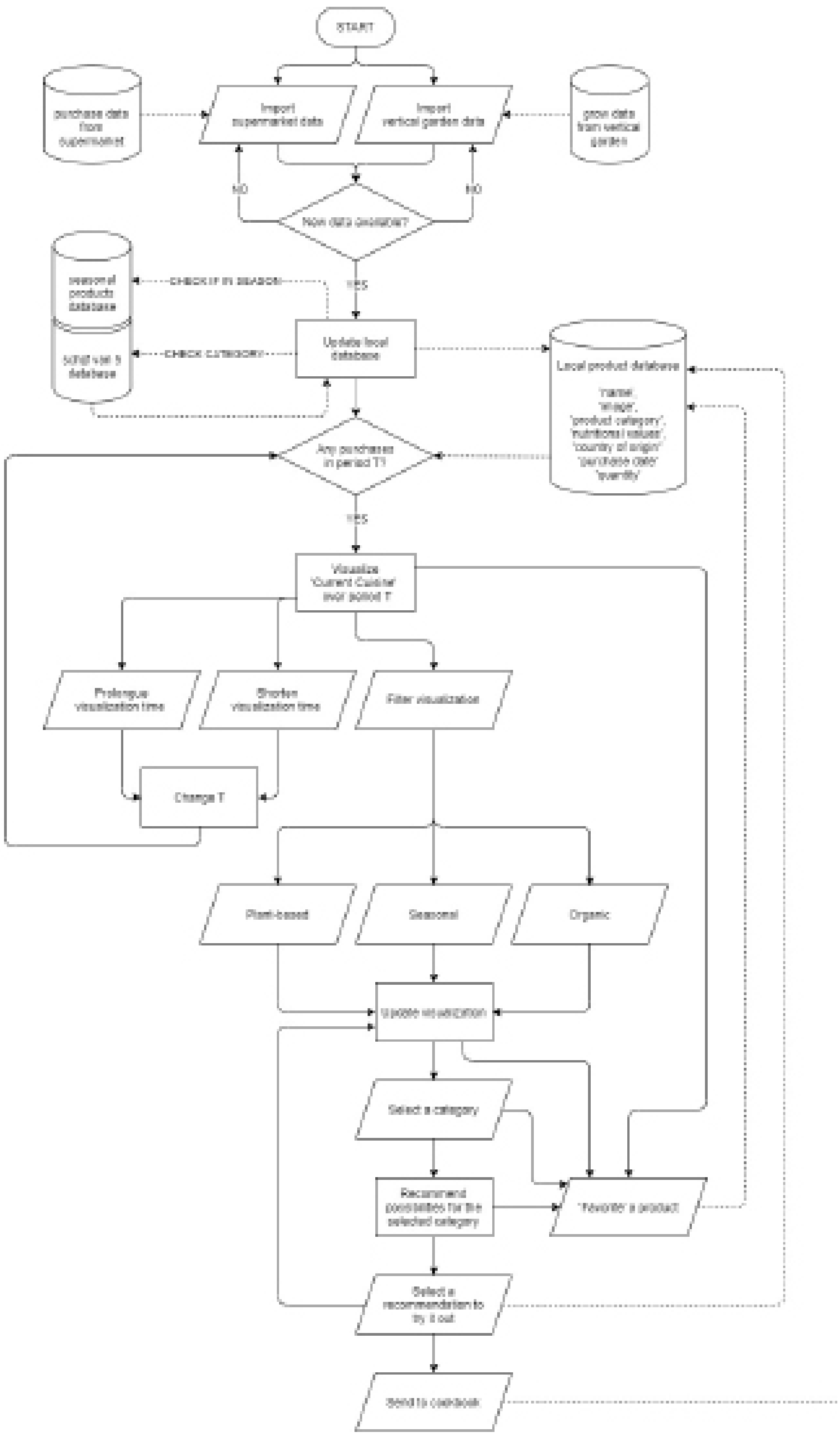
Appendix H - Github

The Github can be found at:

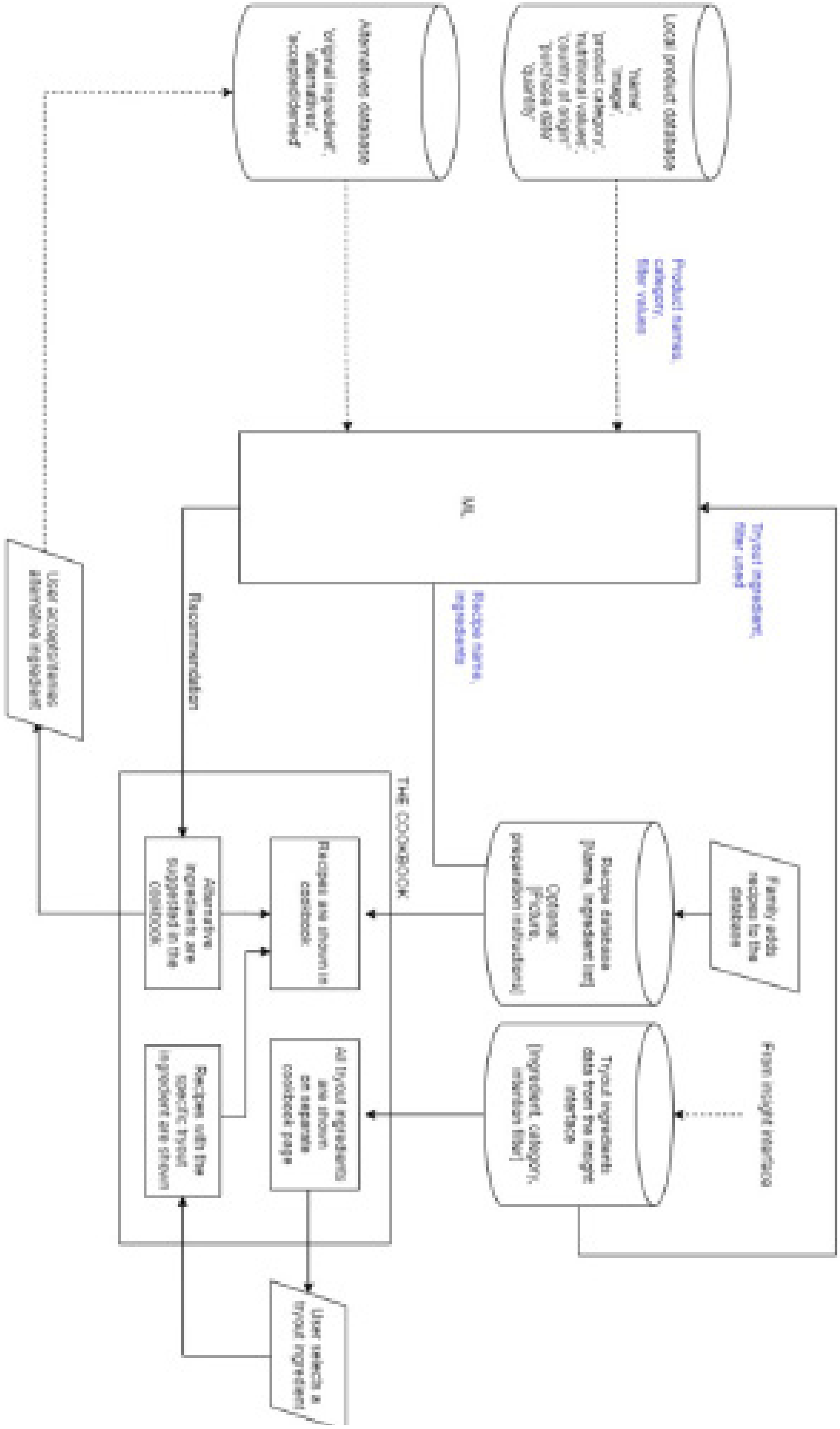
https://github.com/jorritvanderheide/human-ai_collaboration_in_the_kitchen

Appendix I - Programming flowcharts

Insight interface



Family cookbook



Appendix J - Product descriptions

Insight interface

Goal: Support households of the future in making substantiated food choices by providing them with explicit insight in their household cuisine → create awareness

Functionalities:

- Give overview of household cuisine
- is categorized in food type categories (schijf van vijf)
- Allow users to give input about their intentions in:
    - sustainable behavior
        - seasonal products
        - local products
        - more plant-based (less meat & dairy)
    - healthy behavior
        - ratio 'schijf van 5'
        - nutritional values
        - healthy alternatives
- Show progress of intentions
- Allow user to build their own household cuisine

Input:
Shopping list (from supermarket)
Family recipes (from cookbook)
Ripe groceries (from vertical garden)
Intentions (from user)

Output:
Overview of household cuisine (to user)
Intentions from user (to cookbook)

Intended use:

	Individual	Family
First use (0-2 months) Establish family cuisine Form intentions	Uses the system to gain initial insight in what products are consumed by the family and their own influence/role in this (based on their habits) Start reflecting on family cuisine & thinking about personal intentions	Use the system to gain initial insight in what their dietary patterns Start initial discussion on family cuisine & collective intentions for change
Short-term use (2-6 months) Develop family cuisine by implementing intentions	Uses the system to get insight on development of the household cuisine to reflect on their intentions/contribution for the long and / or short term	Uses the system to get insight on development of family cuisine to discuss their intentions for the long and / or short term → food for discussion
Long-term use (>6 months) Use the family cuisine for ... Broaden (diverging) family cuisine through exploratory recommendations Further explore new tastes and products within and beyond the household cuisine	A strong sense of contribution and preference in the family cuisine is established. The system is used to maintain this cuisine or reflect or identify necessary smaller changes	A strong basis for the family cuisine is established. The system is used to maintain this cuisine or identify and discuss necessary smaller changes

Family cookbook

Goal: → give concrete tools for developing household cuisine based on intentions

- create an overview of the ingredient pairings/dishes that are part of the household cuisine
- support implementation of personal health/sustainability goals → further developing family household cuisine
- stimulate people to get out of their comfort zone

Input:
Personal health/sustainability intentions (insight interface)
Family favorite recipes (from user)

- ingredients
- amounts
- preparation instructions (optional)
- photo(s) (optional)

Output:
Recommendations according to intentions (to user)

- different products to buy, not related to recipes → inspiration page?
- different products to swap out ingredients from a recipe, based on season / plant-based / health etc. (intentions). → place at the recipe page

Intended use:

	Individual	Family
First use (0-2 months) Establish family cuisine recipes	Users think of recipes to add and can add these recipes. Users can add individual notes/photos/reviews/proposed changes to recipe pages	Discuss which recipes to add. Collectively add the recipes that are already often used within the household.
Short-term use (2-6 months) Develop family cuisine recipes Support day-to-day implementation of family cuisine and its intentions	The initial cookbook content is established and the user can explore how intentions can change their cuisine. They can still add recipes, and can use the cookbook to use as inspiration for what to eat. Users use recommendations to further develop favorite recipes/create new recipes	Reflect on the development of recipes/new recipes that have been tried out using the recommendations
Long-term use (>6 months) Further explore new tastes and products within and beyond the household cuisine		

Appendix K - Databases

For the databases, see Github:

https://github.com/jorritvanderheide/human-ai_collaboration_in_the_kitchen/tree/main/databases

Appendix L - Questionnaire

For the questionnaire, see the link below:

https://docs.google.com/forms/d/1cUyFEOTAzw4bSBaKVempHvJoDbZhAu-jTURY2eEreom0/edit?usp=sharingtree/main/databases