A recommender system supporting users of an integrated web-based interface

Master's Thesis
Human Computer Interaction

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Abstract

Recommender systems have gained considerable popularity for their helpful suggestions to end-users. However, limited research has been conducted exploring their potential of supporting users as they navigate through integrated interfaces. This research, therefore, focuses on implementing a recommender system as support tool for users dealing with infrequently used complex interfaces. The study was carried out at CashDesk, a company specialising in cash register software (POS) for food delivery and take-away restaurants. The targeted user group included restaurant owners, and the menu editor was selected as a representative complex infrequently used interface. Issues with the menu editor were identified through a customer support log analysis and interviews with CashDesk support employees. Subsequently, three potential recommender system interfaces were prototyped and demonstrated to interviewed customers. Using their feedback, one of the three interfaces has been optimised and evaluated through screenshots and use-cases in a questionnaire. Results indicated a positive reception of the recommender system by respondents, including improved perceived user experience and usability of the menu editor. Users also expected faster menu creation and increased inspiration as additional benefits. While the recommender system is likely to have a positive impact on the menu editor, there is no significant anticipation of a reduction in the need for external support in navigating the interface, as assessed by the participants. However, the recruited subjects primarily identified themselves as highly experienced users. Further research is recommended, involving evaluating an actual recommender system including user interactions in a broader application and user context.

Key words: Recommender System, User Support, User Experience, Usability, Complex Interface

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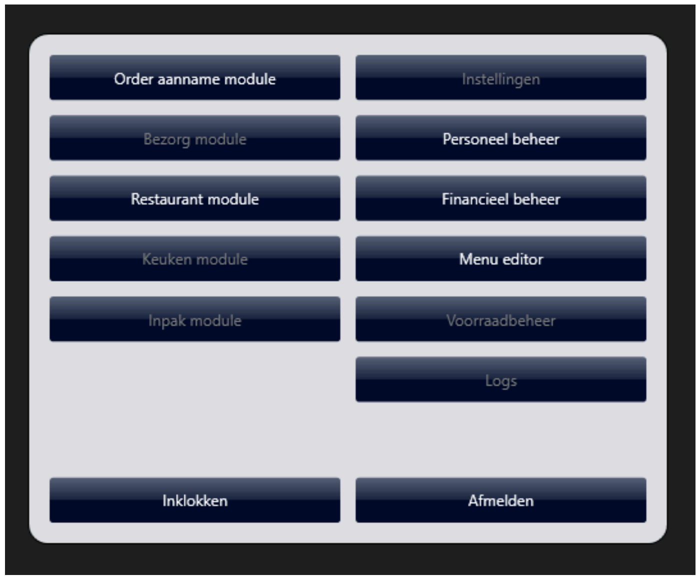
1. Introduction

As software evolves over time, incorporating new functionalities and expanding its capabilities, users are presented with numerous features to explore. However, this increased complexity can pose challenges as users navigate through interfaces, potentially resulting in negative consequences. Users do not adopt the software, are not motivated while using it, or cannot perform job-related tasks. These difficulties may stem from factors such as insufficient user training for new or inexperienced users, infrequent system usage leading to forgotten functionalities, or the inherent complexity of certain interfaces, making users confused and frustrated using it (Hucko et al., 2019). Novices frequently lack knowledge on task execution, desired outcomes, and the realm of possibilities (Fraser et al., 2016a). Effective end-user training programs aim to equip users with the necessary skills to overcome these challenges, and is essential in promoting productive use of technology (Compeau et al., 1995), and the successful implementation of systems (Niazi et al., 2006). The goal of an end-user training program is to produce a motivated user who has the skills needed to apply what has been learned to perform job-related tasks (Gupta et al., 2010). This training offers numerous potential benefits, including increased productivity (Gupta et al., 2010) and enhanced technology adoption (Igbaria et al., 1995). However, end-user training only does not always achieve the desired result, and additional support is needed. One potential solution involves guiding users through the system as they interact with a complex, infrequently used interface. This approach could enhance system navigation effectively, addressing the described challenges. A practical means to facilitate this guidance is through the provision of recommendations. Despite the popularity of recommender systems, their application in guiding users through software interfaces for task completion appears to be an underexplored area in the Human-Computer Interaction (HCI)-field. Therefore, this research investigates the impact of a recommender system on a relatively complex interface utilised by a diverse user group. This research is conducted at CashDesk - a cash register software company for food delivery and take away restaurants - and is focused on the menu editor of the system, a relatively complex software component, which is mostly used on an infrequent basis. Furthermore, CashDesk users undergo user training upon becoming customers, equipping them with a comprehensive understanding of the system's functionalities. However, there persist a considerable number of questions and issues specifically related to the menu editor, as indicated by CashDesk. Consequently, CashDesk customers serve as a suitable user group dealing with a relatively complex functionality on an infrequent basis, aligning optimally with the goals of this research.

1.1 Company description: CashDesk

This research project is carried out at CashDesk - a Netherlands-based company that makes and maintains professional cash registers and order processing systems. This system is used by food delivery and take-away restaurants. The application imports orders from websites of food delivery services, such as Just Eat Takeaway, Uber Eats and Deliveroo, aggregates them in one single application, and enriches them with extra functionalities (e.g. GPS tracking of a delivery agent). CashDesk is currently undergoing the transition of its offline desktop application, CashDesk 2.0, to a cloud-based web application named CashDesk 3.0, a move that brings forth numerous benefits. This transition will streamline maintenance and updates for CashDesk functionality on the company's end, while simplifying user workflows by consolidating the interaction into a single web application, eliminating the need for separate admin web-app and desktop application usage. The CashDesk system consists of several different components and modules, such as a delivery module, order acceptance module, financial management, personnel management and menu editor - the component this research focuses on. Newly onboarded customers receive a 30-minute interface tour remotely as part of their user training. Figure 1 shows the main menu with all modules and components of the CashDesk 2.0 system.

Figure 1: Main menu CashDesk 2.0



1.1.1 Menu editor

The menu editor is an essential software component of CashDesk, allowing users to manage their menu items. Within the menu editor, users are able to add, edit and remove products, optional and mandatory choices, product groups, prices, images, descriptions and many more. The products added or edited in the menu editor will be visible and updated in the order acceptance module of the Point of Sale (POS) system. The changes will also be updated to the restaurant's own website, and to all linked food delivery platforms. Creating or changing a menu can involve many actions and complicated settings. Next to that, changing or creating products including additional options can take a long time due to potential repetitive actions that have to be taken. The interface can be very overwhelming to users due to the many possibilities it offers. Figure 2 shows what the CashDesk 2.0 menu editor looks like. CashDesk has been developing the last few years on a new cloud-based web app, providing the chance to transition from the outdated design to a modern and improved one, which is illustrated in Figure 3.

Figure 2: Menu editor CashDesk 2.0

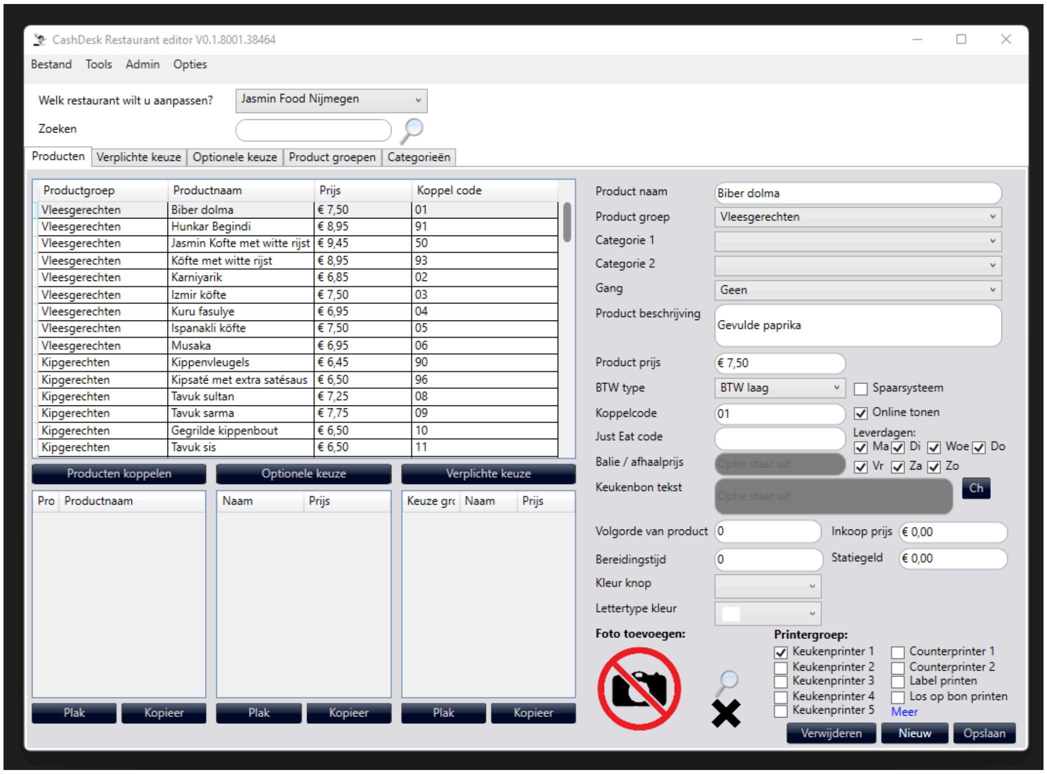
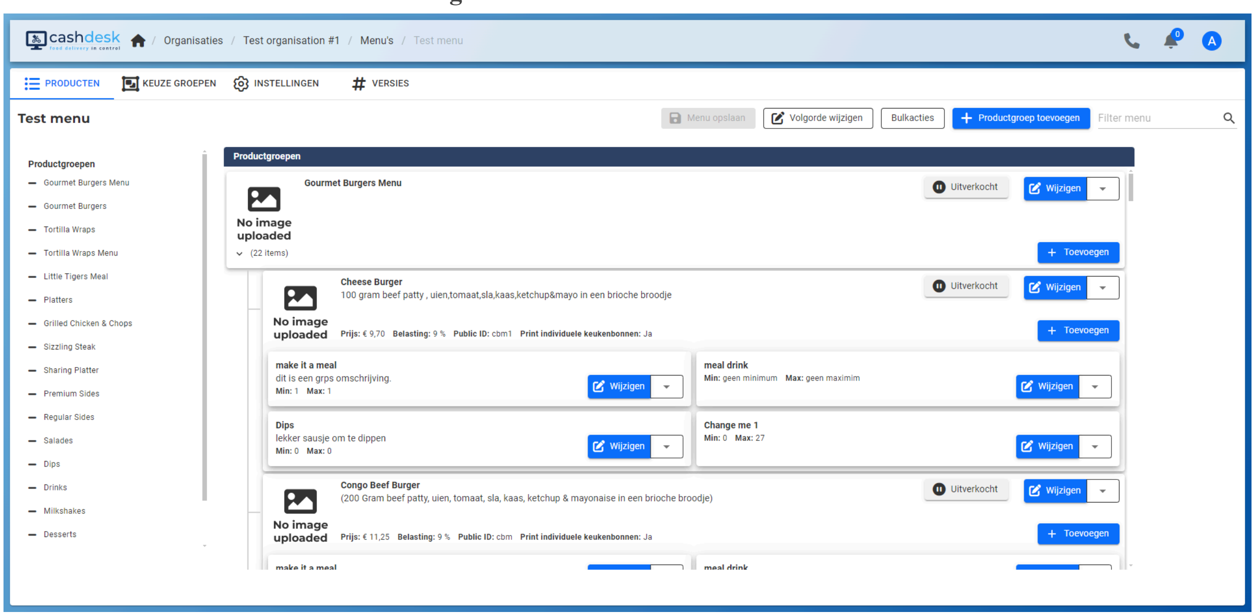


Figure 3: Menu editor CashDesk 3.0



1.2 Problem statement

Users encountering infrequently used relatively complex functions within software often face challenges in effectively utilising the software's functionalities. The software is either not utilised appropriately or not used at all, which negatively affects work processes, user experience, and causes errors and unnecessary repairs. User training alone falls short in this situation due to infrequent usage. CashDesk's menu editor is often recognised as a complex software component, attributable to the relatively high number of customer questions and problem-solving tasks encountered by CashDesk's support employees. Although this system component has been improved by implementing more modern visuals and a more logical flow, the expectation of CashDesk is that some users may still encounter challenges with it. In addition, customers are expected to create their menu by themselves when using CashDesk 3.0, a responsibility previously managed by CashDesk support employees for CashDesk 2.0. CashDesk has been looking into different methods of supporting users during this process, creating the opportunity to research if a recommender system could be a helpful tool for its users while navigating through the system, and executing tasks.

1.3 Goal

The general goal of this Thesis is to research if a recommender system could improve user intuitiveness and provide support while navigating through an infrequently used relatively complex interface. While there are indications that recommender systems can benefit users in various ways, research on their effectiveness as support tools for user navigation, remains limited. This research has been carried out in the context of a menu editor as a complex software component in a POS for food delivery restaurants. The specific tasks undertaken to realise this goal included analysing the current system, identifying common menu editor issues, developing a front-end recommender system interface mock-up within the menu editor, and assessing the perceived recommender system's interface by users through a questionnaire. The results from this Thesis should contribute to the HCI recommender system research field specifically for supporting users through complex interfaces, optimising work processes and job-related tasks and improving user experience, usability and technology adoption.

1.4 Research questions

This research aims to answer the following two research questions (RQs) including their sub questions (SQs).

RQ1: *What is the influence of a recommender system on users within a given integrated web-based interface?*

With sub questions:
SQ1.1: *What are the current user challenges within the interface?*
SQ1.2: *What is the effect of the recommender system on the perceived efficiency of the interface?*
SQ1.3: *What is the effect of the recommender system on the perceived user experience with the interface?*
SQ1.4: *What is the effect of the recommender system on the perceived need for external help while using the interface?*
SQ1.5: *What are the additional perceived benefits that a recommender system can provide?*

RQ2: *What are the desired properties and features of a recommender system within a given integrated web-based interface?*

With sub questions:
SQ2.1: *What are the possible features to recommend?*

SQ2.2: *What are the desired features to recommend?*
SQ2.3: *What are the user preferences for a recommender system interface design?*

1.5 Thesis structure

This Thesis continues with a literature research, presented in Chapter 2, followed by the research methodology in Chapter 3. This chapter describes the methods conducted, starting with a log analysis on customer support issues concerning the menu editor, which indicated various question types and user challenges. Complementing this, interviews with support employees, who have to handle customer's menu editor questions, were conducted to understand their perspectives on prevalent issues within the menu editor. The database containing menus from all CashDesk restaurants has been analysed and provided insights of what, how and where restaurant's menu data is stored and how it can be used by a recommender system. Three interface prototypes for a recommender system integrated into the CashDesk 3.0 menu editor were crafted, and feedback on these potential recommender systems was gathered through interviews with seven CashDesk customers who shared their opinions and preferences. With the results from these interviews, an optimised interface mock-up was developed. The screenshots of this new prototyped recommender system interface together with small use-cases were used for a questionnaire that has been sent to a large portion of CashDesk's customers to gather their opinion about the features of the recommender system and the general potential benefits for them. The results from this questionnaire are reported in Chapter 4 and the obtained results are discussed in Chapter 5. Finally, the conclusion is drawn in Chapter 6.

2. Literature

In the literature section, the background related to this Thesis is presented, starting with an exploration of recommender systems, succeeded by recommender system evaluations and the utilisation of recommender systems as a support tool.

2.1 Recommender systems

Recommender systems were introduced in the mid-1990s and have been becoming more popular and more commonly used over the past years. Recommender systems, as highlighted by Isinkaye et al. (2015), possess the capability to sift through extensive volumes of dynamically generated information. Their purpose is to offer users personalised content and services, thereby mitigating information overload. Acting as tools for navigating large and intricate information spaces, recommender systems, as described by Burke et al. (2011), prioritise items likely to be of interest to the user. This prioritisation provides users with a tailored view of the information space. Recommender systems can be classified broadly into the following three categories: collaborative filtering, content-based filtering and hybrid filtering (Mansur et al., 2017).

2.1.1 Collaborative filtering

Collaborative filtering, introduced in 1992 by Goldberg et al. with Tapestry as its pioneering example, is a recommendation approach suggesting items to users based on the preferences of others with similar tastes who have already experienced the recommended items (Mansur et al., 2017). Collaborative filtering, commonly applied to large datasets available, offers serendipitous recommendations as one of its advantages. The traditional collaborative filtering techniques include user-based, item-based and model-based methods (Mansur et al., 2017).

User-based collaborative filtering calculates similarity between users based on their ratings for the same items. It predicts a user's likelihood to like a target item by computing a weighted average of ratings for this item from similar users. In contrast, item-based collaborative filtering assesses predictions using item similarities rather than user similarities. It establishes a model of item similarities by comparing items rated by an active user, selecting the most similar items, and determining their matching similarities. Model-based collaborative filtering builds a recommendation model based on the entire user-item interaction dataset, often utilising machine learning techniques (Mansur et al., 2017). Without the need for explicit similarities between users or items, these models are able to capture complex patterns and relationships to generate personalised recommendations, in a scalable and efficient way.

2.1.2 Content-based filtering

A content-based recommender system recommends items based on substantive item characteristics. Content-based systems recommend items similar to those the user liked before, differing from collaborative systems that identify users with similar preferences (Mansur et al., 2017). Advantages of content-based systems include user independence and transparency. Case-based filtering operates as a variant of content-based filtering and relies on the similarities between items rather than user preferences (Smyth, 2007).

2.1.3 Hybrid filtering

Hybrid filtering integrates collaborative filtering and content-based filtering techniques to enhance the accuracy and effectiveness of recommender systems. This combination can be achieved through various methods: separate predictions with subsequent combinations, adding content-based capabilities to collaborative filtering (and vice versa), or unifying the techniques into one model (Mansur et al., 2017). The primary goal is to leverage a combination of algorithms to provide more accurate recommendations than a single algorithm, overcoming individual weaknesses and enhancing the overall performance of the system (Isinkaye et al., 2015).

2.1.4 Limitations

Recommender systems also have their limitations, which can vary depending on the approach. In general, there are seven potential limitations to consider (Sharma & Singh, 2016).

1. Cold-start problem: this occurs when a new item is added to the system or a user uses the system for the first time, resulting in inaccurate recommendations due to insufficient information available.
2. Sparsity: in terms of recommender systems, sparsity implies the irregular, insufficient or highly varying user ratings. The major reason behind sparsity is that most of the users do not provide ratings and the ones available are usually too scattered or sparse. Consequently, this sparsity can cause issues with the accuracy and reliability of the recommendations.
3. Scalability: scalability refers to the extensibility of a system, indicating its ability to perform effectively as the volume of data increases. While there are algorithms designed to handle massive and dynamic datasets, the accuracy of their results is not always guaranteed.

4. Privacy protection: at times, the system may possess more information about the user than necessary. Additionally, there is a risk that malicious users could exploit the easily accessible user data.
5. Over-specialisation: this becomes problematic when users consistently receive similar recommendations solely based on their past behaviour. This lack of variety in the recommendation pattern diminishes the element of surprise. Consequently, the chances of users discovering new and potentially beneficial items or content are nearly negligible.
6. Grey-sheep problem: this problem refers to users showing inconsistent behaviour, lacking well-defined preferences. Such users may express a liking for an item at one moment and the exact contrary at another. This inconsistency diminishes the efficiency of recommender systems as they struggle to accurately predict user preferences.
7. Shilling attacks: this issue arises when users provide false positive or negative ratings to boost or diminish the popularity of an item.

Typical limitations of collaborative filtering systems are cold start problems, data sparsity, and scalability, while limitations of content-based systems involve the grey-sheep problem, over-specialisation and privacy protection.

2.1.5 Presentation strategies

Building upon the technical and principle back-end aspects of recommender systems, it's essential as well to consider how recommendations are presented on the front-end within interfaces. Research indicates that the presentation structure of recommendations can significantly impact user satisfaction and decision-making processes. Structured and organised overviews of recommendations per category are more effective in persuading and satisfying users compared to unorganised top N-items lists of all recommendations (Nanou et al., 2010). Additionally, research suggests that the size of the recommendation set doesn't significantly impact user satisfaction, as long as the quality remains high. Larger recommendation sets containing only well-experienced items do not necessarily lead to higher choice satisfaction compared to smaller sets, as the increased attractiveness of larger sets is counteracted by the difficulty of choosing from them (Bollen et al., 2010).

2.2 Evaluation of recommender systems

There are various methods to measure the performance of a recommender system. The most efficient and cost-effective method involves conducting offline experiments using existing datasets and a protocol that models user behaviour to estimate recommender performance measures such as prediction accuracy. A higher-cost alternative involves conducting a user study, where a small set of users is asked to perform a set of tasks using the system, typically answering questions afterwards about their experience. This evaluation type collects qualitative feedback from participants focused on the experience with the recommendations rather than its technical performance, and measures user satisfaction through explicit ratings (Beel & Langer, 2015). Finally, large scale experiments on a deployed system can be set up, which are called online experiments. Such experiments evaluate the performance of the recommender systems on real users who are oblivious to the conducted experiment (Shani & Gunawardana, 2011). Online experiments entail providing recommendations and subsequently gathering user feedback for the item ratings. Offline experiments do not require real users, instead, part of the data is used to train the algorithm, while another sample is used to test the predictions regarding the users tastes (Ricci et al., 2011). Online evaluation is most desired, as it provides accurate results of how well a system performs with real users (Ricci et al., 2011). Nevertheless, due to the often expensive nature of user experiments, many researchers opt for offline evaluations (Silveira et al., 2019). Most recommender systems have been assessed and ranked based on their prediction power, which denotes their capability to accurately predict user preferences. There are multiple metrics for measuring the performance of a recommender system next to accuracy, such as coverage, precision, recall (Sharma & Singh, 2016).

2.2.1 User experience

Recommender systems are mostly tested on their technical performance such as their accuracy, but relying solely on this traditional evaluation only does not suffice to judge performance of recommender systems on the user side. In recent times, researchers have recognised the significant enhancement in the effectiveness of recommendations for end-users by integrating User eXperience (UX) into recommender systems (Champiri et al., 2019). User-centric recommender system evaluation results may not be in line with data-centric evaluation results (Fazeli et al., 2017). Nevertheless, measuring UX remains a challenge due to its subjective nature, and accurate assessment often relies on direct user feedback regarding the recommendations (Champiri et al., 2019). Interestingly, the UX of an interface tends to increase when a recommender system is implemented, as these interactions can be perceived as inspiring and enjoyable (Neidhardt et al., 2015). Moreover, the likelihood of increased user engagement is heightened when fostering a positive user experience (Starke et al., 2017). Perceived quality and variation of recommendations are important mediators in predicting user experience components such as perceived processes or difficulties, perceived system effectiveness, and choice of satisfaction (Munawar et al., 2020). Despite a growing awareness of the importance of UX in recommender systems, limited studies have delved into this aspect, and the research on the UX within recommender systems is still relatively underexplored and warrants further investigation (Champiri et al., 2019).

2.2.1.1 User Experience Questionnaire (UEQ)

Assessing the UX of systems can be conducted with the User Experience Questionnaire (UEQ). The UEQ, developed in 2008, is a widely used tool in the HCI-field for assessing the UX of systems (Laugwitz et al., 2008). It measures as well as positive and negative aspects of the UX by asking users to give their opinion on properties on a seven-point Likert scale, and measures the six factors: attractiveness, perspicuity, efficiency, dependability, stimulation and novelty in a 26-item questionnaire (Laugwitz et al., 2008). A significant benefit is the ease of comparing results obtained from the UEQs, yet, conversely, there is a limitation in terms of depth, as users have no freedom to explain their answers.

2.2.1.2 System Usability Scale (SUS)

Within the user experience area, usability acts as a crucial component, representing the measure of how effectively a product or system allows users to achieve their goals with efficiency and satisfaction. The System Usability Scale (SUS) is a commonly used questionnaire that measures the usability within a set of ten questions related to usability and user-friendliness (Brooke, 1996). The questionnaire uses a five-point Likert scale ranging from “strongly disagree” to “strongly agree.” The scores are then normalised and aggregated to obtain an overall SUS score. A higher SUS-score indicates a better user experience. The SUS is designed to be conducted quickly and easily. An advantage is that the SUS-score can be compared as a benchmark. Since the SUS has a limited depth level, as users have no freedom to explain their answers, it is often used in combination with other measurement tools to get a more comprehensive picture of the user experience.

2.2.2 Technology acceptance

The acceptance and adoption of technology plays a crucial role in the implementation of software. The willingness of users to embrace and adopt new technologies directly impacts the success of information systems (Davis, 1989). When users embrace a new technology, their likelihood of actively using it increases. This use can lead to enhanced performance and efficiency within information systems (Venkatesh et al., 2003a). One study delved into users' initial adoption of recommender technology and their subjective perceptions of the respective systems. The findings reveal that key design features, including a simple interface design, minimal initial effort requirements, and the quality of recommended items (accuracy, novelty, and enjoyability), are instrumental in overcoming the initial entry barrier (Jones & Pu, 2007). Over time, multiple models have been developed to understand and evaluate technology adoption.

2.2.2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed in 1989 by Davis, stands out as one of the most widely used technology acceptance models, also applied to recommender systems as specific software components (Armentano et al., 2015). TAM serves as a theoretical framework for comprehending the factors that influence the acceptance of new technology. Through extensive research, TAM has proven to be a robust model for understanding end-user technology adoption and examining the acceptance of new and evolving technology across users with diverse characteristics in various organisations (Alomary & Woollard, 2015). According to TAM, the adoption rate of a product does not depend on its features but on the user's experience. This model asserts that perceived usefulness and perceived ease of use exert the most significant influence on the technology adoption rate, with perceived usefulness carrying approximately one and a half times more weight than perceived ease of use. These two factors are commonly researched in the evaluation of information systems. Research shows that perceived usefulness significantly and positively affects actual system usage (Godoe & Johansen, 2012). Furthermore, optimism and innovativeness markedly impact perceived usefulness and perceived ease of use. Additionally, users' prior skills strongly influence perceived ease of use, directly impacting the perceived usefulness of the system (Armentano et al., 2015).

2.2.2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

A more modern elaborated technology acceptance model is the Unified Theory of Acceptance and Use of Technology (UTAUT), developed in 2003 (Venkatesh et al., 2003b). UTAUT resulted from a review and consolidation of constructs from eight related models used in previous research to explain information systems usage behaviour. This model proves valuable for assessing the potential success of introducing new technology, aiding in understanding the factors influencing acceptance, particularly among user populations less inclined to adopt and use novel systems (Venkatesh et al., 2003a). UTAUT examines four key factors: performance expectancy (perceived usefulness), effort expectancy (perceived ease of use), social influence and facilitating conditions. UTAUT has undergone evolution, with the latest version being UTAUT2, introduced in 2012, incorporating elements from various models. UTAUT2 demonstrates enhanced explanatory power compared to other technology acceptance models, especially within the context of mobile internet users (Rondan-Cataluña et al., 2015).

2.3 User support

This literature chapter explores related work on supporting users within complex interfaces, often containing extensive information and functionalities. Strategies, including reducing information overload and providing internal action suggestions in the context of recommender systems are discussed.

2.3.1 Information overload

Well-designed recommender systems hold the potential to reduce cognitive load for users. By presenting relevant options, they effectively reduce decision fatigue and contribute to an enhanced overall user experience. This is particularly important in the context of online information overload, which has been associated with decreased satisfaction, lower confidence levels, and heightened user confusion (Lee & Lee, 2004). Research shows relationships between perceived information overload and confusion, which has a negative effect on users' decisions (Özkan & Tolon, 2015). Furthermore, a study underscored the challenges associated with information overload, revealing that users working with full software functionality were outperformed by those with reduced software functionalities (Leutner, 2000). Research findings suggest that in situations of information overload, the utilisation of recommendations and adherence to their suggestions are heightened (Aljukhadar et al., 2012). Particularly in scenarios where an abundance of information is available, and the risk of overload is high, the use of a recommender system appears to enhance decision-making and elevate the overall quality of choices made by users (Aljukhadar et al., 2012). Users consulting recommendations under higher overload levels tend to make better choices and display higher confidence when conforming rather than resisting recommendations (Aljukhadar et al., 2010).

2.3.2 Action suggestions

The integration of action suggestions within interfaces may help novices maintain confidence, accomplish tasks, and discover features within a complex interface (Fraser et al., 2016b). They appear to be most beneficial for users with exploratory goals rather than those with highly specific objectives (Fraser et al., 2016a). Action suggestions are primarily facilitated by virtual agents. However, implementing such suggestions poses challenges, as they may not always be effective and could potentially distract users from their tasks (Barrett et al., 2004). This distraction can lead to decreased efficiency, effectiveness, and job satisfaction (Maedche et al., 2016). In 1999, Horvitz introduced 12 critical factors aimed at effectively integrating automated software suggestions including direct interaction. These principles, such as collaboration between human and machine, providing user control, and supporting natural interactions, have the goal to increase efficiency, improve user experience, and provide support to users completing their tasks and navigating through interfaces. However, not all attempts to provide comprehensive integrated assistance succeed (Maedche et al., 2016), as exemplified by Microsoft Office’s virtual assistant “Clippy, the paperclip”. Instead of providing clear and precise guidance, Clippy was widely perceived as annoying, impolite, and disruptive to users' workflows (Veletsianos, 2007). Nevertheless, proactive suggestions can be perceived as helpful and assisting, without being perceived as obtrusive or distracting, as indicated by Bader et al. in 2011. However, the findings from this study can not be completely applied to a regular HCI-environment, as this study was conducted within an in-vehicle car system where the user's primary focus is on driving rather than interacting with an interface.

Despite all the studies described, there is a noticeable scarcity of research focusing on the utilisation of recommender systems, rather than virtual assistance agents, as support tools for users navigating through complex interfaces.

3. Methodology

This chapter describes the methodology used to address the research questions of this Thesis. A mixed-method approach is used, starting with qualitative methods including customer support log analysis, database analysis, interviews with both CashDesk's support employees and customers, and recommender system interface prototyping. Finally, a quantitative method is used to evaluate a recommender system interface mock-up via a questionnaire.

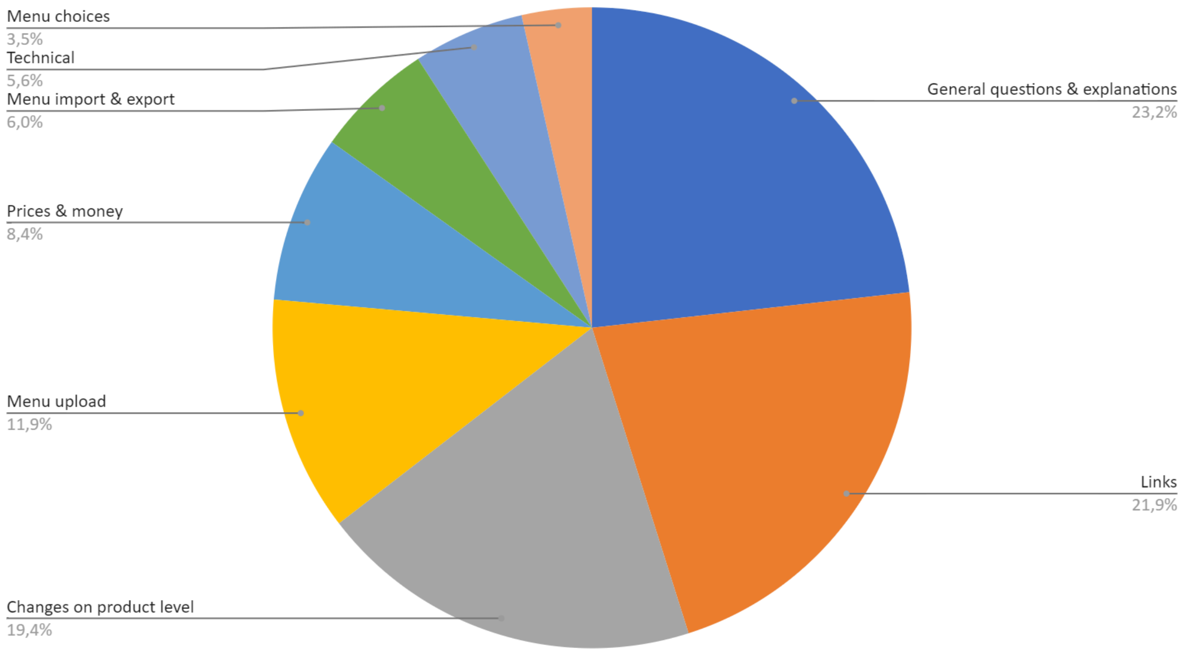
3.1 Customer support log analysis

The first results obtained within this research come from an analysis of customer issues logged by CashDesk. This served as an efficient and accessible method to document all reported issues from CashDesk customers related to the menu editor, providing insights into the challenges users encounter when utilising this software component. CashDesk as a company systematically records all reported issues from its customers, whether received through email or telephone, to establish a comprehensive overview of customers' problem history and facilitate the exchange of customer records among support employees, who have to handle and solve customer's technical questions and problems. These logs contain small summaries of reported issues.

The exported log file contained 14.152 records in the period from January 10th 2020 to November 10th 2021. All reported issues were related to CashDesk 2.0, as CashDesk 3.0 had not been launched or utilised yet during this period. After filtering on working days and times, validated restaurant names and support employees handling the issues, a total of 8.273 were deemed relevant from the initial dataset. Filtering on working days and times and on support employees handling the issues was needed as menu editor issues are exclusively handled by support employees. Moreover, this type of issue does not fall under emergency disruptions, and are handled during regular working days and hours. Still, the exported log file comprising support questions contained a broad spectrum of issues raised by customers. Therefore, a content filter had to be applied to isolate the items related to the menu editor only. To efficiently find logs related to the menu editor, the initial search term used was "menu". Subsequently, the search terms "product" and "link" were used as well, as these terms appeared to relate with the functionality of the menu editor. All filtered logs were read, analysed and coded manually. However, not all logs contained a clear summary, making it challenging to categorise those.

In total, 782 (9.5%) of the total number of logs were associated with the menu editor. Afterwards, all menu editor logs were categorised into 31 different types, which have been consequently merged into the following eight larger, more general categories: "general questions & explanations" (23.2%), "links" (21.9%) - referring to linking menu items within CashDesk to external food delivery platforms - "changes on product level" (19.4%), "menu upload" (11.9%), "prices & money" (8.4%), "menu import & export" (6.0%), "technical" (5.6%) and "menu choices" (3.5%). The division of these categories are illustrated in Figure 4. The results of this log analysis provided insights into the distribution of various issue types. With "general questions and explanations" and "changes on product level" accounting for 42.6% of the reported issues, it indicates that the general core functionalities of the menu editor represent a substantial proportion of user concerns. Addressing these fundamental commonly used functions could significantly reduce menu editor-related challenges for users.

Figure 4: Division of menu editor problem categories



3.2 Interviews of support employees

Interviews with all three CashDesk support employees were conducted, to understand their vision on the difficulties that customers experience while using the menu editor. Support employees receive reports about menu editor issues on a daily basis and handle all reported issues. The interviews were structured around a set of nine questions. The first question focused on the interviewee's overall experience as a support employee and their perspective on handling menu editor-related issues. This was followed by seven questions pertaining to various aspects of the current CashDesk 2.0 menu editor, including both common and different menu editor issues encountered, diverse customer profiles, and menu editing phases. The final question explored their opinion regarding the potential implementation of a recommender system. The interview lasted a maximum of half an hour and support employees were asked to sign an informed consent. An audio recording was made with their permission, and the interviews were transcribed for analysis afterwards. Interview questions can be found in Appendix A.

3.2.1 Customer types and characteristics

Support employees were asked about customer differences and identified the following customer types: new, low-motivated, engaged, non-technical, unaware, inactive and pushy. Participant 2 (P2) said "*You have customers who are like, really involved and they like to keep track and take care of the menu the way it should be I think, whereas different people, they don't care at all*". Participant 1 (P1) said "*You have lazy customers who just don't feel like doing it themselves. Others who just want to know for themselves how it works so that they can do everything themselves, but that is much less common unfortunately*". New customers, engaged customers, and customers with complex menus tend to pose the highest number of questions according to the support employees. Next to that, support employees agree that the majority of issues could be solved by customers themselves. P2 said "*Yeah, actually most of them*". P3 even said "*90 % of the questions*". Reasons mentioned why customers still ask these questions are: forgotten how a function works, insecure about using the system, new employees working with the system, no affinity with computers in general, language barrier, no sense and too busy.

3.2.2 Menu editor

Support employees were asked to estimate how many questions they have to handle per day, and how many of them are related to the menu editor. On average, they estimated having to address 37 questions per day, with eight of them related to the menu editor (21.6%). They noted a substantial difference in addressing menu editor-related questions compared to other support inquiries. Unlike typical issues that require problem-solving, menu editor questions demand an explanation and demonstration of how the function works. Participant 3 (P3) said "*If it's for the menu editor you just have to explain it and then eventually they have to do it themselves, and if they have support questions where there is a problem or malfunction then you have to fix it, then you are working yourself*". They mentioned that the most common problems are related to linking codes, connections to external platforms, linking mandatory and optional choices and adding products in general. Support employees also identified different phases during creating or editing a menu, where editing products, uploading the menu and linking both optional and mandatory choices were expected as the most difficult.

3.2.3 Recommender system

Support employees were also asked what they think of a potential recommender system as a support tool for CashDesk customers within the menu editor. They expected that a recommender system can influence the user experience when customers are creating their menus from scratch, but not as much when they are editing existing menus. What would be helpful to recommend according to the support employees are standard products that belong to its particular kitchen type, such as a "Pizza Salami" for an Italian restaurant. Additionally, they advise suggesting universal products with detailed descriptions and average prices, like a "330ml Can of Coke", instead of a generic "Coke". Other mentioned content to recommend are products in general, drinks, average prices, product groups, optional choices (as upselling) and product descriptions. Tasks within the menu editor to be performed could also be useful to recommend, but only in the form of a step-by-step plan, where buttons and actions are lighting up when they should be used.

3.3 Database analysis

A database analysis has been executed to understand what menu data is stored and could be used to generate relevant recommendations. Unfortunately, there was no user behaviour data available from the CashDesk 2.0 menu editor usage. CashDesk's IT-department exported multiple datasets from its database with menu items from their affiliated restaurants. The datasets contained valuable information that could be utilised for recommendations, including restaurant name, product name, product group name, price and description. Although the restaurant name itself seemed to be an irrelevant item for the recommender system, this can be linked to a kitchen type, which could be a powerful property for recommending items to restaurants with similar kitchens. The IT-department agreed with this idea and added a new column to the database with the kitchen type that belongs to the restaurant, which are labelled manually. In addition, The IT-department added this kitchen type dropdown input field to the CashDesk Self Service Center (SSC) portal as well where users could change this. CashDesk's database offers opportunities for both content-based and collaborative filtering approaches, providing recommendations based on item (e.g. product) and user (e.g. kitchen type) similarities.

3.4 Prototyping various recommender system interface concepts

With a comprehensive understanding of the current user challenges provided by the customer support log analysis, support employee interviews, and an exploration of the possibilities that the CashDesk database could offer, recommender system interface mock-ups have been designed. The mock-ups are developed using Figma, a collaborative web application for interface design. The menu editor screens for designing the recommender system interface could be seamlessly copied and integrated, ensuring uniformity in interface elements. In collaboration with CashDesk's web designer, various recommender system interfaces were conceptualised.

3.4.1 Focus points

To determine what menu editor features to be included in the prototype, insights from both customer support log analysis and interviews with support employees were used. However, CashDesk has already addressed some of the issues appearing in the customer support log analysis in their new CashDesk 3.0 menu editor. For example, challenges related to the second most prevalent category, links (21.9%), highlighted by support employees as a significant issue, have already been resolved. Users previously faced difficulties in manually inputting linking codes into both the CashDesk menu editor and linked external food delivery platforms. CashDesk solved this problem by automatically generating linking codes, eliminating the need for manual changes. Furthermore, the menu upload process (11.9%) has been enhanced by implementing automatic upload upon saving, eliminating the need for users to navigate through multiple technical options, as was required in CashDesk 2.0.

General questions and explanations contained the highest category (23.2%) in the log analysis, and changes on product level the third (19.4%), indicating a focus point. Issues pertaining to the menu import & export (6.0%) and technical (5.6%) categories appear less frequently and do not directly relate to typical menu editor functionalities. Additionally, the menu choices category represents merely 3.5% of the issues and requires a lot of effort to simulate in a prototype. Together with insights from the support employees, it was decided to have the main interface prototype focus on recommending products and product groups as items to add to a menu. This is the most commonly used function, and represents a high portion of the menu editor challenges.

On the product level, it is decided, based on the CashDesk's database possibilities and support employee interviews, to focus on recommending type suggestions, descriptions and average prices. “Prices and money” cover 8.4% of the menu editor issues. Type suggestions, as proposed by support employees, have the potential to clean the database, as the number of wrongly typed product names will be reduced, resulting in better recommendations as well. All design and requirement decisions were made in consultation with the CashDesk's IT-manager and web designer.

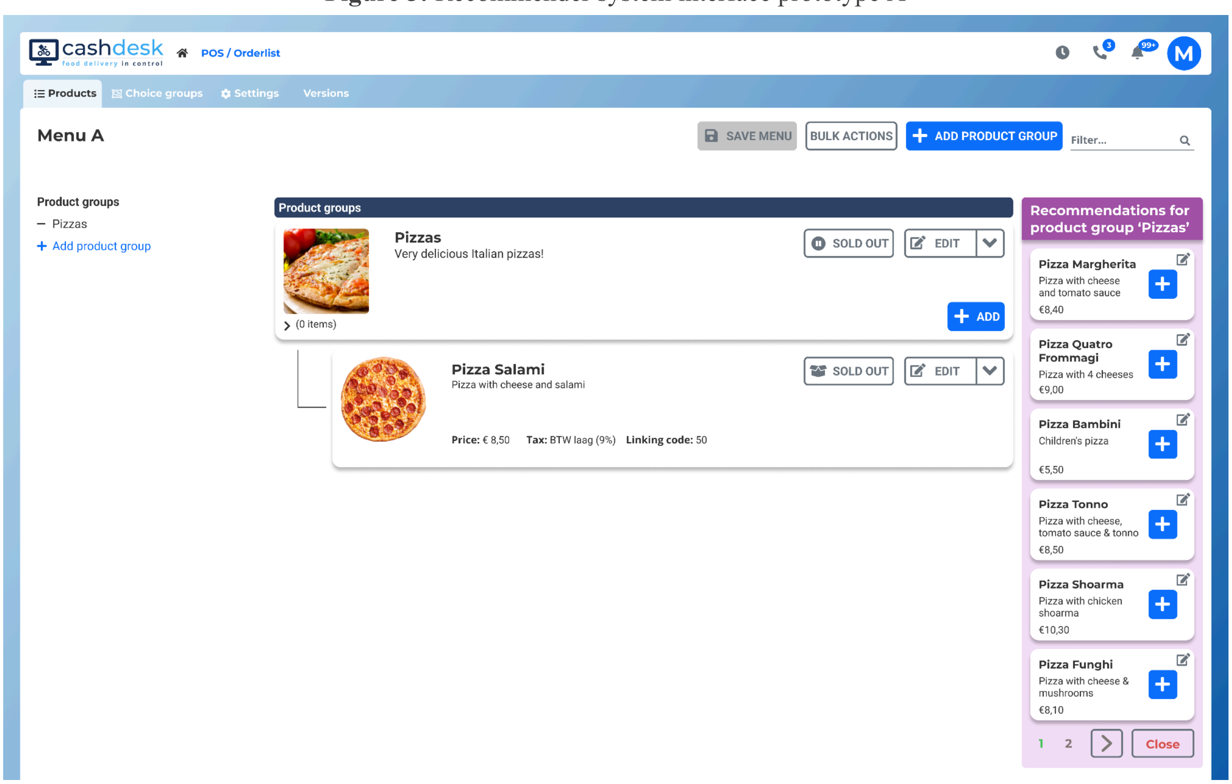
3.4.2 Interface design choices

It has been decided to keep a simple interface design with minimal initial effort requirements (Jones & Pu, 2007). Next to that, a structured overview is used as an efficient presentation method (Nanou et al., 2010). The size of the recommendation set was deemed as non-critical. (Bollen et al., 2010). Given the uncertain success of the implementation of a recommender system, and the fact that it would function as an additional feature within the interface, this function needed to be integrated with the regular functions without disrupting the current design. Multiple options were explored in consultation with the CashDesk's web designer, considering the uncertainty around user preferences for receiving recommendations. Consequently, three interfaces were developed, each designated for receiving recommendations at distinct locations on the menu editor screen. Furthermore, in one of these interfaces, the recommender system must be activated upon user request, while in the other two, it is consistently present. The recommender system is presented in a distinctive purple colour, to ensure that CashDesk users would easily understand and distinct the recommender system from the regular interface, which is designed in blue and white.

3.4.2.1 Interface prototype A

The first designed prototype version (interface prototype A) contains a recommendation box positioned in the right side of the screen. The recommended products are based and structured on the existing product group of the menu, with its displayed name, description and price. The product can be edited or added instantly. Interface prototype A is shown in Figure 5.

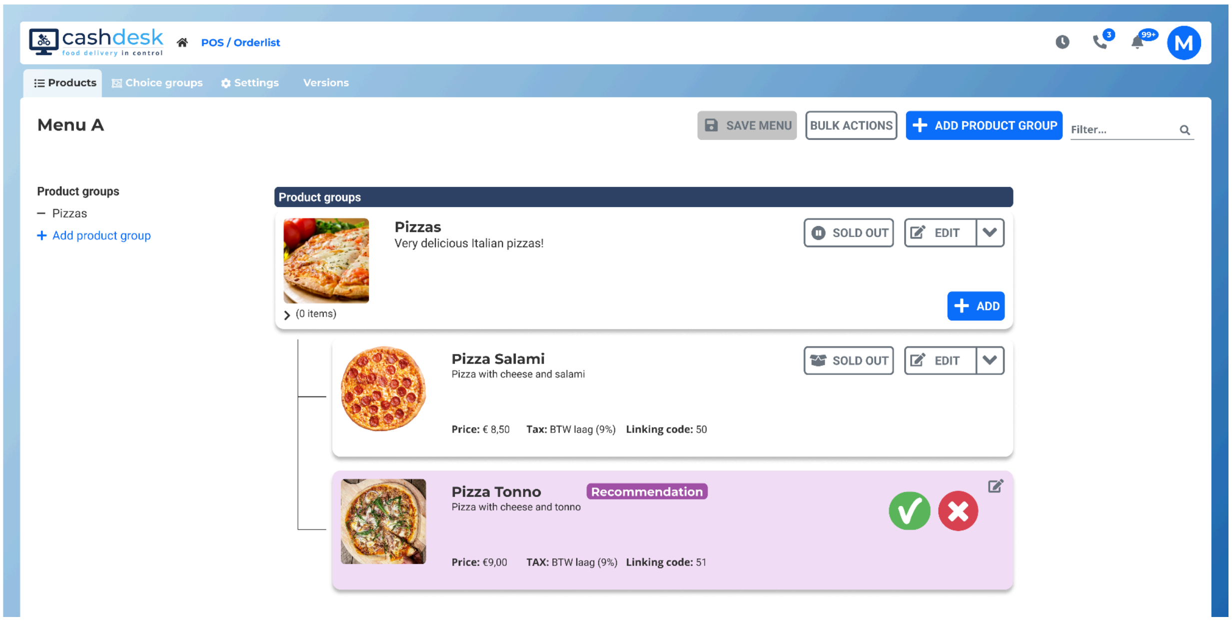
Figure 5: Recommender system interface prototype A



3.4.2.2 Interface prototype B

The second prototype (interface prototype B) is visualised in Figure 6. This particular recommendation type is situated within the interface as a standard purple-coloured product, seamlessly integrated among the products that have already been added. The product can be edited, declined, or added instantly.

Figure 6: Recommender system interface prototype B



3.4.2.3 Interface prototype C

The third prototype (interface prototype C) is not displayed in the interface by default. In this prototype, users have to actively click on the "Recommendations" button in the heading of the interface. Then, a pop-up shows up with recommended items, providing the opportunity to suggest product groups which can be opened to view and (de)select its belonging products. The product group name and description are displayed here, as can be seen in Figure 7a. Products with their descriptions and prices are shown to the user when opening a product group, which can be edited and (de)selected to add them to the recommended product group, as illustrated in Figure 7b.

Figure 7a: Recommender system interface prototype C (product groups)

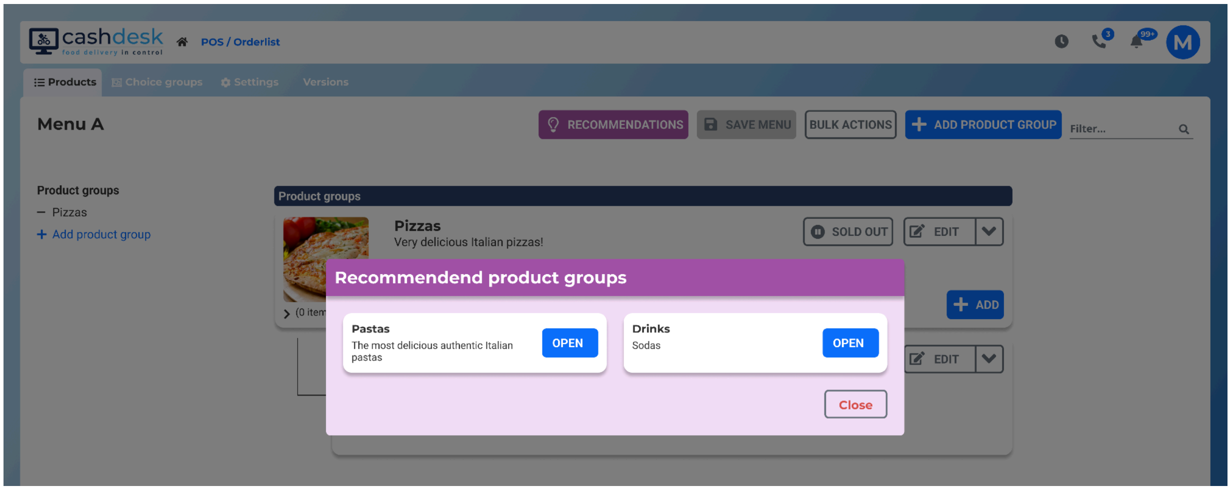
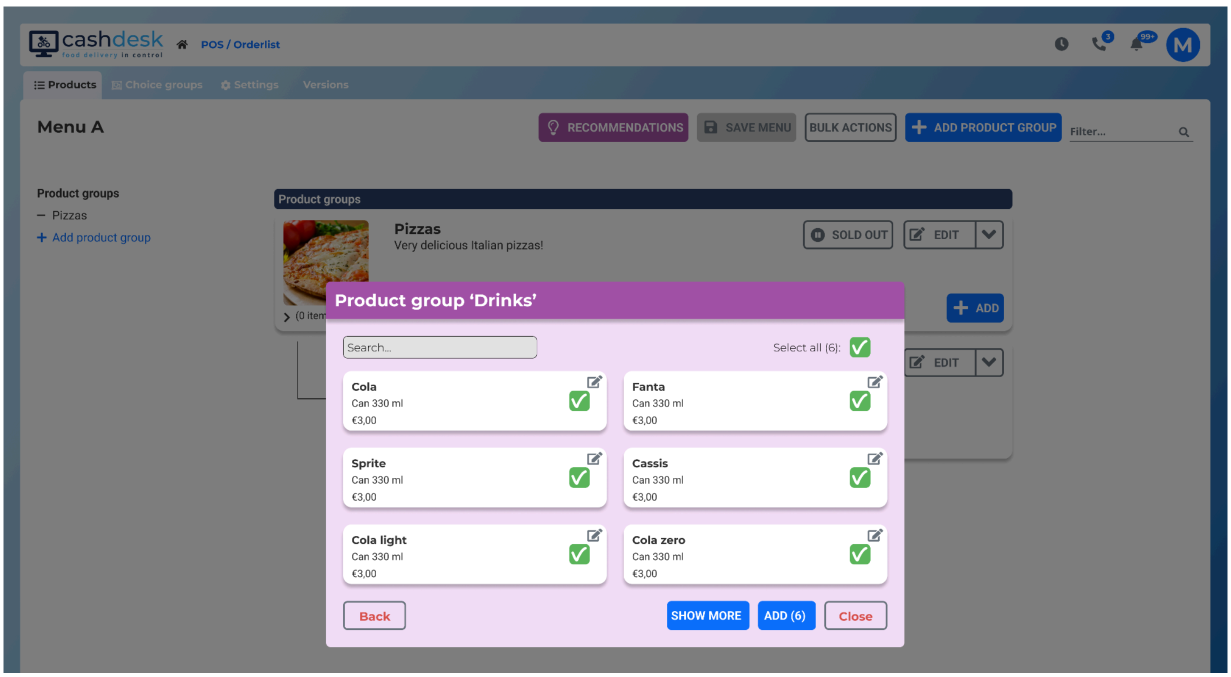


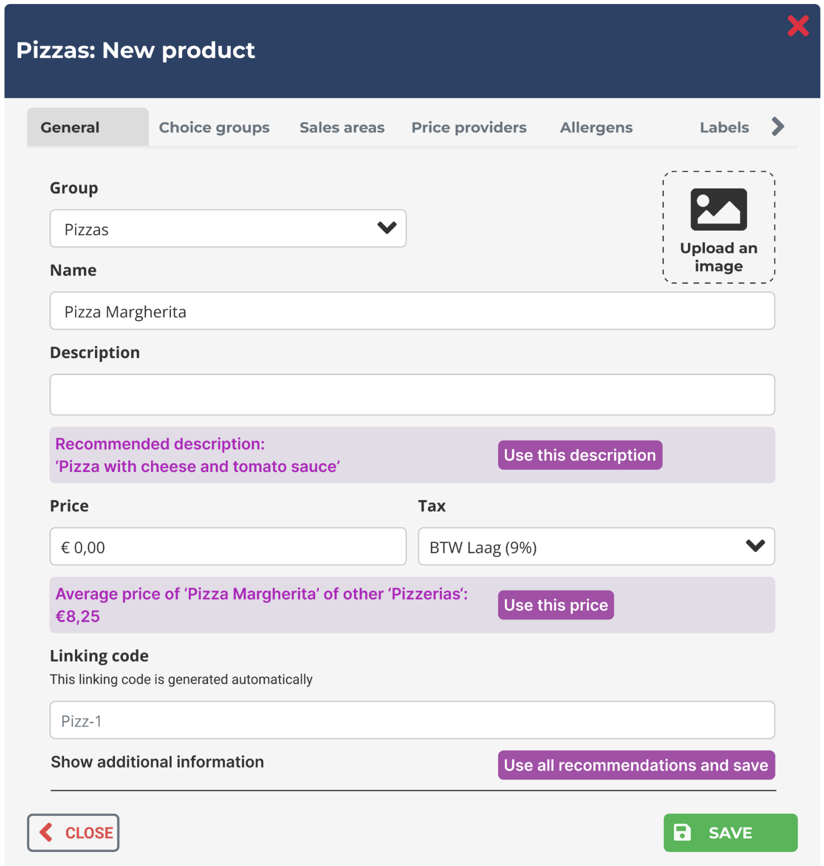
Figure 7b: Recommender system interface prototype C (products)



3.4.2.4 Product property recommendations

Finally, designs have been created with type suggestions for product (group) names including recommendations for descriptions and average prices which can be taken over directly, as illustrated in Figure 8.

Figure 8: Recommender system interface prototype (product properties)



3.5 Interviews and demonstrations with customers

Interviews were conducted with CashDesk customers to assess the reception of the three prototyped recommender system interfaces by actual users. The interviews were structured, consisted of 22 questions and expected to take between 30 and 60 minutes. Customers were asked permission for audio recording, which were used for transcribing afterwards. Interview questions can be found in Appendix B. Seven different restaurants were selected in consultation with CashDesk, based on different kitchen types and organisation sizes. These different types of restaurants are categorised into franchises and small and medium-sized enterprises (SMEs). Franchises are collaborations between franchisees (entrepreneurs) and franchisors based on a formula or concept. This implies that a franchisor may not have complete control over its menu.

The interviewed users are owners of a burger restaurant, Chinese restaurant, snack bar, small-scaled grillroom franchise, vegan restaurant, large-scaled sushi franchise, and pizzeria. The interviews consisted of four goals. The first goal was to understand the CashDesk users in their way of thinking, their workspace and their CashDesk usage. Secondly, to understand their experience with the current system and especially the menu editor. Third, to understand their opinion about the design and functionalities of the new CashDesk 3.0 system and its menu editor. And fourth, the largest portion of the interview, to understand their opinion of the demonstrated interface versions of a potential recommender system implemented in the CashDesk 3.0 menu editor. Demonstrations of CashDesk 2.0 were shown with screenshots and short captured screen recordings, while demonstrations of CashDesk 3.0 and the recommender system were shown using flows of the designed screens in Figma. The CashDesk 2.0 menu editor has been demonstrated shortly before asking its related questions, to be sure that customers remember the interface, in case they have not used it for a long period. This was done for the CashDesk 3.0 interface, CashDesk 3.0 menu editor and the prototyped recommender system interfaces as well. All demonstrations have been carried out on a laptop, presented to the customers.

3.5.1 Current menu editor (CashDesk 2.0)

Users were asked about their goals and tasks related to the menu editor to understand what is crucial for potentially enhancing the functionality and intuitiveness of the menu editor. Restaurant owners mostly use the menu editor for adding and changing products, turning off products in case they are not available anymore, and changing prices. The frequency of executing one of those tasks differs per user, ranging from once per week to once per year, with an average of once per month. In general, interviewed customers typically perceive the menu editor as cumbersome to navigate. They highlighted several different issues they have to deal with the current menu editor (CashDesk 2.0), which are mostly about uploading the menu to their website and to the external platforms, linking optional and mandatory choices to products, and using linking codes. Linking codes pose challenges as they must precisely match the CashDesk system and websites, require uniqueness, and necessitate manual creation and entry by users.

3.5.2 New menu editor (CashDesk 3.0)

It was essential to determine whether users perceive the new editor as more intuitive before being able to explore their opinions on the prototyped recommender system within the new menu editor, as users had not seen or experienced CashDesk 3.0 yet. Overall, customers expressed optimism about the new interface, anticipating it to be more user-friendly and easier to navigate. The terms used describing this new interface were “neater”, “sleek”, “more user friendly”, “clearer” and “easier”. “*It looks friendlier*” and “*In the base it looked good, well-arranged, a bit more user-friendly than the current version, I think*” were positive comments mentioned. However, it's worth noting that two out of the seven users harboured certain doubts. One customer initially had higher expectations of the new interface: “*I expected it to be a bit more modern. It looks very basic, so to speak, but yes, as long as it functions of course, that's what matters*”. Another customer seemed to have difficulties with using new software in general: “*For now it's new, new is always annoying*”. In summary, the majority of users expressed a preference for the new menu editor, believing it to be more user-friendly.

3.5.3 Recommender system

The designed recommender system prototypes were demonstrated to customers, after which they were asked their thoughts and opinions regarding the recommendation functions in general and specifically on which type they preferred. Opinions were divided, with SME restaurants expressing more enthusiasm about a potential recommender system compared to franchises.

Users were asked about the specific menu items for which they would prefer to receive recommendations. The options consisted of complete menus, product groups, products, drinks, prices and optional and mandatory options. Nearly all users expressed a keen interest in price information, particularly in comparing their own prices with those of similar products from other restaurants. However, some users mentioned that a potential recommender system might not be the ideal software component for receiving this data. Additionally, there was notable interest in both mandatory and optional choices.

Remarkably products and product groups were mentioned barely, which could be attributed to their explicit presence in the demonstration.

Users were also asked about their interest in receiving recommendations for products that are not on their current menu but could potentially be added. The majority of the users responded positively to this type of recommendations as a source of inspiration for enhancing their menu offerings. One user explicitly mentioned that this type of recommendations can be interesting, but might not be very relevant at the moment of editing or creating a menu. One franchise user remained uninterested in this data, expressing a desire to maintain uniqueness and refrain from adopting ideas or drawing inspiration from products offered by other restaurants.

While the interviewed franchises showed no general interest in receiving recommendations, they did express interest in recommendations for standard product categories such as drinks and sauces. In response to the question regarding system input automations for product names, descriptions, or prices, the majority of customers conveyed a preference for manual control. They indicated a desire not to have the system automatically incorporate recommended information, as they preferred to make these choices autonomously.

3.5.4 Interface preferences

Three different presentation types of a recommender system, as described in Chapter 3.4, were demonstrated to customers. The majority of users expressed a preference for interface prototype A, with the recommendations presented in a structured vertical block in the right side of the screen, as presented in Figure 5. Next to that, users were asked about their preference for passively or actively receiving recommendations. The majority indicated a preference for actively asking for recommendations. This preference stems from the concern that the interface could become too busy and overwhelming otherwise.

3.5.5 User experience

Opinions about the impact of the recommender system on ease of use, experience, and understandability were divided. On the question of whether the recommender system affects ease of use, responses were evenly split, with half affirming and half negating its influence. One user believed it might depend on the type of restaurant, while another customer thought it might not necessarily make tasks easier but could likely result in a quicker process. Users expressed uncertainty about whether the recommender system would influence the comprehensibility of the software. However, they believed that it does have a positive impact on their overall experience. In addition, clear information and accurate recommendations were highlighted the most as important properties for successfully using the recommender system. In response to the final question regarding the likelihood of customers using the recommender system, four users gave a positive response, two users expressed a partial inclination, and one user responded negatively.

3.5.6 Interpretation of the interview results

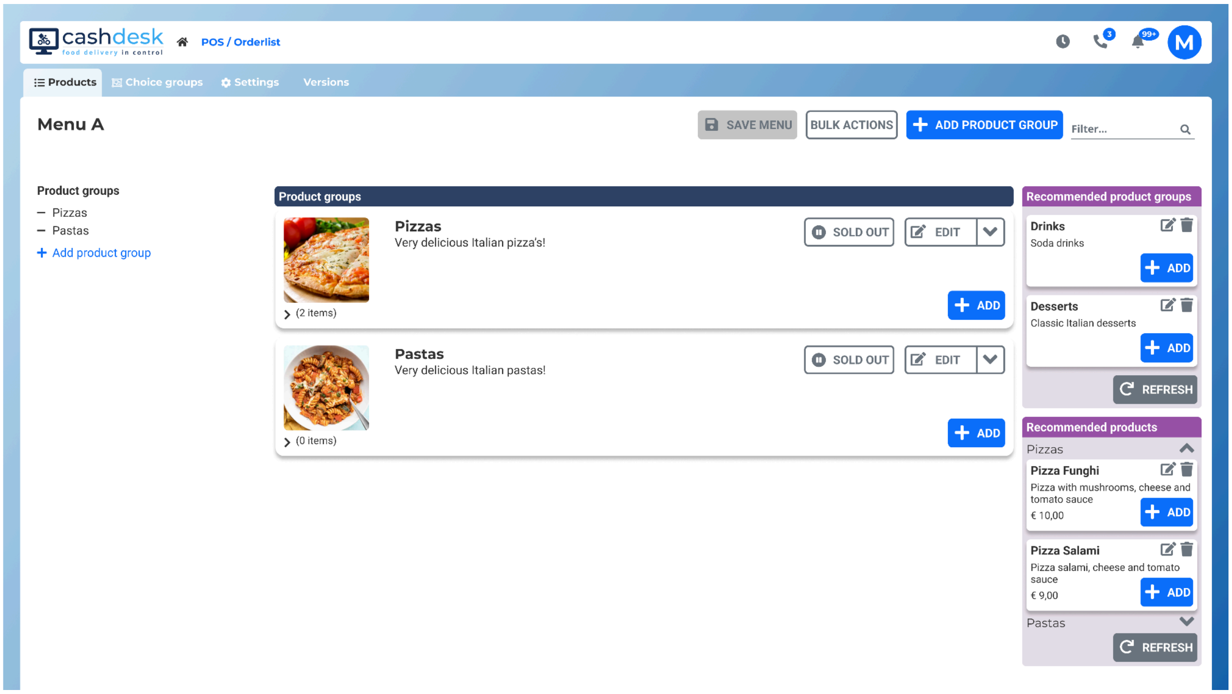
As a result of the interviews, CashDesk customer types can be categorised into two main groups: franchises and SMEs, which will be referred to as “one-store restaurants” from now. One-store restaurants are typical establishments runned by their owners, while franchises operate under a centralised headquarters with a standardised restaurant formula, featuring multiple identical restaurants across various locations. The results from this interview shedded light on the differences between these two restaurant organisation types. Among the one-store restaurant category, two distinct types emerge. Some establishments offer standard traditional common products. For instance snack bars selling fries or pizzerias offering a pizza margherita. In this Thesis, this type of restaurant is referred to as “standard one-store restaurant”. On the other hand, there are one-store restaurants strategically positioning themselves uniquely in the market, offering non-standard products. In this Thesis, these establishments are referred to as “unique one-store restaurants”. This distinction is crucial, as these different restaurant types express different preferences in the content and format of recommendations. Beyond content differences, the reasons for using a recommender system also vary for each restaurant type, given the diverse needs and characteristics of these different user groups. User profiles for franchises, unique one-store restaurants and standard one-store restaurants have been created based on the interview results.

Franchises appear to encounter less challenges while using the menu editor, as they use it on a frequent basis. Consequently, they express a reduced need for a recommender system as a support tool. This user group is not keen on the potential advantage of being inspired by interesting products from the recommender system, as they aim to maintain their unique identity. They feel they do not derive benefits from them, as they are unable to directly adopt products due to their unique menu formula. The unique one-store restaurants share a similar perspective on recommender systems with franchises. They express limited interest in product or product group recommendations, as their focus is on maintaining uniqueness. These users prioritise being distinctive, placing importance on unique product names, descriptions, and images. They are mostly experienced and involved CashDesk users, and use the menu editor regularly. It is therefore anticipated that a recommender system will have the most positive impact on standard one-store restaurants, such as pizzerias, Chinese restaurants, snack bars, sushi restaurants, and similar establishments. This restaurant group showed greater enthusiasm towards the prospect of a recommender system compared to franchises. These restaurants typically offer common products and product groups, making it likely to provide accurate recommendations based on menu cards from similar stores. The products offered often contain generic names, descriptions, images, and prices. This user group appears to encounter more challenges with the CashDesk system and computer usage in general. One-store restaurant owners are running their restaurant solely and rather focus on managing the restaurant, preparing products and carrying its customers and their orders, leading to an increased demand for support. Additionally, this user group tends to be more open to exploring inspiration for other products.

3.6 Designing an optimised recommender system interface

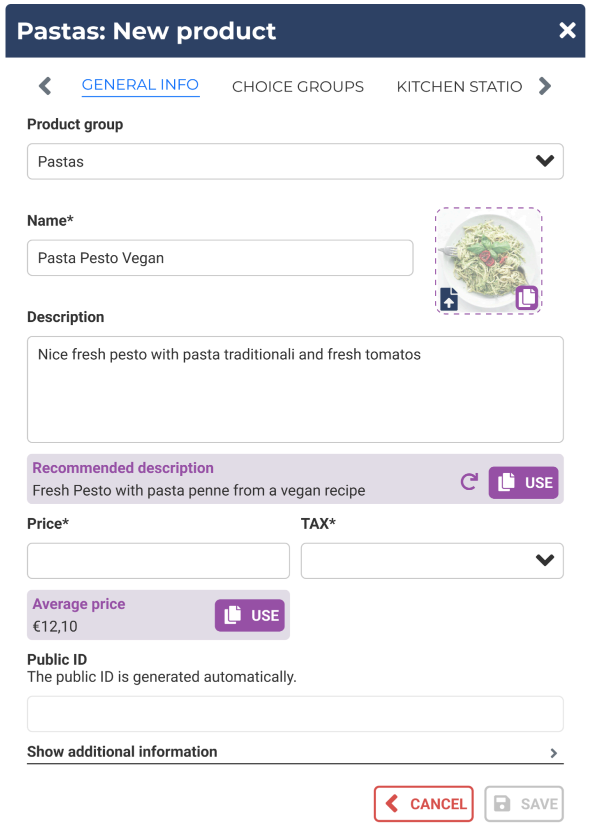
With a clear understanding of all recommender system requirements and preferences, an optimised interface prototype has been crafted to best meet the given criteria. In this updated prototype version, product and product group recommendations are positioned in a box in the right side of the screen, as the majority of the interviewed customers preferred. Minimal alterations have been made in this interface prototype A screen, as illustrated in Figure 9. Although users slightly leaned towards actively requesting recommendations, in collaboration with CashDesk’s web designer and IT-manager, the decision was made to have the recommender system always present. If the recommender system is ever developed and implemented, users will have the option to disable it in the settings. The possibility to enable or disable a feature aligns with similar functions in the CashDesk 3.0 menu editor. The recommendation box in the right side of the screen includes suggestions for both product groups and individual products, each clearly separated for enhanced clarity. Recommended products or product groups can be added, edited or declined instantly, and the entire recommendation box can be refreshed for updated suggestions. Additionally, product groups with its recommended products can be folded and unfolded.

Figure 9: Updated recommender system interface



Furthermore, the designs on detailed product level, where the description and price recommendations are showcased, have been updated as well. While there was no explicit indication for image recommendations, CashDesk sought to ascertain the desirability of this feature. As a result, recommendations for images have been added, as shown in Figure 10. The adoption of these recommendations can be initiated by clicking on the "use" button, represented by the copy-icon. As a small extra feature, recommended descriptions can be refreshed, considering the variability in descriptions for the same product. This enables users to find descriptions that better suit their products.

Figure 10: Updated recommender system interface for product properties



3.7 Questionnaire as recommender system interface evaluation

An online user-centric evaluation has been conducted to validate the designed recommender system prototype. A questionnaire has been created and distributed to all Dutch CashDesk customers (551) present in the customer contact file received from CashDesk, via an invitation email with the link to the questionnaire. The questionnaire was open for responses from 12-20-2023 and closed on 11-02-2024. The platform utilised for this survey is Qualtrics. The questionnaire consisted of 22 questions in total, was estimated to take between 15 and 20 minutes and could be completed in Dutch (default) or English. The answers were collected anonymously. The complete questionnaire can be found in Appendix C. In consultation with CashDesk, it was decided to maintain the questionnaire's brevity, both in terms of number of questions and time. It was therefore decided to combine relevant and essential aspects from commonly used theoretical models and questionnaires which are described in the Literature section of this Thesis (Chapter 2). The TAM and UTAUT models are used for questions related to perceived usefulness, perceived ease of use and performance. Although the SUS questionnaire contains relevant questions for this questionnaire, its primary emphasis is on the practical utilisation of a system in real-life scenarios, while participants of this research did not. Additionally, the exact statements from the UEQ did not align perfectly with this questionnaire for the same reason.

3.7.1 Goal

The main goal of this questionnaire was to find out what different types of users think of the designed prototyped recommender system in the menu editor, which can be split into two sub goals. One of the sub goals was to ascertain the perspectives of various user types regarding the specific features that the prototyped recommender system could provide. This includes complete product and product group recommendations, as well as product property recommendations pertaining to product descriptions, prices, and images. Another important sub goal was to explore users' understanding of the potential benefits that this prototype recommender system could provide across various dimensions at a more general level. The results from this questionnaire are used as evaluation of the prototyped recommender system interface and contribute to answering the research questions of this Thesis.

3.7.2 Construction

The questionnaire included four sections of questions. The first section contained three obligatory multiple-choice questions about the general respondent’s and restaurant information. Respondents are asked about their restaurant organisation type (franchise, SME, or other), kitchen type, and CashDesk version used. During the period this questionnaire was administered, CashDesk 3.0 was launched already, providing the possibility for customers to utilise this new web application instead of CashDesk 2.0. The second question section was comprised of three obligatory multiple-choice questions asking for slightly more detailed information about the respondent’s computer and menu editor experiences with one optional open-ended question at the end where customers could provide additional information about it. The first and second question sections were created with the aim of facilitating comparisons in subsequent analyses and ensuring a balanced distribution among respondents.

The third section included five obligatory questions with a brief introduction of a use-case, screenshots showcasing the prototyped recommendation feature as described in Chapter 3.6, and a statement-formatted question based on a five-point Likert scale. This type of question is applied to product group recommendations, product recommendations, and a composite question encompassing product description, price, and image recommendations. The question regarding type suggestions for product names has been omitted due to its divergence from the scope of recommendations and to reduce the number of questions.

In the final fourth section, respondents could consider the potential added value to the menu editor as the recommender system has been demonstrated to them via use-cases and screenshots before. Respondents were presented with nine obligatory statements outlining their perspective on the benefits of the recommender system, starting with a general statement about their overall satisfaction, followed by statements where they could assess recommendation aspects such as their clarity, usefulness, and inspiration. Furthermore, statements followed about the anticipated impact of the recommender system on the menu editor, indicating whether it is expected to improve speed, enhance comprehension, facilitate ease of use, and reduce the need for external support while using the menu editor. Lastly, respondents could express their likelihood of utilising the recommender system. Additionally, one open-ended, non-mandatory question followed about any unnecessary properties of the recommender system shown, bringing the total number of questions to 22 of which 20 were mandatory.

3.7.3 Reliability and validity

To ensure reliability, the questionnaire remained consistent for every customer and could be completed in either Dutch or English, minimising language impact on the research population and results. The content of the invitation email was standardised for all customers and included a personalised salutation. Notably, there was a variance in the timing of sending invitations to CashDesk customers, as the questionnaire was distributed in phases, rather than all at one moment. This approach, aligned with CashDesk's aim to avoid unnecessary customer outreach, entailed sending invitations via email in phases to engage as few customers as possible in completing the questionnaire. This applied for calling customers for participating in the questionnaire as well.

For validity assurance, efforts were made to establish a clear distinction between franchises and one-store restaurants, and to ensure sufficient variation in the number of different kitchen types, thereby enhancing the sample's representativeness of the target group. To maintain uniformity, five-point Likert scales were consistently applied wherever possible, ensuring that questions were administered and assessed using the same scale.

3.7.4 Target population

The aim was to gather a total of 50 respondents, distributed between franchises and one-store restaurants. Utilising CashDesk's customer database, invitations to participate in the questionnaire were extended via email, and customers were called randomly later in the recruitment process, when not enough customers seemed to participate in the questionnaire via email invitations only. While the questionnaire ensured complete anonymity, respondents were required to select the kitchen type that best represents their restaurant. Additionally, they were asked to specify their business type, indicating whether it is a franchise, a one-store restaurant, or another category they could define themselves. An essential consideration was ensuring diversity in the number of kitchen types and business models represented within the population. This had to be validated throughout the duration in which the questionnaire was available for responses.

4. Results

The results of the questionnaire are presented in this chapter. The questionnaire was opened 40 times in total. However, not every respondent started the questionnaire and some respondents did not complete it. In total, 32 respondents at least started the questionnaire, while 18 respondents successfully completed it. The answers from the incomplete questionnaires were analysed and not excluded from the overall assessment. The received responses were exported from Qualtrics and then imported into SPSS 29. Questions utilising a five-point Likert scale (“strongly disagree” - “strongly agree”) were converted into a numeric scale (1-5) to facilitate the execution of statistical tests. The data derived from these questions is ordinal in nature, prompting the use of non-parametric tests for analysis. (One-sample) Wilcoxon Signed Rank tests are executed for analysis on the complete population, while Mann-Whitney U-tests are executed for group comparisons. A significance level of $p < 0.05$ is employed for statistical inference. Significant values in the displayed tables are flagged with an asterisk (*).

4.1 Population

62.5% of the respondents were SMEs with one store, 21.9% were franchises and 15.6% were others. When respondents selected the “other” option, they were required to manually provide information about their specific category. This textual information has been analysed, and respondents are subsequently categorised into either the one-store or franchise restaurant category. Three participants indicated that they are a SME with two stores instead of one. These respondents were categorised as one-store restaurants, reflecting the consistent underlying principle of a restaurant operated by a single owner without a large corporate structure. One participant only filled in “8 concepts”, but mentioned the name of its franchise restaurant in the final open question, and thus is categorised as a franchise. Finally, one participant who mentioned “company store”, implying a franchise, is categorised as such. After categorisation, 71.9% of the respondents were one-store restaurants, and 28.1% were franchises.

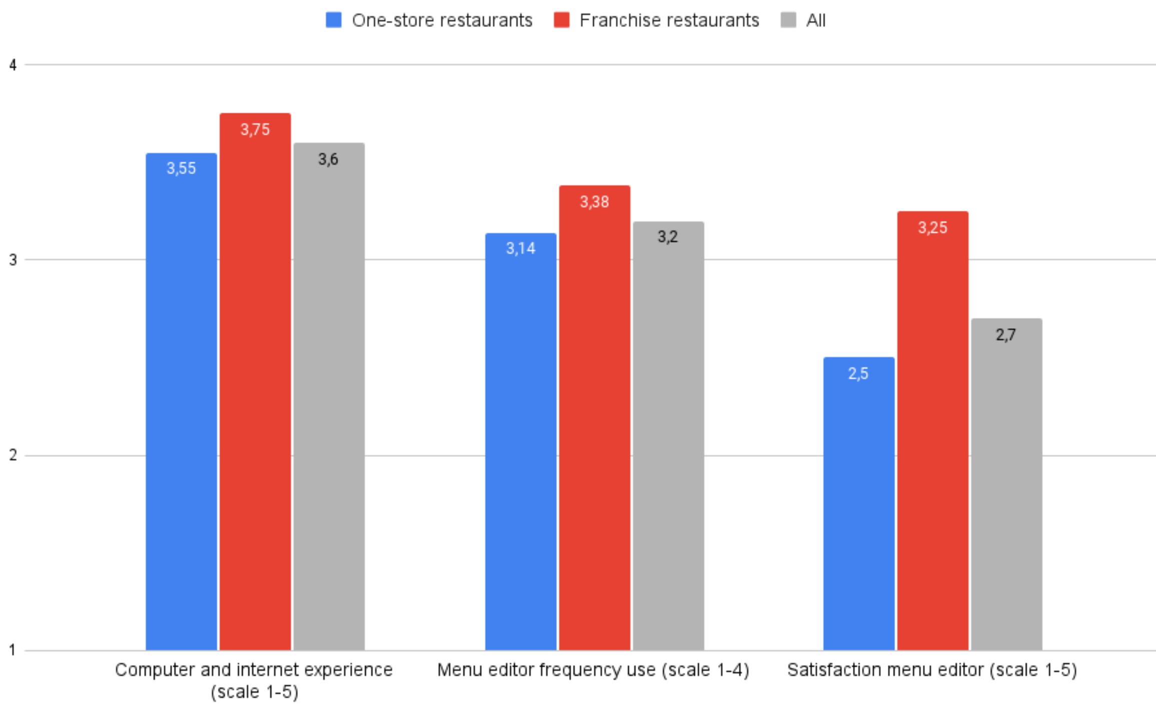
Respondents expressed a high level of computer and internet experience, with no responders selecting the lowest “limited” option, and five respondents selecting the highest option “expert” (36.7%). The results from the one-sample Wilcoxon Signed Rank test indicated that, on average, this population assesses their computer and internet experience as higher than proficient (mean = 3.60, $p = 0.002$). This also applies to the 18 respondents that fully completed the questionnaire (mean = 3.67, $p = 0.011$). The respondents use the menu editor mostly on an occasional level (about one till two times per month) (60.0%), some frequently (about one till two times per week) (30%), a few on rare level (about one till two times per year) (10%), but the option “never” is not chosen at all. The one-sample Wilcoxon Signed Rank test showed that the mean of the asked menu editor frequency usage (3.20) is significantly higher ($p < 0.001$) than the expected median, which is 2.5 on a scale from 1-4. This also applies to the 18 respondents that fully completed the questionnaire (mean = 3.28, $p < 0.001$).

Participants appeared to hold a more negative opinion about their satisfaction with the menu editor, as indicated by a mean score of 2.70, compared to the expected median of 3. Three respondents even selected the “strongly disagree” option, while zero respondents selected the “strongly agree” option, on the statement “I like the menu editor”. However, the one-sample Wilcoxon Signed Rank test did not yield a statistically significant result ($p = 0.068$). Nevertheless, there is a significant difference found between franchises (mean = 3.25, SD = 0.71) and one-store restaurants (mean = 2.50, SD = 0.86) here with the Mann-Whitney U-test ($U = 46.50$, $p = 0.037$). The number of participants (N), means, and standard deviations (SDs) of the technical user characteristics, separated by restaurant type, are displayed in Table 1. Figure 11 graphically illustrates the division of the means.

Table 1: Baseline technical user characteristic

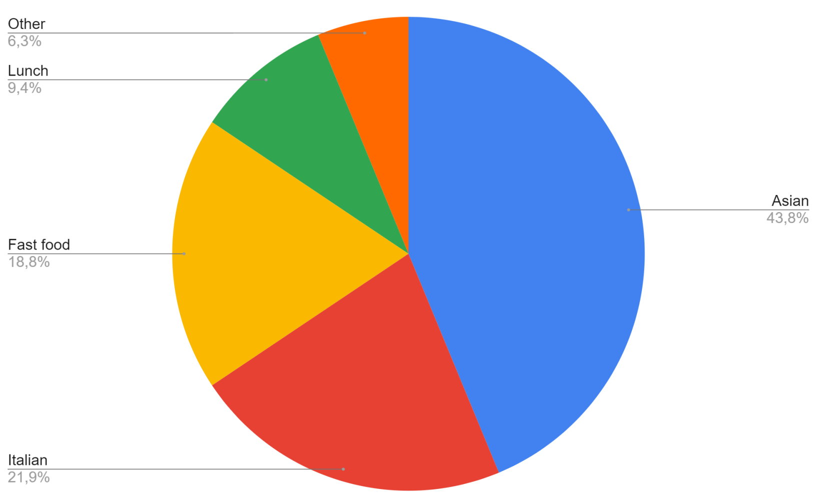
	One-store restaurants	**Franchise restaurants**	**All**
CashDesk version	CashDesk 2.0: 73.9% (N: 17) CashDesk 3.0: 26.1% (N: 6)	CashDesk 2.0: 100% (N: 9)	CashDesk 2.0: 81.3% (N: 26) CashDesk 3.0: 18.8% (N: 6)
Computer and internet experience (scale 1-5)	Mean: 3.55 (N: 22, SD: 0.86)	Mean: 3.75 (N: 8, SD: 1.04)	Mean: 3.60 (N: 30, SD: 0.89
Menu editor frequency use (scale 1-4)	Mean: 3.14 (N: 22, SD: 0.64)	Mean: 3.38 (N: 8, SD: 0.52)	Mean: 3.20 (N: 30, SD: 0.61)
Satisfaction menu editor (scale 1-5)	Mean: 2.50 (N: 22, SD: 0.86)	Mean: 3.25 (N: 8, SD: 0.71)	Mean: 2.70 (N: 30, SD: 0.88)

Figure 11: Bar chart technical user characteristics means



The kitchen types of the responders were well divided, but with a strong majority for specifically pizzerias (21.9%). For a more streamlined overview, the 14 distinct kitchen types were categorised into four groups. The biggest portion consisted of Asian typed restaurants, as shown in Figure 12.

Figure 12: Division of categorised responder's kitchen types



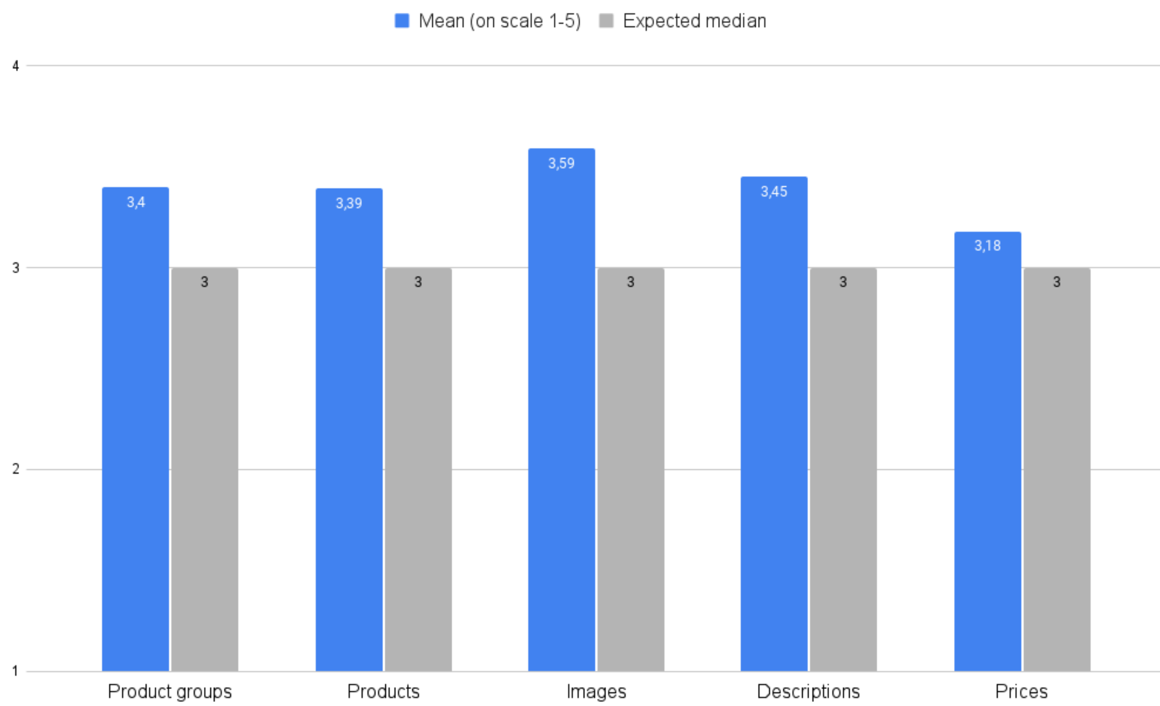
4.2 Recommender system features

The five researched features encompassed recommendations for product groups, products, images, descriptions and prices, which are evaluated on a five-point Likert scale, yielding ordinal, non-parametric data. To assess whether the means differ from the expected median of 3, one-sample Wilcoxon Signed Rank tests were conducted. Results indicate that the means of all five features are higher than 3, suggesting an overall positive impact. However, not all features demonstrate a statistically significant outcome. Specifically products (mean = 3.39, p = 0.049) and images (mean = 3.59, p = 0.010) are significantly positively evaluated features. While product groups and descriptions are evaluated positively as well, no statistical significance was found. Prices are the least popular feature (mean = 3.18, p = 0.396). The described results are presented in Table 2. Figure 13 graphically illustrates the division of the means.

Table 2: Evaluation of recommender system features

Feature recommender system	**One-store restaurants**	**Franchise restaurants**	**All**	**P-value**
Product groups	Mean: 3.39 (N: 18, SD: 1.15)	Mean: 3.43 (N: 7, SD: 0.54)	Mean: 3.40 (N: 25, SD: 1.00)	0.062
Products	Mean: 3.44 (N: 16, SD: 0.96)	Mean: 3.29 (N: 7, SD: 0.76)	Mean: 3.39 (N: 23, SD: 0.89)	0.049*
Images	Mean: 3.47 (N: 15, SD: 0.99)	Mean: 3.86 (N: 7, SD: 0.69)	Mean: 3.59 (N: 22, SD: 0.91)	0.010*
Descriptions	Mean: 3.47 (N: 15, SD: 1.25)	Mean: 3.43 (N: 7, SD: 0.98)	Mean: 3.45 (N: 22, SD: 1.14)	0.075
Prices	Mean: 3.13 (N: 15, SD: 1.13)	Mean: 3.29 (N: 7, SD: 0.76)	Mean: 3.18 (N: 22, SD: 1.01)	0.396

Figure 13: Bar chart evaluation of recommender system features



4.3 Recommender system potential benefits

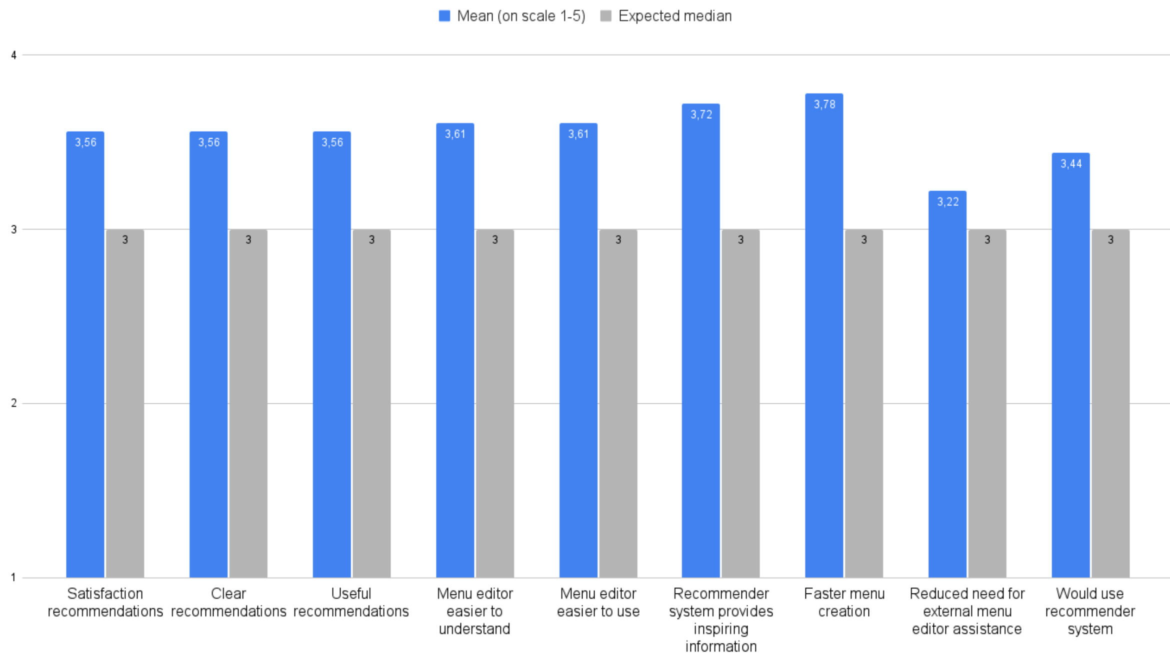
The final page of the questionnaire contained a table of nine statements that should have been answered on a five-point Likert scale. These statements were related to the recommendations in general, the potential benefits of a recommender system and the impact on the menu editor. One-sample Wilcoxon Signed Rank tests were conducted to evaluate whether the means differ from the expected median (3).

The means for all nine statements exceed the expected median of 3, with eight of them achieving statistical significance. Participants generally appreciate the recommendations, as indicated by a mean score of 3.56, with a statistically significant p-value of 0.002. The presentation of the recommendations is evaluated as clear (mean = 3.56, p = 0.002), useful (mean = 3.56, p = 0.008) and the recommender system is expected to provide inspiring information (mean = 3.72, p = 0.005). Participants expressed the highest level of positivity regarding the potential speed improvement achievable (mean = 3.78, p = 0.001). In addition, the menu editor is expected to be easier to use (mean = 3.61, p = 0.005) and understand (mean = 3.61, p = 0.008). However, not all statements received a statistically significant evaluation. Participants have a neutral opinion (mean = 3.22, p = 0.357) concerning whether the recommender system could reduce the need for menu editor assistance from CashDesk's customer support. Nevertheless, participants are likely to use the recommender system, as suggested by a mean of 3.44, with a statistically significant p-value of 0.033. The described results are shown in Table 3, and graphically illustrated in Figure 14.

Table 3: Evaluation of recommender system potential benefits

Potential benefit recommender system	One-store restaurants	Franchise restaurants	All	P-value
Satisfaction recommendations	Mean: 3.57 (N: 14, SD: 0.51)	Mean: 3.50 (N: 4, SD: 0.58)	Mean: 3.56 (N: 18, SD: 0.51)	0.002*
Clear recommendations	Mean: 3.57 (N: 14, SD: 0.51)	Mean: 3.50 (N: 4, SD: 0.58)	Mean: 3.56 (N: 18, SD: 0.51)	0.002*
Useful recommendations	Mean: 3.50 (N: 14, SD: 0.65)	Mean: 3.75 (N: 4, SD: 0.96)	Mean: 3.56 (N: 18, SD: 0.71)	0.008*
Menu editor easier to understand	Mean: 3.64 (N: 14, SD: 0.75)	Mean: 3.50 (N: 4, SD: 0.58)	Mean: 3.61 (N: 18, SD: 0.70)	0.005*
Menu editor easier to use	Mean: 3.64 (N: 14, SD: 0.84)	Mean: 3.50 (N: 4, SD: 0.58)	Mean: 3.61 (N: 18, SD: 0.78)	0.008*
Recommender system provides inspiring information	Mean: 3.93 (N: 14, SD: 0.73)	Mean: 3.00 (N: 4, SD: 0.82)	Mean: 3.72 (N: 18, SD: 0.83)	0.005*
Faster menu creation	Mean: 3.86 (N: 14, SD: 0.66)	Mean: 3.50 (N: 4, SD: 0.58)	Mean: 3.78 (N: 18, SD: 0.65)	0.001*
Reduced need for external menu editor assistance	Mean: 3.21 (N: 14, SD: 1.12)	Mean: 3.25 (N: 4, SD: 0.50)	Mean: 3.22 (N: 18, SD: 1.00)	0.357
Would use recommender system	Mean: 3.50 (N: 14, SD: 0.86)	Mean: 3.25 (N: 4, SD: 0.50)	Mean: 3.44 (N: 18, SD: 0.78)	0.033*

Figure 14: Bar chart evaluation of potential benefits recommender system



4.3.1 Differences between franchises and one-store restaurants

There are no significant differences identified in opinions between franchises and one-store restaurants concerning both the features and the potential benefits of the demonstrated recommender system. Nevertheless, a striking difference appeared in the statement addressing the potential benefit of the recommender system to provide inspiring information. Franchises anticipated this as a neutral aspect, with a mean of 3.00 (SD = 0.82), while one-store restaurants expected this as a positive aspect, with a mean of 3.93 (SD = 0.73), as displayed in Table 3. However, this difference is not statistically significant (U = 11.50, p = 0.061), as determined with the Mann-Whitney U-test.

4.3.2 Differences between CashDesk 2.0 and CashDesk 3.0 users

One difference is found between CashDesk 2.0 users and CashDesk 3.0 users with the Mann-Whitney U-test. CashDesk 2.0 users expressed significantly more positive sentiments (p = 0.049) regarding the impact of a recommender system on the understandability of the menu editor (mean = 3.83, SD = 0.72) compared to CashDesk 3.0 users (mean = 3.17, SD = 0.41).

4.4 Correlations

Relationships between technical user characteristics and evaluated recommender system potential benefits were examined using Spearman's Rank Correlation Coefficient, a nonparametric statistical measure to find relationships between two ordinal variables. A negative correlation emerged between the frequency of the menu editor use and the satisfaction with the menu editor (r = -0.42, p = 0.021), meaning that as the usage frequency of the menu editor increases, user satisfaction tends to decrease, and vice versa. Another negative correlation (r = -0.51, p = 0.031) is found between the satisfaction with the menu editor and the extent to which participants believe the menu editor would be easier to understand with the recommender system. This suggests that as satisfaction with the menu editor increases, the improvement in understandability with a recommender system tends to decrease, and vice versa. A further negative correlation is found between the satisfaction with the menu editor and the extent to which respondents believe a recommender system can provide them with inspiring information ($r = -0.53$, $p = 0.025$), suggesting that the higher the user's satisfaction with the menu editor, the less they expect the recommender system to be a source of inspiration. Table 4 shows an overview of the correlation coefficients found.

Table 4: Correlations (Spearman's Rho)

Measure	Computer and internet experience	Menu editor frequency use	Satisfaction menu editor
Computer and internet experience	-		
Menu editor frequency use	0.10	-	
Satisfaction menu editor	0.24	-0.42*	-
Satisfaction recommendations	0.41	0.29	-0.23
Clear recommendations	0.41	0.08	-0.08
Useful recommendations	0.21	0.16	-0.03
Menu editor easier to understand	0.09	0.47	-0.51*
Menu editor easier to use	-0.06	0.04	-0.19
Recommender system provides inspiring information	0.30	0.24	-0.53*
Faster menu creation	0.07	0.20	-0.38
Reduced need for external menu editor assistance	-0.20	0.20	-0.15
Would use recommender system	0.06	0.14	-0.39

4.5 Open questions

Participants had the opportunity to share if and when they needed assistance while using the current menu editor. This question received 16 responses, including five indicating that no assistance was needed, and two participants reporting problems related to uploading. Nine respondents, however, mentioned relevant both general and specific difficulties. Two participants mentioned the following about their challenges with the menu editor: "*When changing the menu, I often need someone who can take a look and explain how to do a step.*" and "*If a new product group or something like that needs to be created or another* *minor adjustment.*". One participant mentioned problems with the menu editor in general: "*Yes, it's too complicated.*".

In the final voluntary question, participants were asked if any features of the presented recommender system feel redundant to them. This question received six responses, including two indicating "no". One participant indicated that the menu editor is only used by the head quarter of its restaurant. Another participant mentioned that the recommender system does not provide extra benefits for him and his current working process. One participant specifically mentioned images here. Another participant mentioned that he would like to see this recommender system as a replacement for the upselling editor, where optional and mandatory choices can be set up as upselling, noting it as a potentially more user-friendly option.

5. Discussion

This section initiates the discussion of this research by interpreting the questionnaire results, identifying study limitations, evaluating the research conducted, and recommending potential directions for future research.

5.1 Interpretation of results

Participants generally assess the demonstrated recommender system as a positive component within the menu editor. All aspects of the recommender system receive positive evaluations, although not all of them reached statistical significance. Recommendations for products were significantly and positively appraised, in contrast to product groups, although this difference is minimal. Both recommendations for products and product groups serve as the primary components of the recommender system within the interface, positioned to the right of the menu editor's home screen. While it can be cautiously concluded that both elements are of interest, products appear to be more favourably received than product groups. This might be attributed to the likelihood that users are less inclined to introduce an entirely new product group compared to a single product. Incorporating a whole new product group typically requires the inclusion of new ingredients along with corresponding recipes, and may not align with the restaurant's formula.

Despite one participant expressing a sense of redundancy regarding images, images only, as a product property, received a significantly positive evaluation, while descriptions come close to achieving statistical significance. Prices however do not emerge as a popular feature, despite the common interest that customers showed earlier in interviews. A plausible explanation for the lack of significantly positive responses to descriptions and prices may be that users, when adding or editing a product, prefer not to be disrupted or confronted with unnecessary recommendations. Users might already possess a suitable description or know an appropriate price when they are adding a new product, making additional suggestions seem redundant. While the interviewed customers expressed positive thoughts about obtaining price information from similar restaurants and its products, results from the questionnaire do not support this. One plausible assumption is that users may have a strong interest in prices but are not necessarily seeking recommendations for it. During interviews, some participants expressed a desire to see prices from similar products and restaurants, but they emphasised a preference for a distinct, separate interface to access this information.

The positive evaluation of images suggests that users encounter challenges in obtaining visually appealing and professionally presented images, or images at all. This is surprising, as images did not seem to be considered a desirable recommended product feature. Capturing a high-quality image is essential for selling digital products and often costs time and money, especially when the product needs to be prepared carefully, presented with a clear background setting with a photographer involved. This provides a plausible explanation for why images were evaluated as a popular recommendation.

Regarding potential benefits, eight out of the nine statements received significantly positive responses. Users expected that the recommender system could provide them inspiring information, aligning with research findings from Neidhardt et al. (2015), which demonstrate that interactions with a recommender system can be perceived as inspiring and enjoyable. Additionally, they expected that a recommender system could fasten their menu creation process, which has been indicated by interviewed customers as well. While users generally expressed positive sentiments and believe that the menu editor will be easier to understand and to use, there is no significant indication that users anticipate a reduction in their need for external assistance with the menu editor. One possible explanation for this could be that participants acknowledge the helpfulness of the recommender system, but are not entirely convinced that it completely stops their need for assistance. Another explanation could be that participants think that this demonstrated recommender system is meant to replace or reduce the capacity of the support department, which could make them afraid of losing the ability for getting support.

It is important to highlight that the population participating in the questionnaire assesses themselves as a relatively highly computer and internet experienced user group, and use the menu editor on a frequent basis. This type of users probably encounter less difficulties with systems in general, including the menu editor. Consequently, they may perceive less need for its support functionalities. This could explain the lack of endorsement for the recommender system's capability to reduce external assistance among this specific population. However, it's crucial to acknowledge that despite the overall proficiency of the participants, nine respondents, including seven of the 18 fully completed questionnaire respondents, reported encountering difficulties, irritations, and challenges with the menu editor. This indicates that, despite their experience, users still face issues, emphasising the importance of addressing usability concerns for even the more experienced user base.

Despite lacking statistical significance, franchises generally express less positive thoughts towards finding inspiration through the menu editor compared to one-store restaurants. This observation aligns with expectations of the created franchise user profile, derived from customer interviews, where franchises emphasised their desire to maintain uniqueness and imagine their own products without drawing inspiration from similar restaurants.

Interestingly, there is an intriguing dynamic in user satisfaction with the menu editor. Satisfaction tends to decrease as the frequency of usage increases. Moreover, increased satisfaction with the menu editor is linked to lower expectations regarding the recommender system's capability to provide inspiring information, and the understandability of the menu editor. This finding suggests that higher satisfaction with the menu editor may lead to a decrease in expectations regarding the performance of the recommender system.

Overall, participants generally expect the designed recommender system as a positive addition to the menu editor, recognising its potential to enhance user experience and usability. Despite users not expecting that it could reduce their reliance on external assistance, there is a significant indication that the recommender system is actively utilised once implemented, and could support users in executing their tasks.

5.2 Limitations

This section provides a critical examination of the limitations and potential biases of this research.

5.2.1 Generalisability

One limitation is related to the generalisability of this research. This research focussed on a very specific software interface and user group. As a result, the findings may not be generalisable to a large group of users. In addition, respondents participating in the questionnaire assessed themselves as relatively highly experienced computer and internet users, and utilised the menu editor more frequently than expected. This limits the generalisability of the findings to the broader CashDesk customer group and, by extension, to users in general.

5.2.2 Population and biases

One more limitation is associated with the small population size of the questionnaire. The response rate was very low (7.3%) and a considerable number of participants did not complete the questionnaire. Another limitation pertains to several potential biases. Participants who are highly experienced and frequent users, are likely more interested and involved in software developments and researches, introducing a potential self-selection bias. In addition, low-engaged and inexperienced customers may likely face challenges with computers and internet, extending to digital questionnaires, which results in a respondents bias as well.

A social desirability bias may also be present, where respondents provide answers they believe are socially desirable for the research. Furthermore, relying on respondents to assess their own computer and internet experience leads to a self-reporting bias, as participants may have varying opinions about their skills, leading to potential overestimation or underestimation, with each person having a different perceived minimum and maximum capability.

5.2.3 Demonstration of the recommender system interface

Most participants (81.3%) were still using CashDesk 2.0, while the demonstrated recommender system was showcased in CashDesk 3.0. Although participants could envision how the recommender system might function in this new interface, they might be overwhelmed by the entirely new interface, potentially impacting their overall perceptions and introducing a limitation. Additionally, the limitation arises from the recommender system being prototyped and only presented through screenshots and explanation texts. Participants had no opportunity to interact with it, which limits their ability to form a comprehensive opinion. This introduces a challenge in definitively answering the research questions, as the results depend on user expectations and assumptions.

5.3 Research evaluation

This section evaluates the methods conducted for addressing the research questions, the theoretical frameworks utilised, as well as the reliability and validity of this research.

5.3.1 Methodology sequence

Several research methods have been employed in this study, ordered logically and strategically to ensure a comprehensive exploration of the research questions. The sequence of the selected methods proved to be effective, with initial focus on researching and defining interface challenges, laying the groundwork for a thorough understanding of the actual issues and challenges. Subsequently, qualitative data was gathered through customer interviews, providing further insights into different user types, user needs and recommender system preferences, resulting in the development of an optimised interface prototype. Quantitative data was then collected from a larger customer sample through a questionnaire as an evaluation method. The sequence of the executed methods ensured a step-by-step qualitative exploration of challenges, culminating in interviews as the final and most comprehensive method, before applying a quantitative method for evaluating a proposed interface prototype. The integration of qualitative and quantitative data greatly enriched the comprehension of user types, user needs, interface challenges, and user's viewpoint on a potential recommender system.

5.3.2 Theoretical frameworks

The chosen theoretical frameworks were effective in analysing technology adoption, user experience, usability and recommender systems. However, there is potential for further refinement of the theoretical framework to provide more profound explanations for different user characteristics and potential benefits that recommender systems could offer within complex interfaces.

5.3.3 Reliability and validity

The reliability of this research is assured by careful methodological planning and consistent execution. Internal reliability is supported by standardisation of procedures, ensuring that all participants experience comparable conditions for every method conducted. External reliability is ensured by documenting procedures and methods, allowing other researchers to replicate the study. While the questions in the questionnaire are not derived from a standardised survey, they were based and inspired on extensively researched and validated questionnaires within the HCI-field.

5.4 Future research

For future research, it would be valuable to explore a more diverse range of users, characterised by average computer and internet experience and low interface frequency use. Additionally, further investigations should involve testing an actual developed recommender system in an between-subjects design that involves user interactions, within an broader applicable application, and a higher number of participants. An online evaluation is recommended as well, as it provides accurate performance indications with users using the system in their authentic and natural environment, while also yielding a larger volume of data. Subsequent studies could place a greater emphasis on a recommender system focused on recommending navigation actions rather than items.

6. Conclusion

This research centred on implementing a recommender system as support tool for users using a relatively complex interface on an infrequent basis. The study was specifically conducted within the context of CashDesk's POS system, targeting restaurant owners as a user group and highlighting the menu editor as a typical complex interface. To gain a deeper understanding of this complex menu editor, a customer support log analysis of all reported menu editor issues was conducted and CashDesk's support employees were interviewed. Next to the already solved issues in the new CashDesk 3.0 version, the majority of experienced menu editor issues were related to the general core functionalities, such as adding and changing products, answering SQ1.1: "*What are the current user challenges within the interface?*" As a result, interfaces of potential recommender systems were prototyped, based on the capabilities of CashDesk's database, and were demonstrated to customers participating in interviews. Drawing from their feedback, an optimised interface was prototyped and showcased through screenshots and use-cases within a questionnaire. This interface included a recommendation box positioned on the right side of the screen, with the optional setting to turn it off, aligning with the preference expressed by interviewed customers in response to SQ2.3: "*What are the user preferences for a recommender system interface design?*". This interface displayed recommendations comprising various recommendable features, including product groups, products, images, descriptions and prices, answering SQ2.1: "*What are the possible features to recommend?*". The results indicated that respondents generally perceived the recommender system positively, anticipating its potential to improve the ease of use and understandability of the menu editor. This addresses SQ1.3: "*What is the effect of the recommender system on the perceived user experience with the interface?*". Next to that, participants expected a significant positive effect on the menu creation speed, answering SQ1.2: "*What is the effect of the recommender system on the perceived efficiency of the interface?*". Furthermore, in addition to the anticipated speed improvements in menu creation, users expected the recommender system to have the positive side effect of offering inspiring information, thereby addressing the question posed in SQ1.5: "*What are the additional perceived benefits that a recommender system can provide?*". In the context of this particular research, recommended products and images received significantly positive evaluations, answering SQ2.2: "*What are the desired features to recommend?*". While this recommender system is likely to have a positive impact on the menu editor component, the need for assistance in navigating the interface may not be entirely replaced or highly reduced. However, the researched population assessed themselves as a relatively highly experienced user group, with a higher frequency use than expected, posing it not completely possible in answering SQ1.4: "*What is the effect of the recommender system on the perceived need for external help while using the interface?*". Altogether, participants assessed the recommender system positively, including a more positive user experience, improved usability and additional beneficial side effects. Although RQ1: "*What is the influence of a recommender system on users within a given integrated web-based interface?*" can not be answered completely, as no actual recommender system is evaluated in this research, users expected a recommender system as a positive experienced tool that would improve user experience, usability, speed, and menu inspiration.

Nevertheless, it's important to highlight that the evaluation and assessment of the recommender system rely on user expectations generated from use-cases and screenshots. Further investigations should test an actual recommender system in a between-subjects design that involves user interactions, within an broader applicable application and a more diverse user group, and a higher number of participants.

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Appendices

Appendix A: Interviews with CashDesk support employees

Protocol

1. *Script to open the interview*

Thank you for taking the time to participate in this interview. This interview is part of my Master project, in which I am researching the functionality of the menu editor within CashDesk 2.0. I have analysed the logs of customers' requests that you as support employee write down in HubSpot (logging system). In addition to the information obtained from this log analysis, I would also like to interview several support employees. I would like to know about your experience with the questions about the menu editor and, maybe, your ideas about this part of the system since you have handled so many questions about it.

The interview will take about half an hour. If you do not understand a question or you want to hear it again, please, let me know. I would also like to record this interview for future analysis of your answers. I hope you have no problems with this. Please, read this informed consent and sign if you agree with it.

Do you have any questions so far?

2. *Sign informed consent*
3. *Record interview*
4. *Interview*
5. *Script to close the interview*

Thank you very much for taking part in this interview and helping my research.

Questions

1. How long have you been working at CashDesk as a support employee?

    a. How many questions of CashDesk customers do you handle on an average day?
    b. How many of them are about the menu editor?
    [Show participant results of log analysis]
    c. What do you think when you see the percentage of questions about the menu editor?
        i. Does this match your idea about this?
        ii. Why (not)?

2. Do you think there is a difference between handling a support question about the menu editor and handling other support questions?

    a. If so, what exactly is/are this/these difference(s)?

i. And could be the reason for that?

3. What do you think are the most common problems with the menu editor?

4. Do you think there are differences between customers with questions about the menu editor?
   [If participant mentions types of customers]
   a. Can you describe these different types of customers?
   b. Which type(s) of customers have the most questions?

5. Do you think there are differences between menu editor questions?
   [If participant mentions types of questions]
   a. Can you describe these different types of questions?
   b. Which type(s) of questions are asked for the most time?

6. Do you think there are problems about the menu editor that actually can be solved by customers themselves without support?

   a. If so: do you have examples?
   b. Why do you think customers still ask these questions?
      [If participant mentioned types of customers at questions 3]
   c. Which type(s) of customers has/have these questions?

7. Do you think there are different phases while editing or creating a menu?
   [If participant mentions types of phases]
   a. In which stage of menu editing or creation do you think users have the most difficulties?

8. Solutions to which problems about the menu editor do you find hard to explain as a support employee?

<u>Additional questions about opinions/ideas:</u>
The following questions are about a recommender system. A recommender system is a system that makes recommendations to the user based on an algorithm from a user and/or content model.

9. Imagine if CashDesk 3.0 could recommend actions and items to the customers creating their menus.

   a. Do you think such a feature could affect the user experience of CashDesk customers?
      Where user experience means the experience of a user during editing or creating a menu.
      i. Why (not)?
         [If participant mentioned types of customers at questions 3]
      ii. For which types of customers would this be helpful?
         [If participant mentioned types of questions at questions 3]
      iii. For which types of questions would this be helpful?
   b. Do you think such a feature could affect the efficiency of CashDesk customers?

Where efficiency means being able to edit or create a menu efficiently (quickly and correctly).

   i. Why (not)?

      [If participant mentioned types of customers at questions 3]

   ii. For which types of customers would this be helpful?

      [If participant mentioned types of questions at questions 3]

   iii. For which types of questions would this be helpful?

c. What exactly do you think could be useful to recommend to the user?

   i. Suggestions

      1. Products
      2. Drinks
      3. Prices
      4. images
      5. Product groups
      6. Mandatory/optional choices
      7. Descriptions
      8. Actions

End

Thank you very much for your participation in this research.

Appendix B: Interviews with CashDesk customers

Protocol

First of all, thank you for participating in this research. My name is Floris van der Werf, and for my MSc thesis I am doing research within CashDesk about the menu editor, which is a part of CashDesk's software as you might know. I am looking into how to make the menu editor easier to use. This interview will go like this: I will ask you a few questions, then I will demonstrate the current menu editor, followed by a few questions about it. Then I will show you the interface of the future menu editor, after which a few questions follow, and finally I will show you one particular feature of the future menu editor's ability to give suggestions and advice to a customer working on a menu, after which some more questions follow. All this together will take between 30 and 60 minutes. Do you agree with recording this interview?

Interview questions CashDesk customers

1. How would you describe your own restaurant?
   Help: type of cuisine, size, location, typical customers, year of opening

2. How long have you been a CashDesk customer?

3. How often do you use a computer?
   a. For what? Browsing, watching movies, videos, social networking, emailing, work, documents?
   b. Have you personally used CashDesk before?
   c. How often do you use it?

[Show the old menu editor]

4. How many times have you used CashDesk's menu editor?
    a. How many times a year do you use the menu editor?
    b. Why do you use the menu editor?

5. What were your experiences with this menu editor?
    a. Did you experience problems with it?
    b. Please describe them

[Show the new menu editor]

6. What do you think of this new menu editor?
    a. What do you <u>like</u> about it?
    b. What do you <u>not like</u> about it?
    c. Do you think this new menu editor will be easier or harder to handle?

[Show the recommender system]

7. What do you feel about these suggestions?
    a. What additional ideas or criticisms do you have for the suggestion system just shown?

8. What do you think of suggestions within systems in general?

9. Would you like to get suggestions of
    a. Whole menus?
    b. Product groups?
    c. Products?
    d. Drinks?
    e. Prices?
    f. Mandatory and/or optional choices?
10. What would you <u>not</u> like to be suggested?
    Help: product name, product description, image, price (average, high, low)

11. Would you like to get suggestions of products that are actually not on your menu but could be, because of menus of similar restaurants?
    Help: imagine you're a pizzeria that does not sell pizza tuna, but is suggested based on an added pizza salami.

12. What do you prefer? Be <u>advised</u> with information to fill in, or get <u>pre-filled</u> information?
    a. Description
    b. Image
    c. Price
    d. Other

13. Would you like to ask for suggestions or to be given?
    Help: show them the difference in the slides

14. At what moment are recommendations useful for you to receive?

15. You just have seen multiple ways of giving recommendations. Would you like to see recommendations in the form of a pop-up, ready-made between or among your other products, or in a block on the right side of the screen?
    Help: see slides

16. Would you like to receive notifications or reminders from CashDesk once in a while to refresh your menu or adjust your prices?

17. *Imagine you can see how many percent of similar restaurants sell a particular product.*
    Would you like to see this information?

18. What is the most important aspect for you in such a system?
    a. Good suggestions
    b. High number of suggestions
    c. Nice layout
    d. Clear information
    e. High speed

19. Do you think this system affects how you <u>experience</u> the menu editor?
    a. Please explain why

20. Do you think this suggestion system affects the level you <u>understand</u> the menu editor?
    a. Please explain why

21. Do you think this suggestion system affects the
    a. Ease of using the menu editor?
    b. Speed of using the menu editor?

22. Do you think you will use the suggestions when creating or editing your menu?
    a. Why?

End
Thank you very much for your participation in this research.
Would you also like to be involved in the pilot version of CashDesk 3.0 if this research confirms a positive opinion about a suggestion system?

Appendix C: Questionnaire

Start

Dear participant,
We warmly welcome you to this research on the use of a recommender system within CashDesk's menu editor. This survey is designed to gain your experiences, opinions, and perceptions as the customers of CashDesk and the users of its menu editor. We would like to understand if a recommender system can potentially improve your experience with the menu editor and to what extent.

The survey consists of 22 questions and will take you approximately 15-20 minutes to fill in.
We would like to emphasise that all your responses are confidential. There are no right or wrong answers, so we appreciate your honest opinions.

Thank you for your participation in this research.
Sincerely,
Floris van der Werf
Utrecht University

General restaurant information

The first questions are general questions about your restaurant.

1. What is the type of your restaurant?

   o SME with 1 store (1)

   o Franchise restaurant (2)

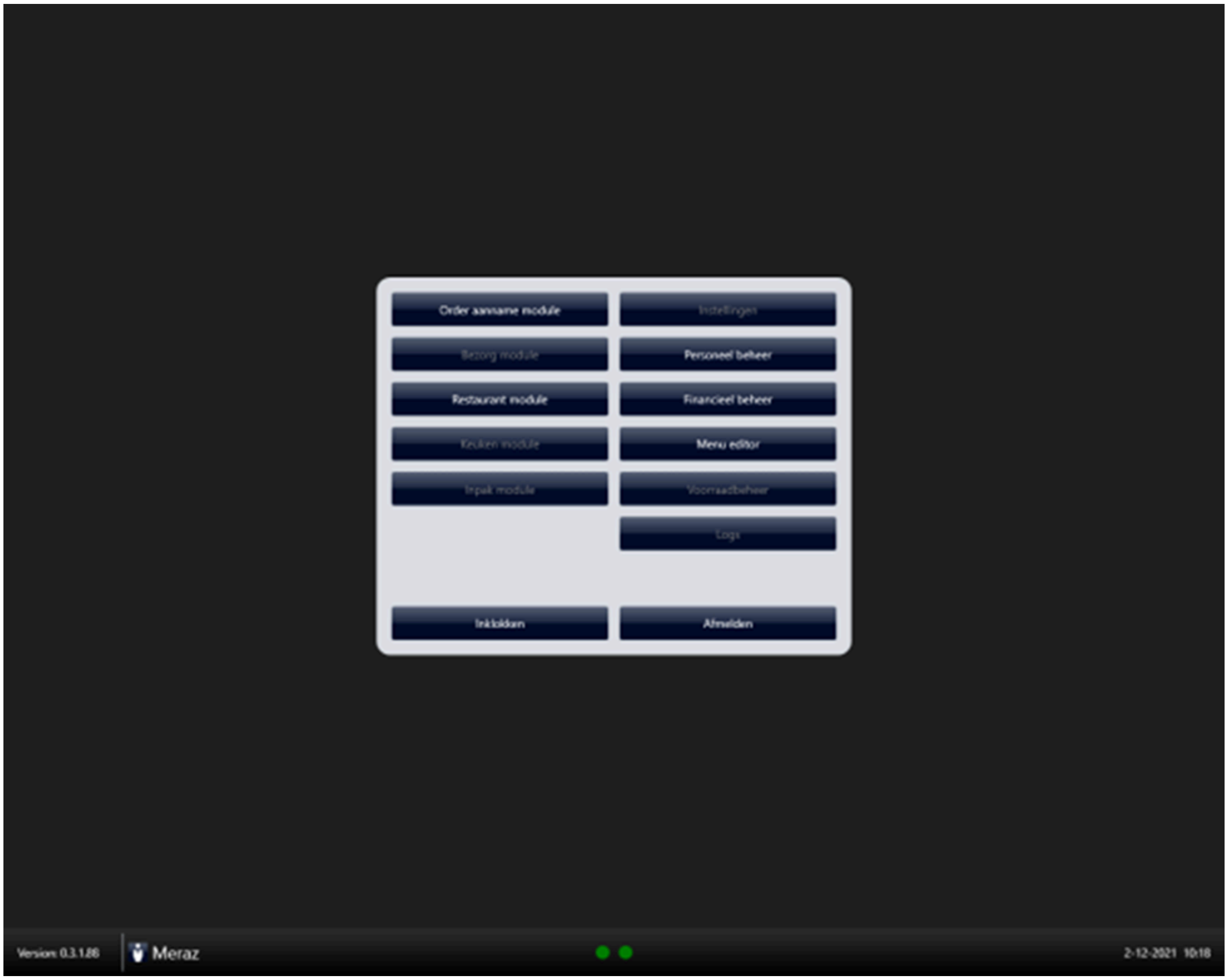
   o Other, namely: (3) ____

2. What type of kitchen does your restaurant serve? Please choose the kitchen that suits your restaurant the best.

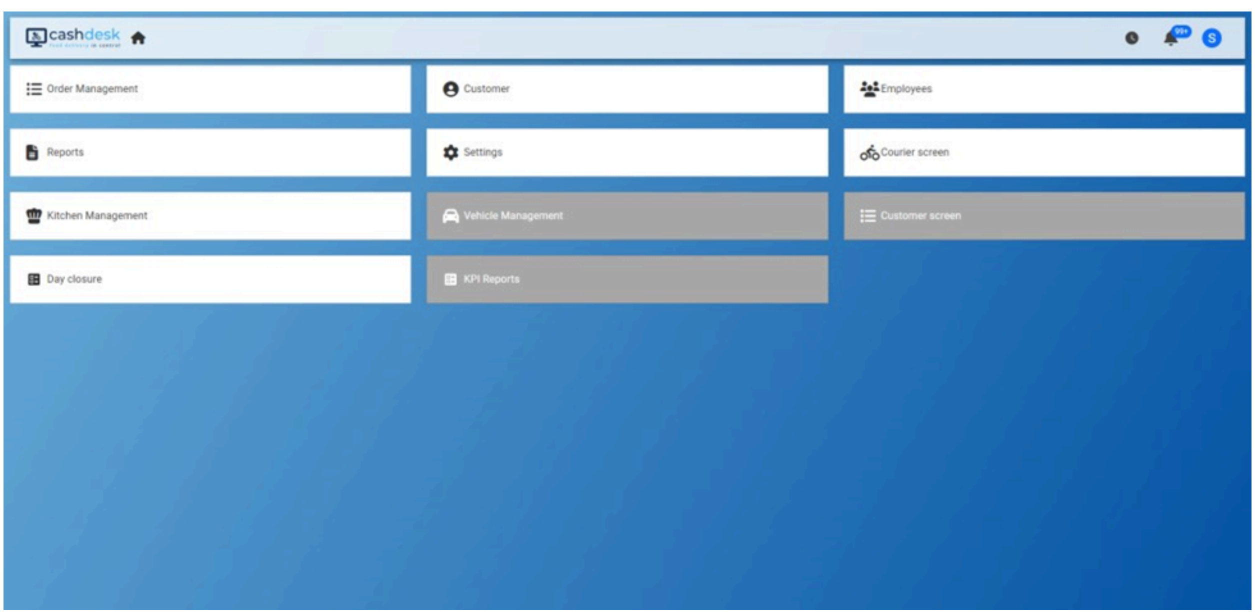
▼ Burgers (1) ... Other (23)

3. Which CashDesk version do you use?

   o CashDesk 2.0 (desktop application) (1)



o CashDesk 3.0 (web-based version) (2)



General user questions

4. How would you characterise your level of computer and internet experience?

o Limited (1)

o Basic (2)

o Proficient (3)

o Advanced (4)

o Expert (5)

5. How often do you use the menu editor?

o Never (1)

o Rarely (about 1 till 2 times per year) (2)

o Occasionally (about 1 till 2 times per month) (3)

o Frequently (about 1 till 2 times per week) (4)

6. How much do you agree with the following statement: “I like the CashDesk menu editor.”?

o Strongly disagree (1)

o Disagree (2)

o Neutral (3)

o Agree (4)

o Strongly agree (5)

7. Do you ever need assistance with the menu editor? If so, would you explain with what, and what sort of assistance?

____

____

____

____

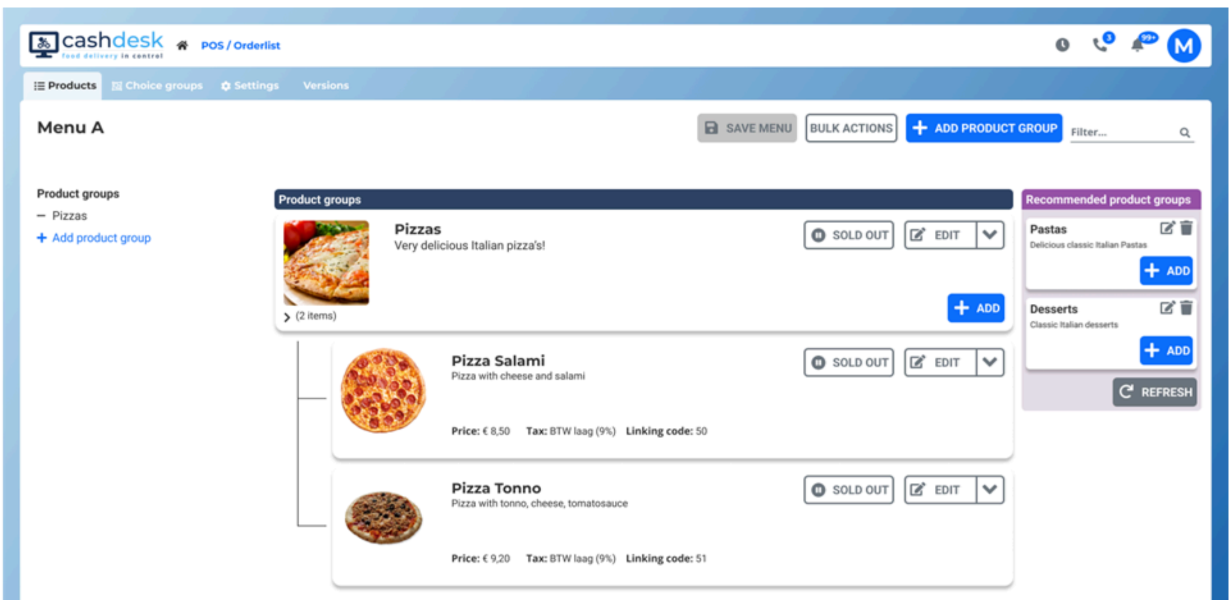
____

Functions recommender system

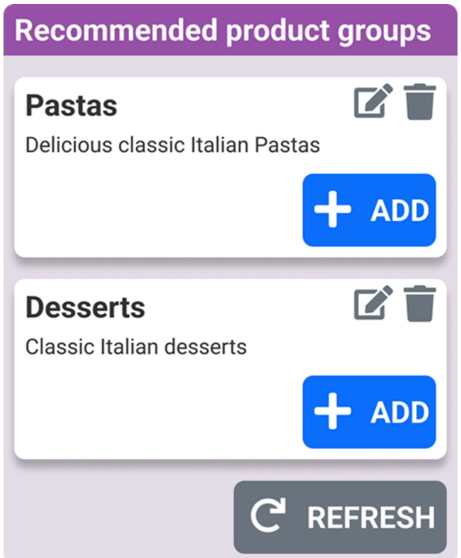
A possible way to help users of the menu editor is to add a recommender system. It can suggest products, product groups, prices, descriptions and images as you work with the menu editor. Users can accept or decline these suggestions.

The following images illustrate how such a recommender system could help the users of CashDesk. The accompanying questions ask your opinion about these images.

8. Imagine you run an Italian restaurant where you're setting up your menu with product groups “Pizzas” and “Pastas”. CashDesk's recommender system now suggests the product groups 'Drinks' and 'Desserts'. The accompanying image illustrates these product group recommendations, displayed within the purple box next to the menu:



You can add, edit, or remove the recommended product groups. If you choose to add it, the name, description, and image will be taken over directly, but without any products included yet.



How much do you agree with the following statement: “I see benefits in receiving product group recommendations.”?

o Strongly disagree (1)

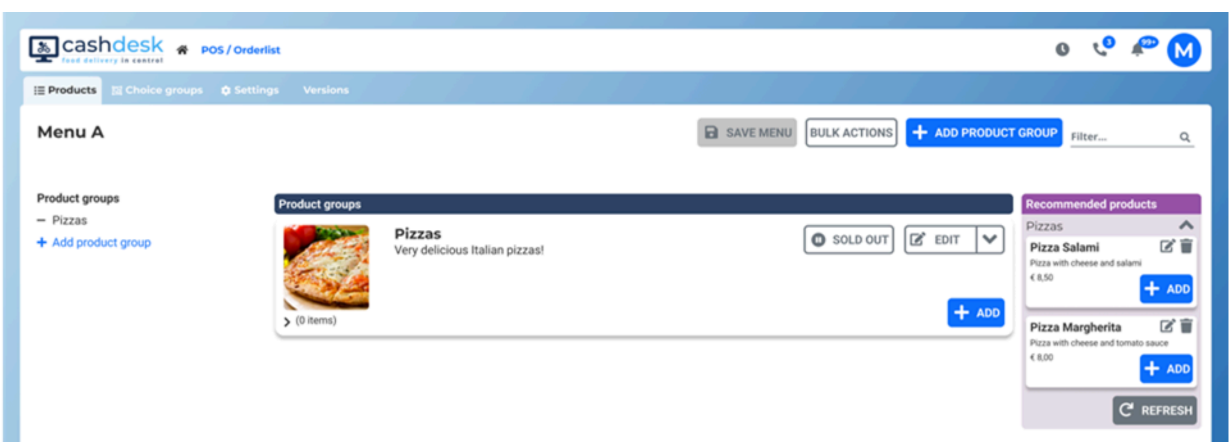
o Disagree (2)

o Neutral (3)

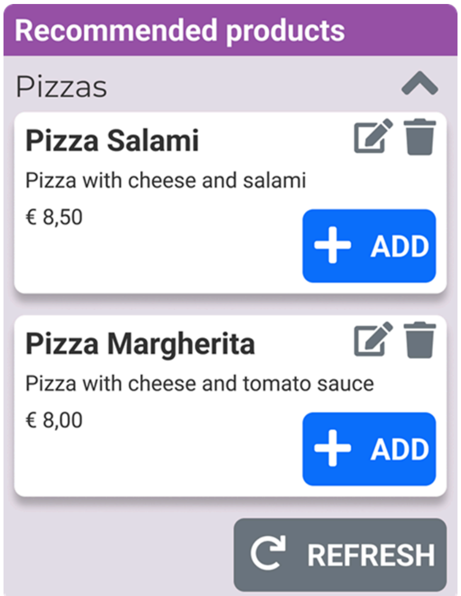
o Agree (4)

o Strongly agree (5)

9. Imagine you run an Italian restaurant where you're setting up your menu with the product group “Pizzas”. CashDesk's recommender system now suggests products for this “Pizzas” product group, as illustrated in the following image displayed in the purple box next to the menu:



You can add, edit, or remove the recommended products, and by choosing to add them, their name, description, price, and image will be taken over directly and the product will be added to the corresponding product group automatically.



How much do you agree with the following statement: "I see benefits in receiving product recommendations."?

o Strongly disagree (1)

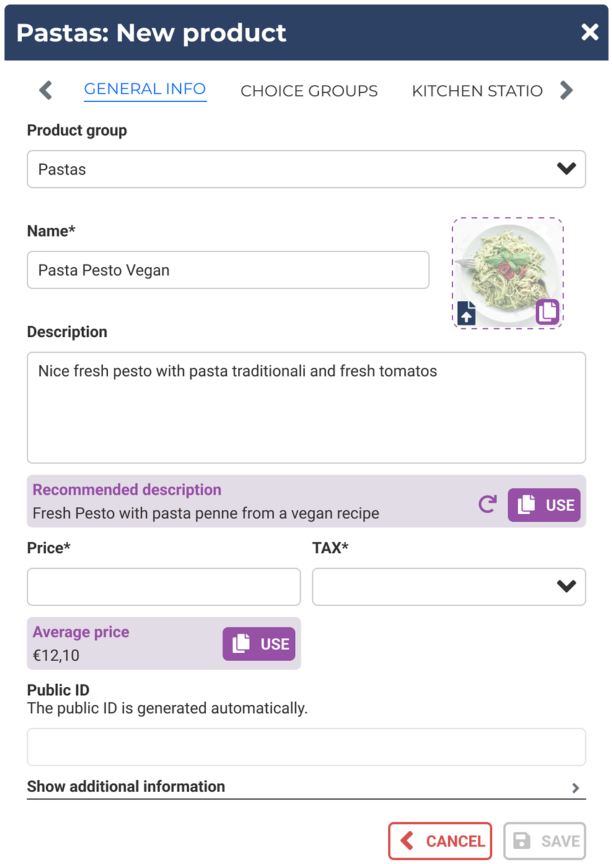
o Disagree (2)

o Neutral (3)

o Agree (4)

o Strongly agree (5)

10-12. The following image illustrates three different product feature recommendations: product image, product description & product price. All recommendation features can be adopted directly by clicking on the purple button, and the description recommendation can even be refreshed.



How much do you agree with the following statements: "I see benefits in receiving recommendations for…"?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
Product images (1)	o	o	o	o	o
Product descriptions (2)	o	o	o	o	o
Product prices (3)	o	o	o	o	o

Potential added value recommender system

The following questions are about the possible added value of this recommender system for you. You may indicate your opinion here based on a 5 point scale.

13-21. How much do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
I like these recommendations. (1)	o	o	o	o	o
Such recommendations are clear to me. (2)	o	o	o	o	o
Such recommendations can be useful for me. (3)	o	o	o	o	o
The recommender system will make the menu editor easier to understand. (4)	o	o	o	o	o
The recommender system will make the menu editor easier to use. (5)	o	o	o	o	o

The recommender system can provide inspiring information. (6)	o	o	o	o	o
The recommender system can make the menu editing and creation faster. (7)	o	o	o	o	o
The recommender system can reduce the need for assistance from CashDesk's customer support. (8)	o	o	o	o	o
I would use this recommender system. (9)	o	o	o	o	o

22. Are there any features of the recommender system that feel redundant? If yes, which?

____

____

____

____

____

End

We thank you for your time spent taking this survey. Your response has been recorded.