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WHAT'S FOR DINNER

Project
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Abstract

Aiding recipe selection during busy working days can possibly enhance the experience of cooking and improving recipe variety. Simultaneously the cognitive load required to contemplate about different dishes is reduced. This paper presents a design process in which the behaviour of working couples and individuals are explored with regard to cooking and recipe selection. A triangulative user research was conducted, providing several insights into the process. A design is proposed, which offers personalized recipes based on user preferences, and previous experiences through a machine learning algorithm. Different levels of interaction intensity have been explored, and are used in the design to offer the user different levels of control. Also, different designs and materials were explored to optimize the design for its context. Afterwards a small user study has been conducted to evaluate the experience of the design. This study revealed interesting insights and opportunities for the future work.

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Introduction

"Household food practices are a complex set of routines, including food purchasing, preparation, and consumption." [7] Everyday, these routines are influenced by all sort of factors like time, weather, company, diets and more. Research on everyday cooking has shown that dinner decisions are often made right before dinner. At this point in time hunger decreases one's ability to think creatively or conscientiously about what to eat. Therefore, dinner decisions are made based on convenience, resulting in recipes that are tasty, quick and cheap. However those recipes are often not in line with personal values around health, variety, and ingredient choice. Next to convenience, familiarity is a major influence in the decision process. Although this often leads to repetitive eating since people tend to use the same palette of meals every week [20]. Research among 3344 Dutch participants has shown that they know (on average) 5 meals by heart [21]. This means that the variety based on familiarity will be very minimal, creating a relatively high threshold for varied dining.

The aim of our design is to decrease the cognitive load around this dinner decision, resulting in healthier and more varied dining. Hereby we focus on people who work (semi) full-time, since we believe the challenge of making proper dinner decisions is bigger after a day of hard work. Within this group the design is aimed at people who live alone or as a couple. This decision has been made since family settings (especially with young kids) are a large influence on dinner decisions and outside the scope of this design process.

This paper describes the current state of the art around 'stock management' (purchasing), 'recipe selection' and 'recipe execution' (preparation). Qualitative user research has been conducted to explore the behaviour and values of the selected target group within this context. Based on the insights of this research several design iterations evolved, which led to a final design proposal. Elements of this design have been evaluated in a small user study leading to interesting insights for the future.

Figure 1. Daily Dinners

Theoretical Background

As eating habits and preferences differ between people. It is important to validate the obtained insights of studies. Triangulation is used to do so. This method has been described by Denzin [8], stating four types of triangulation all implemented in user studies of social sciences. Triangulation is a method where different methods, insights, approaches and other inputs are used upon the same subject to validate the different outcomes. This relates to methods, sources, analysts, and theory/perspectives. Triangulation with regard to methodologies is used the most frequently, as it provides insights upon the difference in research results. The other methods of triangulation are used frequently, but might be less evident. To ensure that the user research executed in this process is valid the method of triangulation is applied multiple times in order to validate research outcomes.

Machine Learning

As eating preferences differ per person, a lot of variables are required to be taken into account. It is important to match these preferences without overburdening users with different parameters. Machine learning can be used to learn about habits, simplifying the process of matching a system to a specific user. Machine learning enables systems to perform a certain learned action despite the fact that the machine is not programmed to do so explicitly. It allows products to perform actions that would have taken an extensive amount of time when programmed manually. Machine learning is implemented to recognize voice, calculate routes, and recommend movies and songs. There are various machine learning methods and algorithms. One of them is supervised machine learning wherein the machine is able to figure the predicted mapping of input units and output units out by itself [13]. A regularly used learning algorithm is the k-Nearest Neighbors algorithm. Using this algorithm, the past experiences are mapped in relation to several input features. When the system requires a recommended output, the features are measured and the k (amount) closest experienced outputs are selected [15]. This can be used in combination with content-based filtering, wherein the past-results are compared to find overlapping output features [17]. This can be used to create a proper item profile. This profile is compared to various output options, and the best match is selected as recommendation and communicated to the user. Because the project is about given a personalised dinner suggestion, machine learning will be helpful to improve the provided recipe suggestion over time.

Interaction-attention Levels

Different types of designs allow for different types of interactions. When looking at interactive systems the majority of interactions take place in the centre of attention, respectively called 'focused interactions'. On the other hand, an increasing amount of smart systems are developed to act autonomously. This allows users to interact with these systems without paying any attention to them, the so called 'implicit interactions'. Next to these two extremes, research is done on whether it is possible to have the interaction with digital information and smart systems in the periphery of attention, enabling so called 'peripheral interactions' [3]. The combination of these three types of interaction, focussed; peripheral and implicit (and everything in between) is called the interaction-attention continuum (Figure 2). This continuum is built on the idea that design should allow shifts between different types of interaction, based on the need of user(s) [4]. What we propose should reduce the time required to make dinner choices but not limit the user, which is why the interaction-attention levels will be used. This will provide the user the ability to interact with the design to an extend as he desires, where a more focussed interaction will result in more specific recipe suggestion control.

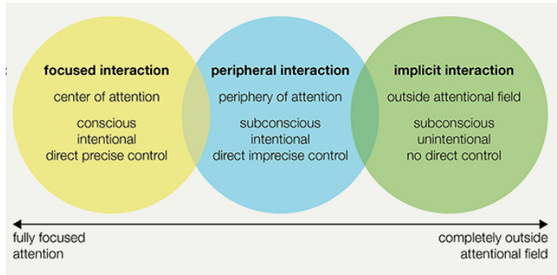

Figure 2. Attention-Interaction Continuum [4]

Related Work

Within the kitchen context many innovations are possible and explored for the entire cooking process including: stock management, recipe selection and recipe execution (cooking). Furthermore there is a growing market for services such as foodboxes. These boxes, if used daily, take away both stock management and recipe selection. After selecting some preferences online, a box with all the ingredients and recipes needed (for a week) is delivered at the doorstep [6]. One of the most known examples are HelloFresh boxes (Figure 3) [19]. However some people, especially non-regular subscribers, experience trouble with those type of boxes because of misalignment with delivery timing and their schedule [11]. Furthermore many people experience those type of subscriptions as too expensive in comparison to 'general' grocery costs [22].

Stock Management

Currently designed 'smart fridges' offer the possibility to have a look inside your fridge when standing in the supermarket. Via a smartphone application one can access a camera inside the fridge to see its content (Figure 4). Which can prevent one from buying items they all ready have in stock [23]. Some designs even offer the possibility to make a shopping list or select a recipe on the fridge itself, via a touchscreen that is inserted in the door [14].

Figure 3. Hellofresh Box [19]

Recipe Selection

The more traditional way of selecting recipes is by using cookbooks. However these books don't offer the possibility to quickly filter information based on preferences. Currently there are hundreds of smartphone applications for searching recipes, which allow more searching and filtering functionalities [16]. Most of these applications work in a similar way; Users can select one or more ingredients, the type of dinner (starter, lunch, main dish etc.), the kitchen, certain diets or even the available time available to cook. Based on these preferences recipes are presented, usually ordered by rating. Some applications also have a form of user feedback, where one can score a dish, save favourites or to like. Often these reviews are visualized with the dish as well, creating a sense of community feeling (allerhande for instance shows a five-star rating system with every dish[1]). Most of these functionalities are offered through websites as well, however applications are more phone-friendly and thus more appropriate for its context (supermarkets and kitchens). Next to these many websites and applications there are a few more physical designs. One example is SuChef—an in-kitchen display that shows a list of everyday meal suggestions to help users find cooking inspiration [20]. However often, similar designs are kept conceptual due to its high development and production costs. Resulting in various research prototypes and only a limited amount of commercial products.

Recipe Execution

While cooking, several steps are necessary such as: weighing, cutting, baking etc. Many people use more low-threshold and cheap tools for this (scales, kitchen timers etc.). However there are more complete and intelligent products for this as well. Some designs offer the possibility to weigh and bake at the same time (Figure 5) [2]. Based on selected recipes these designs give feedback on the right amounts per ingredient, the desired temperature, the cooking time or even seasoning. Next to these 'smart stoves' there are 'smart cutting boards' that offer similar functionalities with respect to amount and seasoning (Figure 6) [24].

Ideating

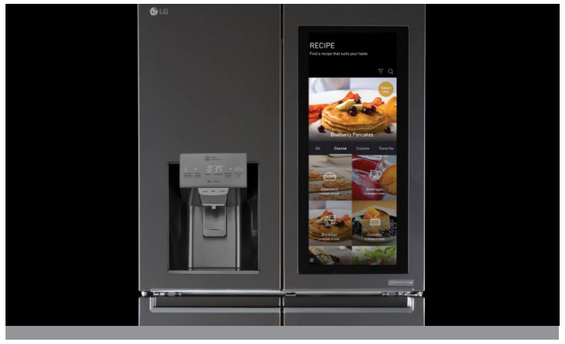

Figure 4. Smart Fridge [23]

Figure 5. Smart Cooking [2]

Figure 6. Smart Cutting Board [24]

This selected target group for this design process consists of singles and couples working semi-full time. As the design context is generally relatable, various hypothetical design opportunities and directions were explored, with the specific target group in mind.

Hypotheses

As starting point of the design process several hypotheses were formulated:

Stock management

Often, the real recipe decisions are made in a supermarket. On that moment, it is difficult to remember the stock at home. This might result the purchase of a product that was already in stock at home. This will be especially relevant when cooking for more people than normal, as it might be difficult to estimate the required amounts of ingredients.

Recipe exploration

It is expected that people often are in a hurry and they do not invest a lot of time in the selection of a recipe. Also, it is expected that recipes are chosen based on memory or previous experiences, rather than scrolling to a list of recipes on apps or websites on general basis.

Cooking timing

While cooking in a hurry, it can be difficult to time the preparation of the ingredients. This is especially relevant for multi-pan cooking. For example, when cooking a curry with rice it might be difficult to ensure the rice is cooked at the same time the rest of the ingredients are cooked-through.

Order of cooking

It can be difficult to determine the correct order of ingredient preparation, especially while cooking an unfamiliar recipe. More concrete, you might forget to marinate the meat before cutting the vegetables, resulting in minimal meat ;marination and thus a meal of less quality.

User Research

In order to confirm or decline the stated hypothetical opportunities and directions, a user research was conducted among the selected target group.

Setup

As the research was used inspirationally and to possibly confirm the stated hypotheses, a qualitative research method was selected. Next to this, the research was required to provide insights upon possible machine learning features. The defined context is a broad topic, relevant for everybody, but experienced in different ways. Therefore, the research is approached from different angles using triangulation, as described in the theoretical background of this report [8]. As cooking habits were examined qualitatively, it was important for the participants to feel at ease to share their habits at their own pace. In order to do so, cultural probes were selected to trigger participants to participate actively [10]. The first component of these probes was a high quality journal. The journal was personalized, and contained a small daily questionnaire, inspirational recipes, information and a herb, star anise, that they could use (Figure 7).

Next to this, a personalised website for every participant (or couple) was developed, allowing them to upload daily photo of their meal (Figure 8). This will provide clear insights into the participants' cooking behavior.

Next to this a contextual inquiry was chosen in order to allow the researchers to ask the participants about 'why' they acted in a certain way. During the inquiry it was the intention to attend the entire cooking process: recipe selection, grocery shopping, cooking, and eating.

The probes were distributed among 6 participants (3 singles and 3 couples, where couples were counted as 1 participant) over the course of 5 days. The participants were accommodated throughout the Netherlands, and the contextual inquiry was conducted on different moments throughout the duration of the study (Figure 9).

Figure 7. Cultural Probes

Figure 8. Photo Challenge

Figure 9. Contextual Inquiry

Findings

Over the course of a week 30 photos of meals were collected (5 for each participant or couple). These photos were logged for the moment and date on which they were uploaded. The photos were mapped along the week to observe cooking behavior. This data was combined with the logs from the data collected during the contextual inquiry. The data was used to find overlapping and reoccuring observations, in order to assess their relevance. These inquiretic findings were combined with input from the diaries, in which a.o. the recipe related satisfaction was stated, in order to conduct a thematic analysis [5]. Reoccuring observations and findings were categorised under the following themes:

- Recipes become more extensive/special when guests are coming over
- Recipe instructions are only used when extremely important (e.g. minutes and temperature when cooking chicken in the oven)
- Recipes are used for inspiration in the form of ingredients
- If new recipes are satisfying, they are saved and used more often (both physically and digitally)
- Timing of cooking is done by intuïtion, or by tasting
- Healthiness of a recipe is an important variable while selecting one
- Groceries are done for one or multiple meals
- Recipes are selected based on a certain preferred ingredient
- When in doubt upon current stock state, the product is bought to be sure
- There is no need for another app regarding recipes

Discussion

The triangular approach proved to be successful, since it offered a diverse amount of data. The collected photos resulted in the finding that pre-cooking (defined as cooking for multiple days) is something that mainly occurs at people living alone.

Based on the findings, it can be concluded that more complex recipes are explored when guests are coming over. This change is found to be positively linear, as the recipe becomes more special as the guests are more special as well. This offered an interesting machine learning input feature, as a calendar can be used to read out activities and thus potential guests.

A finding that came forward from the contextual inquiries implied that recipes are not used for the instructions on the recipe within the selected group. Recipes are used to be inspiring; they show a suggestion (e.g. pasta) and the ingredients. The participants stated that they are able themselves to choose the correct order and timing of cooking/slicing the ingredients, and barely use the instructions. Which results in contradicting the stated hypothesis "Order of cooking" and "Cooking timing". On the other hand, it can be disputed whether this insight also holds for less-experienced cooks as the skill or experience was not assessed.

"Stock management" was confirmed to be a problem of the participants. However, this was not something they experienced as annoying, as they bought the product to be sure. This mostly related to herbs and other non-perishable groceries. However the stock of the user could be an interesting machine learning input feature, as this potentially prevent the user from overbuying products.

Some participants have a standard set of dishes that they cook repetitively, partly confirming the hypothesis for "Recipe exploration". New recipes were mostly explored when they had plenty of time to cook (the weekend), especially when guests were coming over. A machine learning input feature can be derived from this finding, as the preference of previous recipes can improve the overall knowledge of the system.

Conceptualising

As the previously mentioned study resulted in multiple design opportunities. An iterative design processes was conducted. During these iterations, there was a focus on the facilitation of interactions dispersed along the interaction continuum. This would allow the future user to provide the system with enough detail in order to specify its preferences, without continuously being burdened with extensive interactions.

First Iterations

The results of the first phase of iterations are described below, supplemented with small points of reflection.

Herb Rack

A herb rack (Figure 9), which is able to suggest certain herbs based on the current recipe cooked. Machine Learning could be implemented by remembering the preferences of the user, e.g. "does the user like spicy food?" by implementing a feedback loop into the system. The iteration was thought to be to specific, and did not allow enough value to the projected user as preferences can be found easily by experimentation.

Stock Monitoring

Using a product/inventory scanner (Figure 11) and dedicated locations of certain ingredients, machine learning can be implemented to monitor the stock of certain ingredients and communicate this to the user when something needs to be bought. Despite its functionality, the product is thought to offer to little value for the amount of effort needed. The ability to keep track of the stock was thought to be interesting, but another forms of interactions to implement this idea are required to be explored.

Phone Applications

Multiple ideas were envisioned as smartphone applications. For example, a smartphone application wherein recipes are suggested which could be liked or not. Through machine learning, the suggested recipes could be improved over time as the user would provide more input over the accepted or declined recipes. Another idea involved a layered choice system (Figure 12), in which the user could first select its prefered carbohydrate (rice, potato, grain etc.) category. On selection, ingredients that are suggested with this choice are shown as an combinational option to give the user more control over the chosen ingredients. If the user demanded more control over the selected ingredients, he or she would have to put more effort into the interaction in order to choose more ingredients.

Recipe Printer

A basic ticket printer (Figure 13) was designed to provide the user with a basic recipe description. It was however disputed how these recipes would be selected and how feedback would be provided to the user. One of the explored methods to provide feedback involved a smart table mat on which the user would be able rate the recipe after dinner. It was however disputed whether a 5-star rating, which was used in the design, would be enough to provide the system with enough feedback regarding its recipe suggestion.

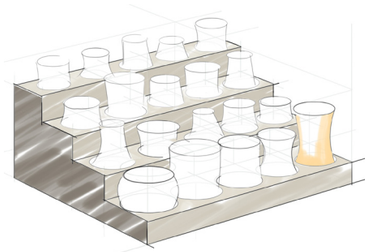

Figure 10. Herb Rack

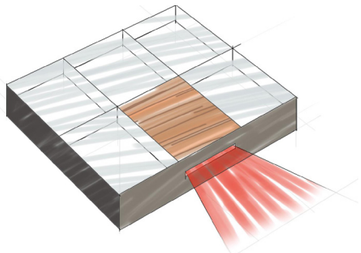

Figure 11. Stock Monitoring

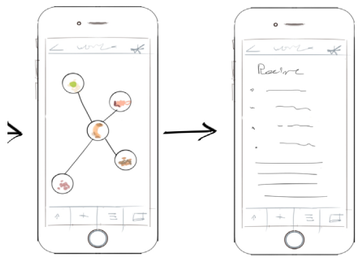

Figure 12. Phone Applications

Converging

The printer was thought of an interesting starting point for a design. But despite this fact the provided input by the user was still underdeveloped. The insights of the previous phase where implemented into a new iteration (Figure 14). The design facilitates different levels of interaction, allowing the design to shift along the interaction continuum in order to properly match the interaction to the demands of the user.

Implicit Interaction

A recipe suggestion is made based on machine learning, with cooking habits and recipe history as machine learning input features for its (to be defined) algorithms. The recipe does provide a small description of the meal (e.g. pasta with spinach), but exact instructions are left out; as most everyday recipes are so simple that they do not occur in regular cookbooks [20]. The provided recipe consists of a grocery list of products, potentially excluding the products in stock (based on machine learning), required to be bought. The list is printed on a physical ticket, as it allows the user to recall the groceries while shopping without using their phone and opening a specific application.

Peripheral Interaction

As our study concluded, recipes are often selected upon one preferred ingredient. An interaction was designed to enable the user to indicate this preferences. This could be done by shifting one of the pillars (equals an ingredient) towards the ticket. As some pillars (for often used ingredients) are taller, the interaction to indicate these ingredients as preference is easier.

Focussed Interaction

Furthermore, the design allows more extended recipes, selected in full detail, as well. This is especially relevant when special guests are coming over, according to our conducted user research. To address this need, a focussed interaction was designed. A supplementary smartphone application allows the user to select detailed preferences or an entire recipe. The recipes' grocery list is printed which can be used in order to ease the process of grocery shopping.

Reflection

The design was thought to be an interesting next step in the process. However, the representative ingredient pillars required improvement as it would require the user to extensively search for a certain ingredient in order to (de)select it.

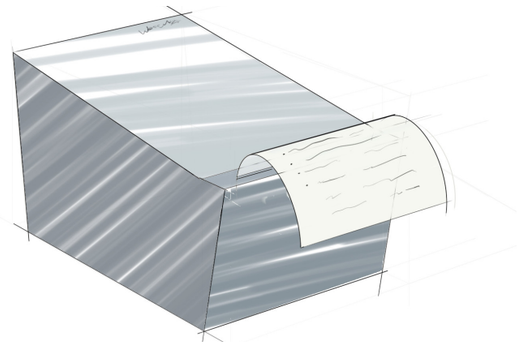

Figure 13. Recipe Printer

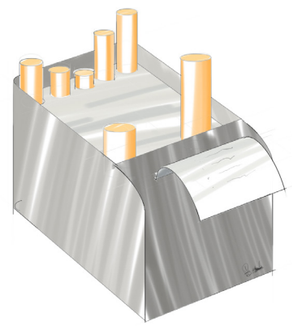

Figure 14. Converging Concept

Mid-term design

The findings of the process described above where used to conclude in a mid-term design iteration Figure 15). This iteration was similar to the converged design iteration with regard to the focussed and implicit interaction. On the contrary, the peripheral interaction changed almost completely. The looks of the device changed as well, in order to create a intuitive experience in which the interaction could stay peripheral.

Changed Peripheral Interaction

After several iterative interactions, it was decided to offer the user a limited amount of control regarding prefered ingredients. In early iterations, the user would be able to indicate the preference of every possible ingredient. This would have resulted in a tedious process to find every ingredient, and indicate the preference accordingly. It was assumed that most recipes are selected based on their carbohydrate ingredient (for example: pasta, rice and potatoes) and meat (for example: cow, fish or meat replacements). This resulted, as can be seen in figure 2, in two respective distinct rows. The provided ingredients on the toggles are interchangeable, as the user is able to print prefered- or most used ingredients. An implicitly optimized recipe is printed, where upon the user can provide feedback by tumbling one or multiple toggles. In order to simplify the process of providing feedback to the system, the toggles representing an ingredient provided on the recipe will light up. Based on the provided feedback, the design will print a new and better matching recipe.

By facilitating these types of interaction, the user is able to choose the amount of effort put into the interaction and its respective level of control. As the interaction with the product becomes more detailed and focussed, the control of the printed recipe increases. Although the user was able to switch between the three interaction types, the way it was integrated into one was lacking a lot of subtlety and felt like three separate things molded into one design. The integration between the different interaction states of the design lacked, providing an input for a next design iteration. The currently chosen machine learning inputs, cooking habits and recipe history, needed a redesign as well as they were thought to limit the amount of learning behavior and recipe variety. The peripheral interaction was thought to require a large cognitive load in order to provide simple feedback to the system, offering room for improvement.

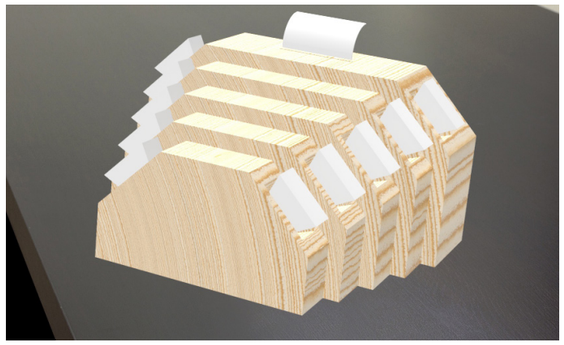

Figure 15. Midterm Design

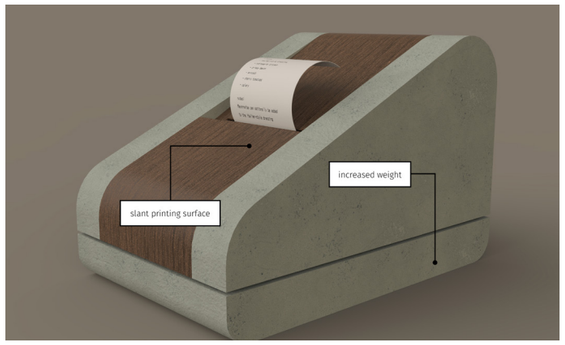

Figure 16. Final Design Render

Final Design

The processes' insights were combined into a final conceptual design. The design focuses on an easy, peripheral interaction while providing a personalized, fitting recipe suggestion. A recipe is presented on a physical ticket, which the user can easily tear off the design. The information presented on the recipe is minimal, as our user study revealed the insight that detailed recipes are barely used for their instructions. The ingredients used in the dish are presented next to a basic recipe description, making the ticket ideal for doing groceries. Apart from this, important information (oven temperature and time, for example) is presented to ease the cooking process without over informing the user with unnecessary information.

The design will always present a ticket, making it as easy as possible to tear one off when in a hurry. The device will immediately start printing a new ticket when the ticket has been teared off. If the user has time on its hands to explore different recipes, does not feel like eating the suggested recipe, or wants to do groceries for multiple days, he or she can grab as much tickets as he or she would like to explore and/or select multiple recipes.

The printed recipes are personalized based on several inputs. First of all, the user is able to provide a user profile through a supplementary smartphone application. Within this user profile, allergies and preferences can be communicated to the design. Next to this, using K-nearest-neighbors and content-based filtering machine learning algorithms an optimised recipe is provided based on the current windchill temperature and day of the week. There is a distinction made in the day of the week, making it relevant whether it is almost weekend or not. From our study, it came forward that it is important for the suggested recipe to differ depending on whether it is a working day or not. Through the stated phone application, the user is able to enter its working days improving the accuracy of the provided recipes.

For this design, it is assumed that the bought groceries are communicated to the design. This information is used as feedback for the machine learning system. This can be achieved through various methods, for example: a smart fridge which recognises the products placed or a phone application in which the bought products can be entered. Better yet, a connection with grocery shops can be made. Grocery shops often offer a customer's card, which is used for discount and registering customers buying behavior. The knowledge of the bought ingredients are used to evaluate whether the provided recipes where used, adjusted, or not used at all. This will enhance the quality of the provided recipes over time. Also, if the feedback to the system is provided through a customer's card. The design could provide recipe suggestion based on the current products in discount as well.

The supplementary application provides various functionalities. Next to the stated user profile, the user is able to save their favourite recipes if the recipe is liked a lot. Also, the user is able to request more cooking instructions regarding a previously printed recipe when he or she needs more guidance while cooking.

The design would not necessarily be placed in a kitchen. However, it is projected to be placed on a table, cabinet or another similar hip-heighted surface. In order to simplify the reading of the recipe in the periphery of attention, a slant printing surface has been designed (Figure 16). Also, the design is partly made out of concrete to make the design increase in weight. This is necessary, as the device would otherwise be torn of the surface due to the ticket tearing interaction.

Prototyping

In order to increase the weight, required by the tear off interaction, both the bottom and the sides of the prototype are made from concrete. To achieve the desired shape of these parts, a 3D model was created. While designing the 3D version of the prototype, the basic mdf thicknesses were kept in mind to simplify the realisation process. The 3D model was used to create laser cut mdf slices, which were glued together and sanded in order to match the desired thickness. With the mdf model a vacuum formed mall was created. Which was then filled with concrete mixture. After 24 hour the parts could be extracted which are completely made out of concrete, to create the heavy look which was desired. The described steps for creating the concrete shape are shown in figure 17.

In order to house the electronics, the middle section of the prototype was made from a laser-cut skeleton. To make the printer, which is mounted in this skeleton, easily accessible the wooden shape consists of two parts. This makes the process of changing paper rolls easier. To cover up the mdf a thin piece of wood was bend into the curvature of the device. This was done using the heat of an ironing iron, water, and lots of patience. This piece of wood was then stained and glued to the mdf. The back part is used as cover for the electronics and printer. Between the two parts a small gap is created to create room for the sensor which can detect receipts on the design. In order to cover the sensor, a piece of perspex was coated black and placed in front of the created gap. The steps for creating this wooden shape are shown in figure 18.

Figure 17. Concrete Shape

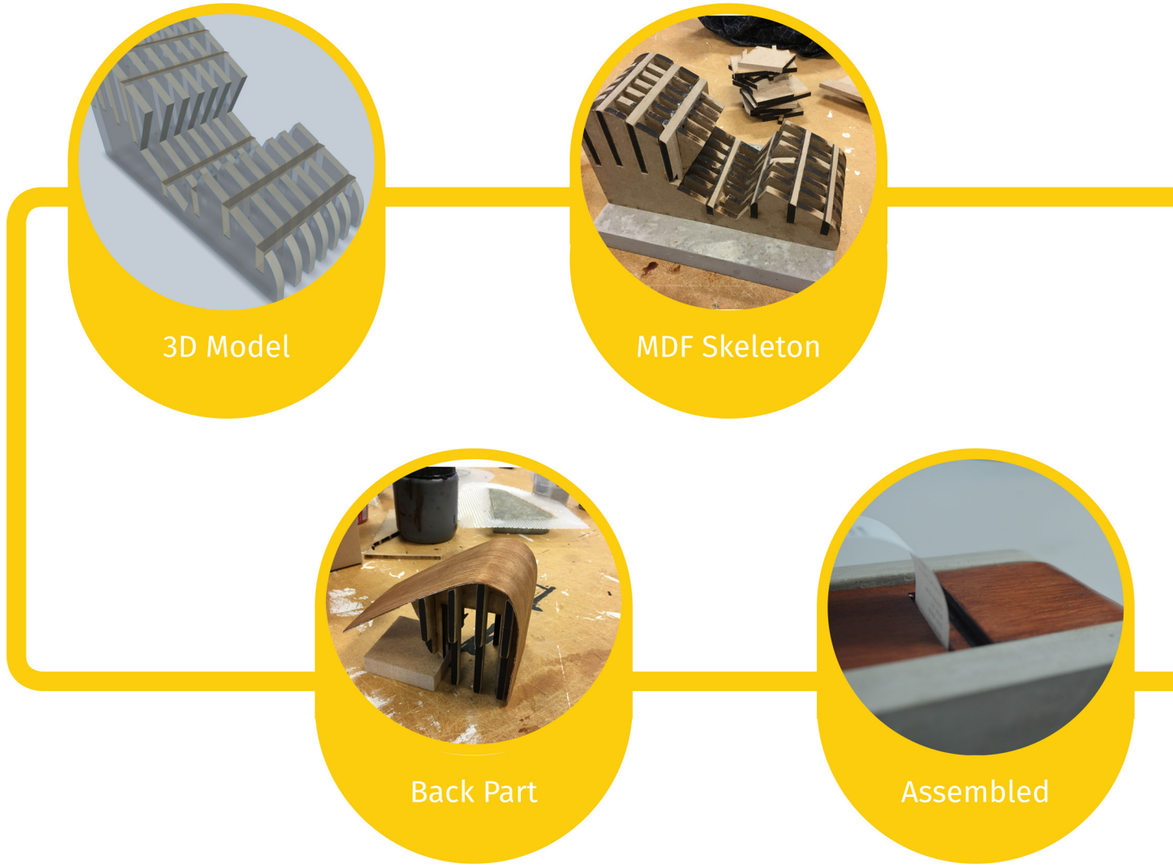

Figure 18. Wooden Shape

The electronics of the prototype were developed prior to the prototype. There were a couple of aspects of the design that were required in order to realise its functionality:

Mini printer
A microcontroller compatible ticket printer, which was compatible with platforms like arduino, was bought and tested.

Microcontroller
In order to drive the mini printer, a microcontroller (wemos d1 mini), was selected due capabilities to easily connect to wifi.

Ticket sensing
Various methods were explored in order to explore the sensing of the ticket. Initially, a LDR was used beneath the ticket which would provide less resistance as there would be no ticket to block the light. Eventually, a IR distance sensor was used, as it was influenced less by external factors (e.g. sunlight).

Database connectivity
The microcontroller was required to be able to fetch recipes from a database and print them. The microcontroller was connected to wifi, which allowed for an online database to be developed. As mySQL [9] is the most popular (properly online documented) open source online databases, it was selected as a mean to develop our recipe database. The microcontroller was able to request a recipe by executing a http-request to a php file on the same server as the database. The php-file would fetch a recipe from the mySQL database and return it back to the microcontroller, which would eventually print the recipe on the physical ticket. For exhaustiveness, the server runs on Linux with Apache installed, and the design relies on MySQL and PHP to request the recipe. This combination used to facilitate online services is referred to as a LAMP-stack [11] and is implemented and functioning in the prototype.

User Study

In order to test the user experience of our design a small user study has been conducted. The aim of this study was to evaluate how (and if) the given suggestions influence dinner decisions and therefore stimulate more varied dining.

Setup & Approach

During this study one participant tested a simplified prototype (Figure 19) of the design for a period of five days (three free days and two working days). This prototype works similar to the design in the sense that it prints simple recipes on little receipts about ten seconds after the last receipt has been removed. The physical prototype connects (via wifi) to an online database with 44 different recipes. Each recipe consisted of an unique id number, a title and cooking time in minutes. As previously mentioned, the recipes only showed a minimal description of the recipe. Next to this the recipe has a ranking number (ranging from 0-10), scoring the recipe based on whether it has been rejected often. Next to this a variable 'days ago', which represents the last time it has been printed is taken into account. The sum of the variables 'ranking' and 'days ago' are used to determine the selected recipe. The prototype will print the recipe with the highest 'sum', which is a different type of selection than the earlier described machine-learning method (based on K-nearest neighbor and content-based filtering.) which will eventually be implemented in the concept.

Before the user study the database had been manually adjusted in order to test the experience of a personalized recipe suggestion as if it were based on a personal profile and a learning period of machine learning. To do so, the 'ranking' and 'days ago' value were adjusted in such a way that the prototype would give recipes that were in line with the user preferences. These preferences were determined based on the data gathered during the earlier conduct user research as described in the design process. While doing so the difference in preference during free days and working days had been taken into account as well as the supplementary smartphone application was not mentioned or implemented in this test, thus disabling the participant to do so.

To gather insights on the behaviour and thoughts of the participant we used a similar triangular method as during the user research at the beginning of this process Qualitative data is gathered through a diary study, a photo challenge and a contextual inquiry (Figure 20). The diary study asked the participant to self-report on the chosen dinner, the made decision, the influence of the receipt and the given suggestions. The photo challenge used a QR-code and a personalized website to ask for a picture of every meal, similar to the initial research. The contextual inquiry took place on the fifth evening of the user study and was used to get more in depth insights. Afterwards a simplified thematic analysis was conducted on the combination of the gathered data.

Figure 19. Prototype User Study

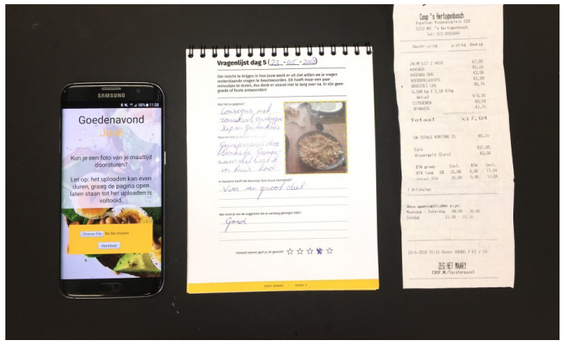

Figure 20. Data Gathering Methods

Findings & Discussion

The user study was performed by one participants, resulting in limited findings as they are the reflection of one participants thoughts towards the presented design. The participant however confirmed that the use of smaller notes on the recipes could be enough to decide whether to cook the recipe or not. Due to personal circumstances, like planned dinner dates, the participant only used the recipes half of the time. However she appreciated the daily recipe and felt like the suggestion was more relevant for her, then if an application or site would give a suggestion. Even when she did not completely agree with the given suggestion she used it as a source of inspiration and adjusted it to her own preferences. From this it can be concluded that the design did succeed in influencing dinner decisions and stimulated the participants to try new recipes. Furthermore the participant stated that she enjoyed the fact that she was greeted with a new recipe suggestion every morning due to its element of surprise. This feeling of surprise was also found delightful by test subject in other studies [25]. However this experience might be influenced by the novelty effect of such a short testing period.

The machine learning aspect of the design was not implemented yet, resulting in no relevant findings on this aspect of the concept. The smartphone application (Figure 21) was also not part of the user study. Despite this fact, the user did indicate that sometimes she felt the need to find out more about the recipe and started searching the web for it. This meant that the way the app was meant to be implemented in the concept would also be desired by the participant, this is especially the case because the participant was not aware of the intended application in the end product. The participant also came up with some features for a smartphone application. These features were already implemented in the envisioned conceptual application. For example, a printed grocery list at the start of the week so that she would have the ingredients already in advance, which is a feature of the application. On the other hand, this would take away the daily element of surprise during the week.

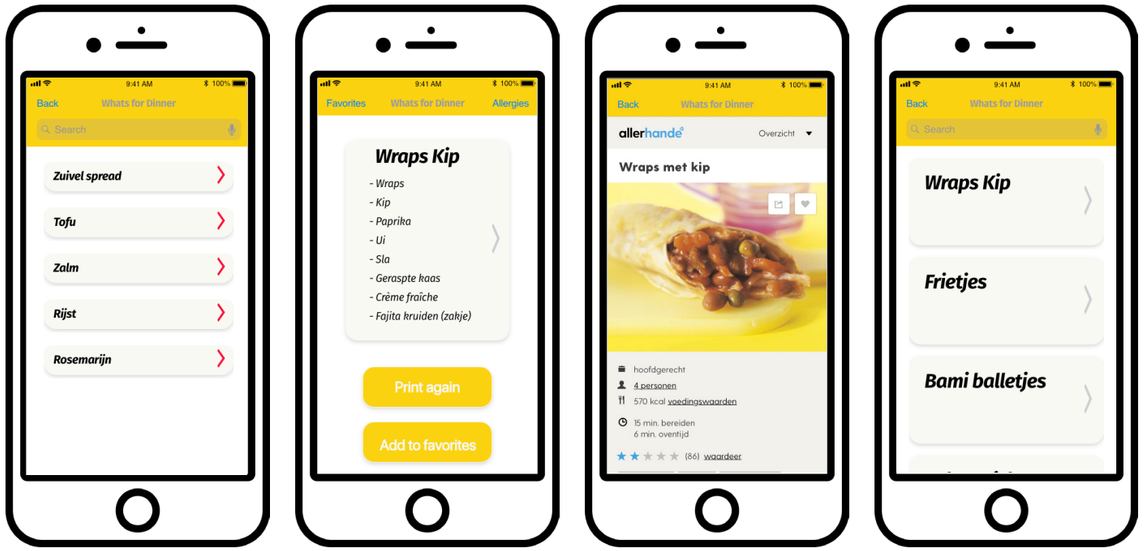

Figure 21. Screens Envisioned Application [1]

Future Steps

Currently, the first iteration of the design has been completed. The machine learning aspect has top-priority to be implemented and tested into the design as next step. Apart from this, the smartphone application should be developed further, in order to make future participants able to set their preferences and save favorites. This will allow them to experience the design to its full extend. Both of these aspects were not required up to this point of the processes, as the printed dinner suggestion experience was designed, implemented and evaluated during the described process. The concept should be evaluated further in future works as the amount of participants was limited. In order to properly test the machine learning aspect, a user study over longer amount of time is required in order to utilise the machine learnings' optimisation capabilities, and counteract the possible novelty effect.

The information of what recipes are bought and cooked is gathered by the shopping info or smart inventory, as was mentioned previously in this report. To obtain this data a partnership with one of the major grocery store would be really helpful. The design could be placed at the entrance of the store, providing personalised recipes to its customers. A change would have to be made upon the users' interaction with the design, as it is required to identificate the user in order to provide personalised recipe suggestions. A possible solution might be to use the grocery stores' customer card. As a result of the partnership, an extensive recipe database would be available to use as most stores offer a recipe serviceonline. This would decrease the development costs of the prototype, as further development of the database would not be required. Also, this would also be beneficial for the grocery store as they would improve the user experience in their store. Using the knowledge of products currently in discount, recipes can be provided which take these products into account. This would entice customers to the mentioned stores as well. The possibilities of such a business model and its opportunities have yet to be explored in depth in future works. This aspect should not be overlooked, as it results will influence the concept in terms of form, machine learning feedback, financial feasibility and user interaction. It has to be evaluated whether the projected user experience is still evident, as removing the concept from the domestic context might cause the loss in the feeling of personalisation.

Conclusion

Based on existing research, related work and qualitative user research an opportunity for design is found within the context of daily dinner decisions. The presented design (Figure 22) aims to reduces the cognitive load around these dinner decisions. Which will result more varied, and therefore healthier, dining. The design tries to reach this aim by providing personalized and optimized dinner suggestions based on a personal profile and machine learning. These suggestions consist of simple recipes and are presented on printed receipts in a domestic context. A small user study has shown that these receipts can trigger elements of surprise and creativity in everyday life. Which was experienced as a positive influence on the experience around dinner decisions. However, a decrease in cognitive load has yet to be found. To evaluate the completion of the design aim, a longer time-period is required to evaluate the design, as the novelty effect of the design might have been a major influence. Furthermore the user study has shown that the design stimulated to try new recipes. Which implies that the use of the design will result in more varied (and therefore healthier) dining.

Figure 22. Final Design

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Appendix