An Architecture for Context-aware Food and Beverage Preparation Systems

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Abstract. This paper introduces a universal architecture for CONtext-aware Food and bEverage preperation System (CONFES) addressing the optimization issue in food and beverage preparation, with the aim of achieving nutritious, sustainable, and tasteful results. The concept is based on a comprehensive review of the state of the art in Machine Learning (ML) approaches for food preparation, and the latest technical developments in Cyber-Physical System (CPS). The system requirements, overarching architecture, essential components, and data model for CONFES are defined, leading to a more concrete case study. The latter describes a context-aware coffee machine as a practical implementation of the proposed architecture. The study demonstrates how CONFES can be customized to meet the specific requirements of a coffee machine, showcasing the adaptability and versatility of the overall architectural framework. The research findings contribute to the development of intelligent and context-aware systems in the domain of food and beverage preparation.

Keywords: *Context-aware systems, recipe recommendation, sustainable food preparation, machine learning, food waste reduction*

1 Introduction

Sustainability is of paramount importance, as demonstrated by the exponential growth in the number of papers published on the subject [1]. Can sustainability and taste be reconciled? Meeting both objectives is challenging, but artificial intelligence could provide a solution.

In this paper, we introduce a concept for CONtext-aware Food and bEverage preperation System (see Definition 1) with the aim to provide consistent taste without being unsustainable. Current research on CPS includes various classes of intelligent systems. However, this is the first time such a system is thoroughly described, so we did introduce the term "CONFES".

Definition 1 (CONFES). *A food and beverages preparation system which is enhanced by context-awareness to adjust recipe parameters for different optimization goals, such as sustainability, nutrition value and taste. This awareness is achieved by integrating user feedback and environmental data.*

At the outset, it is imperative to comprehend the patterns of human taste perception. The perception of taste is subjectively unique, and it varies over an individual's lifespan and throughout the day, depending on the context (see Definition 2) [2].

Definition 2 (Context). *Context encompasses all factors that influence human taste perception, including environmental factors like temperature, weather, and humidity, as well as human factors such as wakefulness, stress levels, and mood [3].*

This paper will detail the factors that may influence taste perception, grouped into *human*, *food*, and *environmental* contexts. Human factors consist of vital signs, expectations [4], alertness levels, mood [5], pulse, hunger [6], and thirst. Food factors encompass recipe, ingredient quantity, food type, food structure [7], food color [8], serving vessel [9], and preparation methods. Finally, environmental factors consist of weather, humidity, air quality [10], temperature [11], air pressure [12], and ambient noise [13].

Sustainability in food preparation is mainly driven by three approaches: amount, type, and preparation method. Using an excessive amount of any ingredient leads to food waste. Therefore, reducing the quantity of individual ingredients that significantly contribute to wastage of water or carbon emissions, can be an effective solution. Coffee beans have a substantial carbon and water footprint throughout the entire production process, from plant cultivation to final consumption. The carbon footprint of coffee ($5.6\,\mathrm{kgCO_2e/kg_{food}}$) [14], as well as its water footprint ($21.000\,\mathrm{L/kg_{food}}$) [15] rank among the highest. To provide a more concrete example regarding the amount of water wasted for a single cup of coffee, approximately 140 L of water is needed - equivalent to the volume of one bathtub. For comparison, for reference, in Table 1 are the values for some other examples according to [14] [15]. The validation of the taste through humans is

Table 1. Carbon footprint of food and beverages

Food	Carbon footprint in $\frac{\mathrm{kgCO_2e}}{\mathrm{kg_{food}}}$	Water footprint in $\frac{\mathrm{l}}{\mathrm{kg_{food}}}$
Beef	13.6	15,490
Cacao	5.0	27,000
Coffee	5.6	21,000
Nuts	0.9	5,000
Tomatoes	0.8	110
Oat drink	0.3	300
Milk	1.7	600
Pork	4.6	4,730

described as multi-sensory perception. Defined as a mixture of the five human senses (taste, sight, touch, smell, and sound). It is important to consider contextual parameters that may influence the overall rating. If a person evaluates food as "very good", this perception is not solely based on the recipe itself, but is also influenced by external factors and the expectation of taste [16]. However, humans excel in detecting bad taste, which stems from the evolution of humans. In the Stone Age, food with a sour or bitter taste was mostly toxic or rotten and could cause illness or death [17]. In terms of ingredient quantity, it is possible

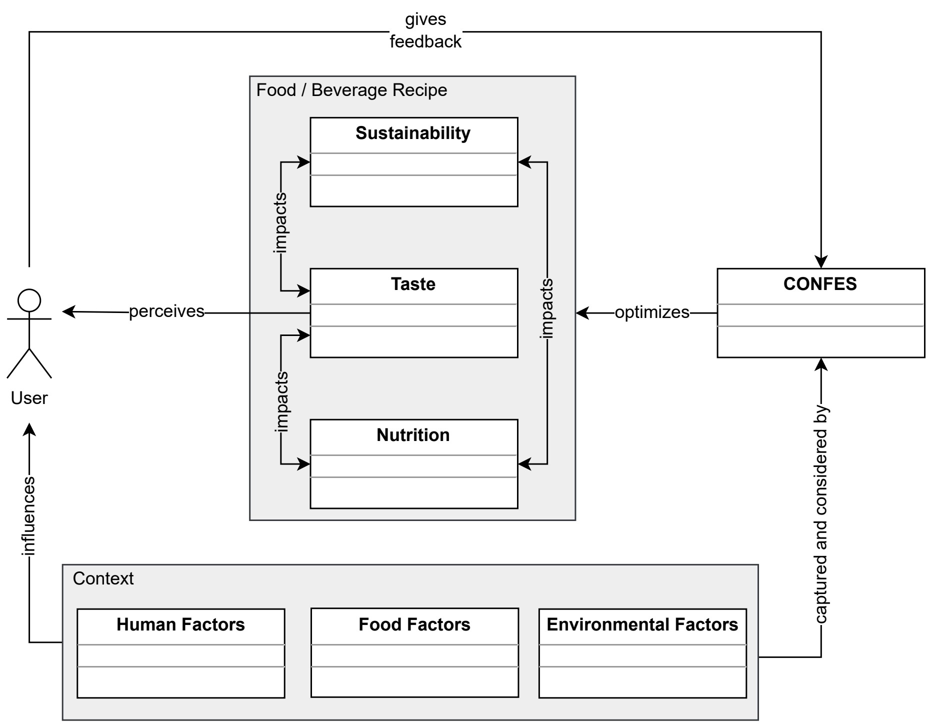

Fig. 1. The environment for the use of CONFES

to have both an insufficient or excessive amount. The quantity of coffee powder used in a cup of coffee affects its taste. The quality of coffee can vary depending on the context, affecting whether it is considered top-notch, satisfactory, or subpar. The aim of a sustainable CONFES is to reduce the amount of an ingredient to a minimum so that the overall result is still good or acceptable. Our work aims to gather evidence demonstrating how ingredients can be reduced, in consideration of the context, to enhance the environmental sustainability of food preparation. Reducing the amount of unhealthy ingredients, such as sugar, in food can improve its nutritional value [18]. This can be accomplished without compromising taste, while improving the sustainability of the food or beverage.

The three competing objectives in the preparation of food - taste, nutrition, and sustainability - are illustrated in Figure 1. CONFES optimizes the recipe with human feedback while considering the context.

2 State of the Art

2.1 Recipe Analysis, Recommendation and Optimization

In the domain of recipe optimization, there exists one methodology that examines whether an ingredient is essential for the overall flavor or texture of a dish or beverage and if so, in what amount. Within this approach, the following cases exist:

1. One crucial component for achieving the desired outcome is absent - it is recommended to include the missing element.
2. An ingredient that does not contribute to the final result is present in the recipe - it is advised to eliminate it.
3. Additionally, a pertinent ingredient is included but in the incorrect amount. It is suggested to decrease or increase the quantity of the ingredient.

The correlation between ingredients is also examined, especially those that frequently appear together within one recipe or if the use of one ingredient excludes the need for another [19]. Another instance of CONFES endeavoring to enhance sustainability in the context of cooking is a refrigerator equipped with content monitoring and a recipe recommendation system. The system keeps track of the contents of the fridge, along with the freshness of the food stocked. The aim of the recipe proposals generated is to utilize all the items in the refrigerator in order to prevent any waste [20] [21]. There is an increasing number of recipe recommendation systems emerging which base their suggestions on the user's past food choices. Users receive an overview of the most commonly prepared meals in their history, and if a meal is chosen again, they are provided with hints on how to alter the recipe. For such recommendation systems, there are various objectives. One way to increase culinary inspiration is to receive feedback on suggested new dishes and uncommon ingredients [22]. Another approach is to prioritize healthier cooking practices [23]. The primary obstacles facing food recommendation systems entail identifying the taste preferences of a user through previously consumed dishes, which may not always precisely reflect their preferences. Additionally, there is the challenge of combining nourishing food with the most palatable flavor [24]. People often fail to optimize their eating and cooking behavior because of habit and inertia to change. This is where such a system can help, as it is more convenient for the user to receive recipe recommendations that take into account the nutritional value of the dish, while at the same time adapting it to personal taste preferences. Normally, people have to acquire a lot of knowledge about food and food preparation to change to a healthier lifestyle; here the system takes over the whole effort [25]. There are many decisions that need to be made when creating recipes. Ingredients, cooking utensils and preparation methods have to be selected, and finally a recipe has to be created. Modelling the quality of a recipe in terms of an objective function is challenging and time-consuming, complicated by the subjectivity of human judgement. To address this problem, Merchán and Molina pursue an approach to generate recipe suggestions using a Machine Learning model and Bayesian optimization [26]. Tasting panels are used to create new food products. Motivated by the high cost and time involved in "trial and error", Zhang chose an approach using a hybrid ML model. The model is trained on historical data to predict sensory ratings. The underlying database consists of information on ingredients, their properties, chemical composition and preparation methods. The taste and evaluation criteria are linked to this data. Compliance with design constraints is ensured by the integration of so-called "penalty functions" [27].

2.2 Food Preparation and Processing

Optimizing preparation through human feedback plays a particularly important role in the vision of fully automated and intelligent robotic kitchens. Advances in robotic manipulation, sensing and ML are making the vision of a robotic kitchen increasingly realistic. The benefit of using robotic chefs that mimic human skills is the reduction of human labor in the cooking process. There is also the potential to improve the dining experience. When learning human skills, the cooking process is simulated and then evaluated by a human. The system learns from this and improves itself. The greatest challenges here are directly related to human evaluation, as various psychological phenomena play a role, such as the urge to give good ratings [28]. Another approach is to use a 'cooking navigator' to help with successful cooking. This is aimed primarily at inexperienced users to help them parallel the steps in the preparation process and thus achieve good cooking results more quickly, but the navigation system is also intended to help experienced users to further improve their cooking skills. Three parameters are always taken into account: The duration of the cooking process, the accuracy of the cooking and the learning effect. The system ensures that the user receives the right signals (i.e. text, video or audio instructions) at the right time. In the first experiment, all chefs were able to successfully prepare two dishes in parallel within the specified time using the Cooking Navigation System [29].

2.3 Sensor Systems to Recognize Food and Cooking Stages

Modern ovens measure temperature and humidity using various sensors. These sensors are crucial in determining absolute values and their fluctuations over time. The gathered data is employed to anticipate the best timings for concluding cooking and baking procedures. A corresponding concept was disclosed in a patent dated 1994, wherein an oven adopts variations in humidity, weight, and the Volatile Organic Compounds (VOC) measurement to determine the optimal moment to complete cooking or baking [30]. Another example for CONFES, are electronic tongue systems, they are based on nanostructured films and impedance spectroscopy. Thus far, they have successfully been implemented in detecting traces of impurities in water and complex liquids, as well as distinguishing between different types of wine and coffee. A major challenge in applying this technology is matching the electric reaction with the human taste perception of experts. One objective of the system is to predict the overall quality of coffee. Hence, the hybrid regression technique is utilized, which is grounded on the random substance method and principal component analysis. As per the study by [31], it produced excellent outcomes; presenting a high correlation between the predicted values and values measured by the tasting experts, with a Pearson coefficient of 0.964. Odor and taste sensors are successfully used today in a wide range of applications. One of these is to detect the freshness of food. An artificial or electronic tongue can be used for this purpose. The development of electronic noses and tongues is motivated by the importance of fresh food. Fresh food plays an important role in nutrition, as consumers are attracted by its high nutritional value, healthy image and appealing taste, which increases demand. The electronic tongue has many advantages over the human taste buds, including the ability to measure toxic substances, provide objective analysis and the fact that it does not cause fatigue [32].

2.4 Architecture of Cyber-physical Systems

CPSs (see Definition 3) are found in a wide range of application fields: well-known examples are automotive systems, medical devices and industry 4.0 facilities.

Definition 3 (CPS). *A Cyber-Physical System is a system of embedded computers and networks (part of the so-called "cyberspace") which monitor and control physical processes, usually with feedback loops where the physical processes affect the computations and vice versa (according to [33]).*

Since it interacts with physical processes (preparation of food and/or beverages) as well as with the cyberspace through electronic embedded and cloud components, a CONFES is nothing else than a special type of CPS.

CPSs need to achieve their tasks efficiently and flexibly all along their lifecycles. For that, they (e.g., automotive systems), should be easily updatable [34] and – in a more general sense – reconfigurable [35]. These properties, as well as modularity, safety and security, must be thoroughly considered in the CPS design. Ahmed et al. introduced in [36] an architecture for unifying the logical organization of the components constituting a CPS (see Figure 2). In this architecture, the *Sensing Modules* and *Actuators* form the interface between the CPS and the physical world. The *Service Aware Module (SAM)* provides the high-level functions for the whole system (e.g., decision-making, task schedule) after receiving the sensed and processed data from the *Data Management Module*. The realization of the different modular functionalities based on the input of the SAM is achieved by the services of the *Application Module*. Throughout the CPS lifecycle, the processed data can be saved in a *Secured Database* (see right-top corner of Figure 2).

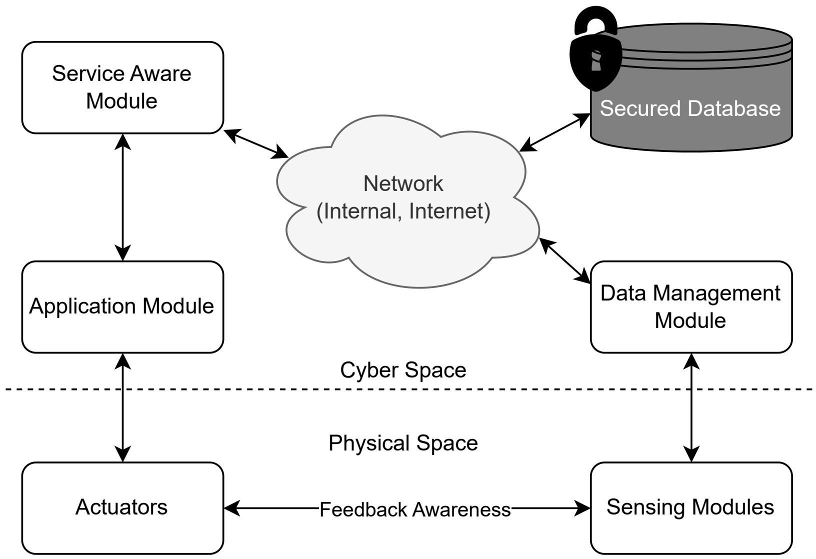

Fig. 2. Standard CPS architecture (based on [36])

3 Related work

Rehman et al. introduce in [37] an architecture for interactive context-aware applications based on the *model-view-controller paradigm*. This architecture comprises a chain of context components to adapt the application models and views to different user contexts. The investigated context is determined by the sensed location of the user. This work, however, targets software UI programs only with the goal to achieve a better transparency and explainability during the application's usage. Thus, it does not involve influencing physical processes.

In [38], a system assisting users and stakeholders in recommending and optimizing the ingredients of miniature food ("tapas" and "pintxos") is presented. The system is based on a knowledge-graph integrating collected information from different sources, such as users' ratings and opinions. The resulting knowledge model can assist businesses, such as bars, in selecting the list of their offered products according to their location and other contextual factors. Despite the knowledge-graph-based architecture being a promising approach, the system is focusing on taste optimization and does not consider the sustainability aspect.

Diaz et al. present in [39] an overview of applications in which context-aware systems and control methods are relevant, with "Food" being one of them. They also define a unified life-cycle of context-aware control systems consisting of the four phases: *Acquisition*, *Modeling*, *Reasoning* and *Dissemination*. Based on the introduced life-cycle model and an analysis of the different application domains, a concept of a generic context-aware control system, leveraging artificial intelligence methods, is introduced. The concept uniquely specifies information flow, yet remains domain-agnostic and does not define concrete context data.

4 CONFES System Requirements

To allow a context-aware recipe configuration, a CONFES must fulfill a set of system requirements covering data sensing, data processing and control functions. These requirements are shown in Table 2. Beyond the collected requirements, CONFES, like other CPS systems, e.g. in the medical sector, are subject to strict privacy requirements and therefore require appropriate protection measures. However, this is not the focus of this paper [40].

Table 2. System Requirements for CONFES

ReqID	Description
Req1	The system should be capable of monitoring context parameters that affect human taste, such as weather, temperature, pressure, humidity, and ambient odors (i.e. VOC values).
Req2	CONFES should detect the vital factors of the human context, such as heart rate, wake state level, momentary heat sensation, and mood, in order to adapt food preparation accordingly.
Req3	The system should adjust recipe and preparation parameters, such as ingredient selection, amount, grind size, preparation techniques, time, and temperature, based on Req1 and Req2. Furthermore, it must optimize taste.
Req4	System should communicate with other smart kitchen devices, such as food storage (e.g. fridge), to recommend edible food and reduce waste.
Req5	The system must authenticate and identify the user to ensure accurate mapping of collected data to person and feedback and securely store and manage user profiles, including taste preferences, smoker status, diet, and preferences for specific foods, in compliance with General Data Protection Regulation (GDPR).
Req6	The system must handle a user network within the user database to recommend and share recipe changes.
Req7	CONFES should record feedback from each user after consuming food, categorized by temperature, taste, mouthfeel, and overall rating.

5 CONFES System Specification

5.1 System Architecture

Based on the requirements of Table 2, we designed a universal, extendable architecture for CONFES. This architecture is described by the Unified Modeling Language (UML) component diagram in Figure 3. It consists of the following

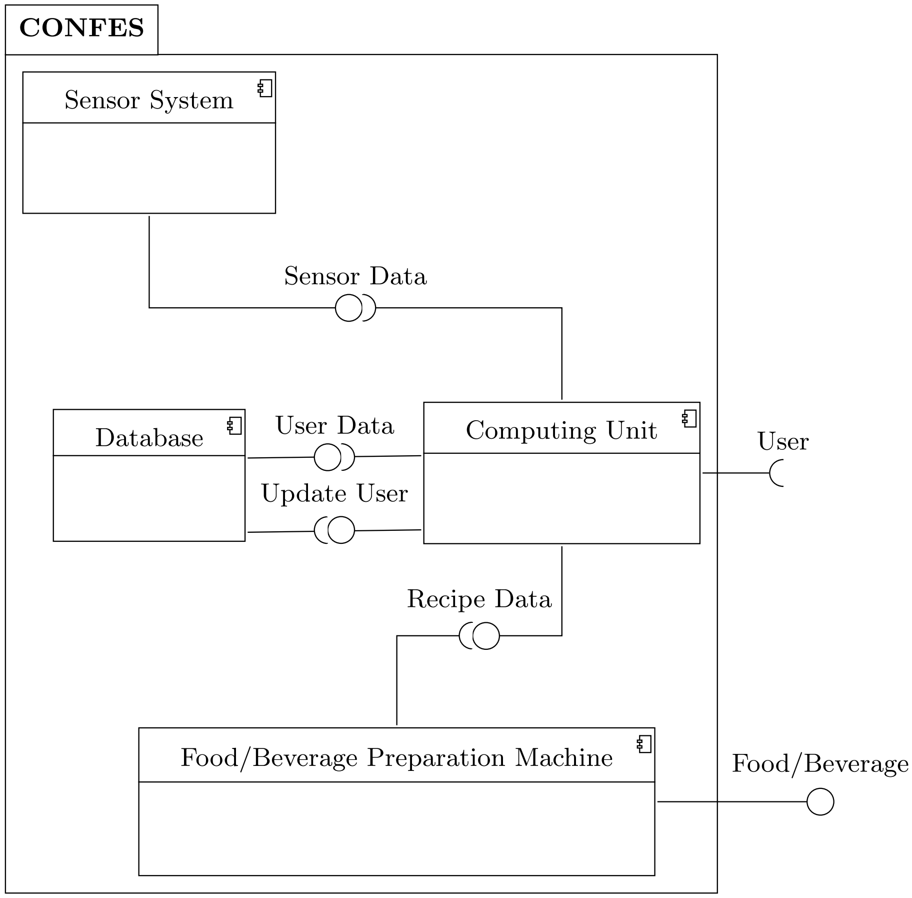

Fig. 3. Component diagram of general CONFES setup

four main components: The **Sensor System** incorporates various sensors, operates in real time and provides a continuous information stream of environmental data. Possible sensors are temperature, pressure, humidity, sound, brightness, air quality, and image sensors. The **Database** stores encrypted the general user data as well as all sensor data at while the food/beverage was prepared. When initially opening an account, the user is asked about their age, weight, smoking status, and general food preferences. In addition, the ordering history with corresponding feedback is stored in the database. Firstly, the **Computing Unit** provides an interface where the user orders a desired food/beverage. In order to personalize the output of the food/beverages prepared, the computing unit utilizes several inputs such as sensor data (e.g. temperature, machine parameters, etc.) and seamlessly integrates those into a data acquisition system, in this case a database. To store personalized data within the database, a user identification is necessary. Utilizing the identified user data, the system then orchestrates personalized food and beverage preparation based on the feedback history of the user stored. Through this, ML algorithms, such as supervised learning frameworks, are trained based on the aforementioned data to finally achieve a personalized experience. The ML parameters are continuously updated based on the user feedback provided. It also provides a user interface which serves two main purposes, to order food/beverage and as a feedback loop. The **Food/Beverage Preparation Machine** is used for the actual preparation of the food/beverage. It receives personalized recipe data from the computing unit and controls the machine parameters to follow the recipe as close as possible.

5.2 Data Model

The Entity Relationship Diagram in Figure 4 illustrates the interdependencies of the data. The diagram is divided into four entities: User data, Recipe data, Sensor data, and Update user. User data stores all relevant information about the user, including body parameters, diet, and current vital state. Recipe data collects all information about the processed food and processing procedures. Sensor data collects environmental factors and machine parameters to create a snapshot of the context. The user update also saves the feedback history for consumed food. The data presented is not complete, as it can vary significantly between different systems. For instance, comparing a heating food processor to a coffee machine may yield different results.

6 Case Study: Context-aware Coffee Machine

The decision to use a coffee machine as case study was primarily motivated by the significant environmental impact of coffee beans, as well as the 3.2 billion cups that were traded in 2022. [41]. The objective is to produce a delicious cup of coffee using the least amount of coffee grounds possible. Additionally, the impact of context on taste perception should be fully explored to achieve this goal. Another benefit of a coffee machine is that only one ingredient is used for the final drink. In contrast, the preparation of a meal typically involves many different ingredients and herbs that can affect each other, and the overall taste. [42]. An additional advantage of the coffee machine is its automated preparation process. All process parameters are controlled and cannot be influenced by human error or individual preparation methods.

The before presented data model for CONFES, is partly universal but, some data is special for each system. Table 3 presents a partial example of the 'context-aware coffee machine' system. It is important to note that this example is not comprehensive.

Figure 5 displays the proposed system setup for the context-aware coffee machine. There will be a difference in the order of the first cup compared to the second and subsequent cups of coffee. Prior to ordering their first coffee, the user is required to complete a user profile. This profile is intended to identify patterns between users, group users with similar taste preferences, and feed the

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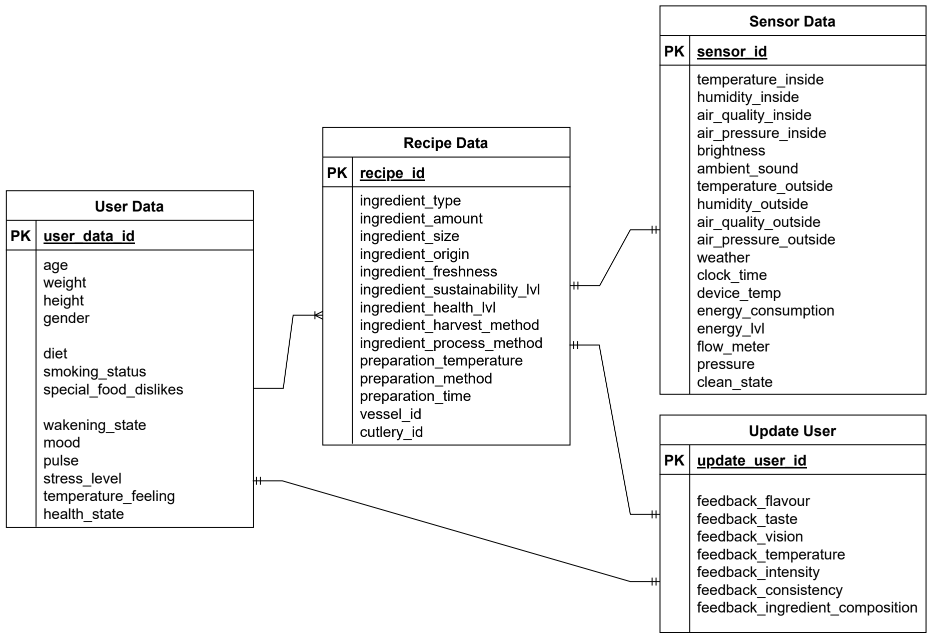

Fig. 4. Entity Relationship Diagram CONFES

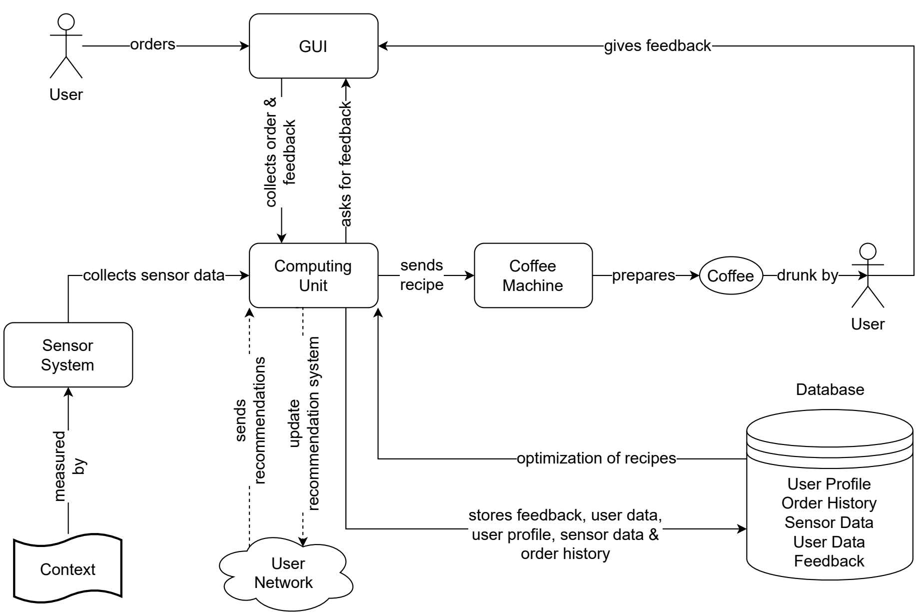

Fig. 5. System Overview of a context-aware Coffee Machine

Table 3. Examples of associated data for the Coffee Machine [43]

Data Type	Example of Case Study
`ingredient_type`	Type of coffee beans, such as Arabica, Robusta, or a blend of both.
`ingredient_amount`	Grams of coffee powder required for one cup of coffee
`ingredient_size`	Grinding level of coffee beans
`ingredient_origin`	The location where the coffee bean was grown, harvested, and processed.
`ingredient_harvest_method`	The harvesting of the coffee cherries can be carried out either by hand or by machine.
`ingredient_process_method`	The processing method for coffee cherries can be either natural or automated.
`feedback_intensity`	The intensity is classified into three options: too weak, good, and too strong.

recommendation network. Once the user profile is complete, they must identify themselves through the Graphical User Interface (GUI) at the start of the ordering process. When the user places an order, the information is sent directly from the GUI to the connected computing unit. The computing unit then gets the order history from the database and sends the recipe to the coffee machine, which prepares the coffee. At the same time, the context is measured by various sensors in the sensor system, and the collected data is forwarded to the computing unit, which stores it in the database. The computing unit sends a questionnaire to the user to collect feedback on the taste of the coffee. The detailed feedback is stored in the database. Using a combination of user feedback, recipe, and context parameters, the computing unit learns how to optimize the coffee recipes to suit the context. The user network aims to merge the databases of multiple context-aware coffee machines to create a strong foundation for a coffee recommendation system and speed up in learning. The lines are dotted because the update will be over the air. This is a concept idea that may be implemented in the future. Here, the text mentions the information to provide a complete picture. One benefit of the user network is that a user will receive a suitable coffee after filling out their user profile, without having to drink a coffee from the machine beforehand, also as described before the learning process is accelerated. For the second and subsequent cups of coffee, the procedure differs slightly from the 'first cup procedure' in the behavior of the computing unit. The user must log in using only their username. Identification can also be achieved through the use of a camera or Radio-frequency Identification (RFID). When the user places an order, the computing unit collects sensor data and searches for a suitable recipe to offer the user. The process remains the same, with changes to the recipe such as grinding level, brewing temperature, or the amount of coffee powder. The case study aims to determine how less coffee powder can be used, in consideration of context, to offer sustainable and tasty coffee. In addition to the coffee to water ratio (i.e. the amount of coffee powder in grams divided by the amount of water in grams), other factors such as water quality, particle size, and temperature also affect the final result [44]. However, we focused on the coffee to water ratio because it is a variable that can be easily and precisely adjusted and has a direct impact on the amount of coffee beans used.

7 Conclusion and Outlook

In summary, our efforts to improve taste parameters within sustainable and nutrition value have led to the systematic derivation of the system requirements for CONFES. A key outcome of this investigation phase was the clear representation of the CONFES architecture through a component diagram, which shows the details of the data components and their interrelationships. This overall representation serves as the basis for the specification of the system requirements relevant to the implementation of a context-aware coffee machine.

Following this concept, our focus will shift to the implementation of this architectural framework for the target coffee machine. A crucial aspect hereby is the selection of relevant datasets to enable a full assessment of context-awareness. An experiment will be conducted to gather all relevant data. Various ML models will be utilized to analyze the gathered datasets in order to identify patterns, user groups, and thresholds of user taste perception based on the context. These findings will serve as a basis for improving the overall user experience by optimizing flavor according to sustainability and nutrition-driven parameters.

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