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MASTER THESIS

**Evaluation of Map-Based Menus and  
Apartment Categories in Online Shops**

submitted by

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## **Abstract**

In current online shops, menus rarely benefit from new technologies and research findings. Therefore, this work aims to design and implement new intuitive menu types for online shops, which enrich and improve shopping experience. By introducing new methods for product classification and visualisation, menu interaction shall be made easier, quicker and less frustrating. Therefore, a new apartment categorisation was developed. It is based on an intuitive metaphor and classifies products into rooms and furnitures. Furthermore, a realistic map-based menu representation was developed. It functions as an interactive map and supports user orientation by providing visual cues in form of icons. A user study was conducted to evaluate the new menu categorisation and representation in comparison with the current standard in online shops. In total, four menu types were tested. The results showed that the newly developed methods have a clear advantage in almost all considered aspects of task performance (success, click count, task completion time) and user preference (user experience, usability, workload, immersion). Overall, searching for a product via the map-based menu with apartment categories proved to be the best regarding performance and preference.



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# Chapter 1

## Introduction

### 1.1 Motivation

In this day and age, online shops such as “amazon.com” or “zalando.com” are well established and represent an indispensable part of everyday life for many people. They offer several advantages like availability, time savings and comfort. Since purchases are made from home, no long distances have to be travelled. In addition, the time-consuming and tiring transport of goods is no longer necessary, as the purchased products are delivered directly to the customer’s home. The available online shops cover various product segments ranging from clothing and accessories through electronic devices, movies, books and games to food, drinks and numerous other segments. Online shops have experienced an enormous upswing over the years resulting in a clearly increased amount of purchases made through the internet [33, 49]. In 2017, 10.1% of worldwide purchases were made online and a proportion of about 15.5% is expected for the year 2021<sup>1</sup>. In the past, the design and interaction methods of online shops have changed in many ways, thus offering more comfort and pleasure and contributing to today’s success. While online shops were initially focused on product presentation and purchase transaction regardless of customer needs, they have become more and more user-centered [18, 23, 58]. For instance, several self-service capabilities were integrated giving customers more insight into the processes and providing them with more information and functionality. Examples include customer registration, order overviews, personal wish lists, help functions, recommendations, product review and social media integration. While also much attention has been paid to the improvement of the search bar [37], e.g. through the development of

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<sup>1</sup> [www.emarketer.com/Report/Worldwide-Retail-Ecommerce-Sales-eMarketers-Estimates-20162021/2002090](http://www.emarketer.com/Report/Worldwide-Retail-Ecommerce-Sales-eMarketers-Estimates-20162021/2002090) (accessed 19.11.2017)

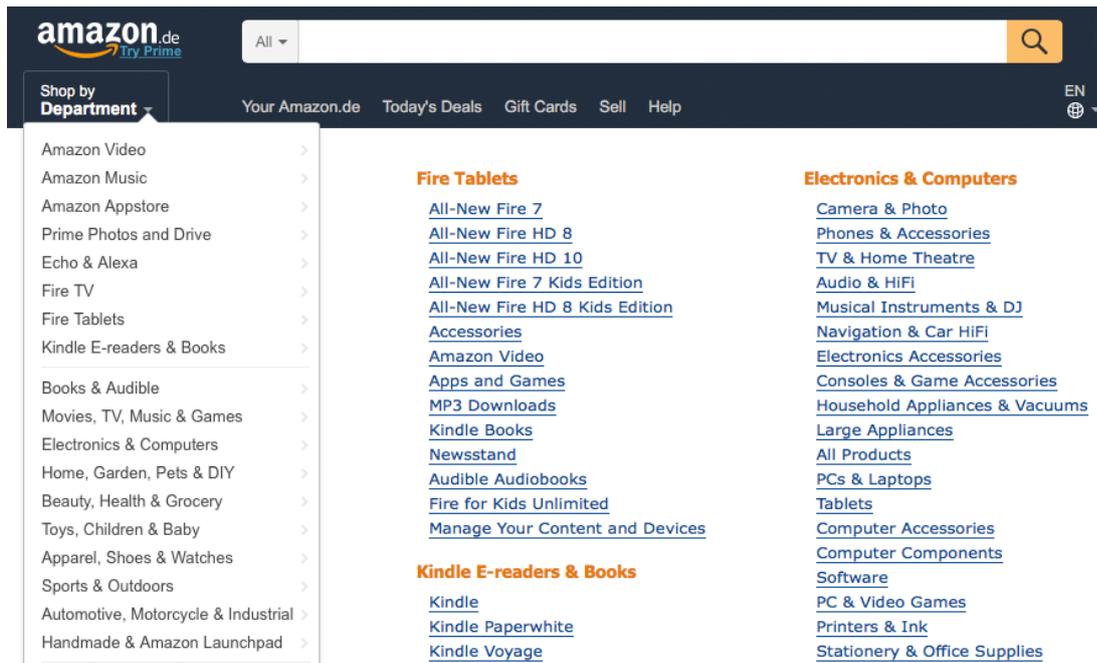


Figure 1.1: Exemplary online shop with a text-based menu representation.

powerful algorithms, the menu search functionality has been largely neglected. Contrary to general expectations, search via search bar is not necessarily preferred by the user nor is it generally more effective [20]. In some cases, the use of the menu functionality is the more suitable search option. That's the case if a customer doesn't know the explicit name of the product he is looking for. Or if the customer just wants to browse through the products under a specific category, e.g. if he is looking for a gift. Therefore, the product search via menu represents an essential component of online shops. It is thus important to further investigate possibilities for menu optimisation. Research has shown that visualisations such as logos, icons or images can enhance the shopping experience of customers compared to the exclusive use of textual representations [8, 42]. Therefore, one possibility for menu optimisation is represented by the field of visualisation. Although the benefit of visualisations used in online shops is well known, menu representations are still mainly text-based (see Figure 1.1). Furthermore, the underlying categorisation depicted by the menu is often inconsistent throughout different online shops. It often reflects the characteristics of each individual shop in terms of product classification as well as chosen category names. This often makes it difficult for the customer to understand the underlying classification and to use the given menu's functionality easily [38]. In sum, finding an illustrating menu representation and an intuitive categorisation for online shop menus could facilitate the interaction and lead to a more satisfying shopping experience.

## 1.2 Research Question

Today, menu representation and categorisation in online shops often do not benefit from well-established new technologies and research findings. They are often still reminiscent of the beginnings of online shops. Although they are an essential part of online shops, there is no common strategy for their implementation. Moreover, the different strategies are usually not even scientifically researched and confirmed. This results in various usability problems that make it difficult to use the menus successfully. Since the categorisations in the different online shops are often inconsistent, the product classification is often difficult to understand. Even if a customer knows exactly where to search for a product in one known online shop, he might not find it in another one. Either because the given product is classified among two completely different categories, or because the category terms differ widely. Even within one online shop, categories are often inconsistent and overlapping, failing to make clear where to search. In addition, since present knowledge about the positive effect of visualisation is not applied to menu representation so far, no visual hint is given to the user which could facilitate the selection of appropriate categories. Menus are still realised through simple vertical or horizontal text arrangements which describe the available product categories. Overall, the fundamental problem is that menus in online shops are hence often very unintuitive to use. Thus, this work is dedicated to the question of how online shop menus can be improved by developing new strategies for their representation and categorisation.

## 1.3 Significance of the Work

The research objective of this work is to develop, investigate and evaluate new menu types based on a study procedure. By means of a spatial and illustrating menu representation as well as an intuitive product categorisation, the shopping experience of consumers shall be enriched and facilitated. Fundamental knowledge of previous research findings form the basis for the three menus. These differ in the underlying representation and/or their categorisation. The new categorisation is based upon a metaphoric scenario which uses the fact that everyone is familiar with an apartment environment and its functionality. It can be assumed that most apartments are structured in a similar way which makes it easy for users to get along in such a scenario. Based on this principle, apartment categories are developed which are independent from a specific shop structure. Therefore, they are easily transferable. In order to strengthen the underlying categorisation, be

it the apartment categorisation or another one, a new menu representation that uses real-world characteristics illustrating the related categories and facilitating user orientation is examined. Therefore, menu items are arranged in a map-like visualisation in order to benefit from spatial knowledge and familiarity with spatial environments. In case of the apartment categories, the menu represents the floor plan of an apartment and functions as an interactive map. Before integrating such new menu types in real online shops, it should be thoroughly tested if the previous findings concerning representation and categorisation can be successfully adapted to online shop menus. By means of a user study, the new menu types are tested for task performance and user preference to determine if they can support the user in shopping online. Overall, this work contributes to the further development of online shop menus by:

- Introducing new methods for menu realisation regarding representation and categorisation.
- Evaluating different menu types in a comparative study.
- Providing user insights and proposals for designing and developing shopping environments.

## 1.4 Outline

In the following, some related work is introduced in a first step to present an overview of previous research in the areas concerning the reviewed topic. This includes research in the area of online shops, menu design and categorisation (see Chapter 2). The findings of these research topics are analysed and the knowledge gained will be used to introduce an own concept for menu realisation in online shops (see Chapter 3). Preliminary investigations are presented as pilot studies (see Chapter 4). Then, the implementation of an online shop prototype is described (see Chapter 5). The design and the procedure of the main study are given in detail, which is conducted in order to test and verify the implemented menu types. Further, the findings of this study are presented and discussed in relation to the underlying concept (see Chapter 6). Finally, the gained insights are summarised (see Chapter 7) and the possibilities that evolve from them are presented in form of a future outlook (see Chapter 8).

# Chapter 2

## Related Work

In this chapter, a selection of research projects is presented in which researchers already examined the topic of menus in online shop interfaces, in similar interfaces or in general. Their findings give insights in certain methods and techniques and show in which manner they can be used to improve task performance or user preference when interacting with web interfaces. The common features of the presented methods are pointed out and how they are used to develop own menu types for the usage in modern online shops. Furthermore, an overview of available evaluation metrics is given. They can be used in order to review newly developed menu types and to check if they meet positive expectations which represents an essential part of this research work.

### 2.1 Menu Representation

The representation of a menu is one of two characteristics considered in this research work. It is a widespread topic in research. Different menu representations differ in the arrangement or the shape of the menu items. Past research has shown that these aspects have a strong influence on user interaction with web interfaces including online shops. Adapting the menu representation can therefore result in higher performance results and/or better preference values. The following research examples demonstrate different representation possibilities and their consequences on user interaction with menus.

Menu-driven interfaces are already a well-established component in software applications or web sites for a long time. Menus are used to structure the underlying amount of information hierarchically. Enabling an effective and comfortable interaction with menus is essential to provide successful access to desired parts of

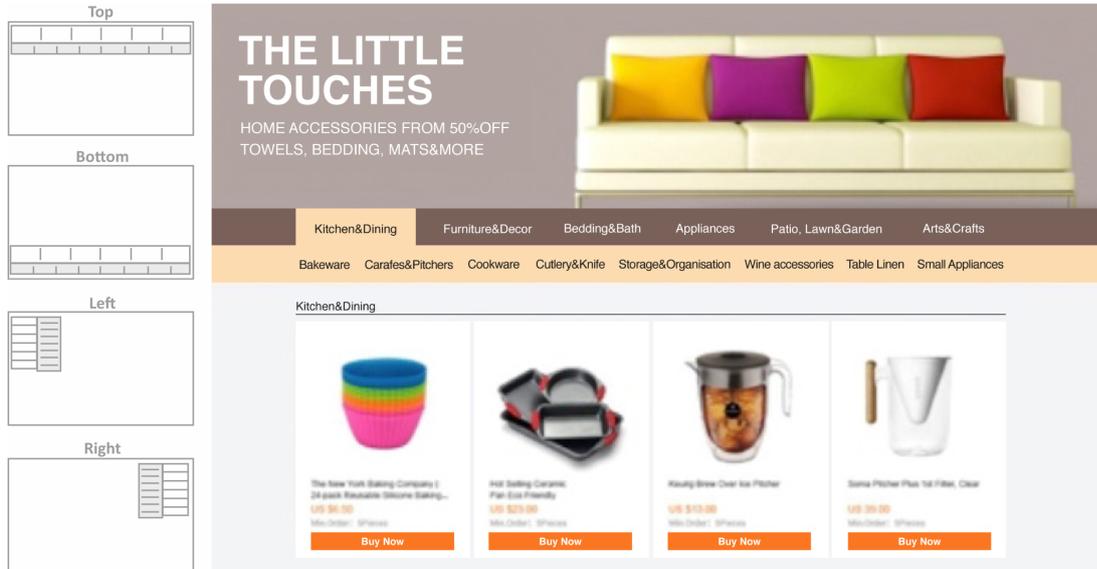


Figure 2.1: Menu positions and configurations of linear menus used by Zhang et al. [60]. Left: Visualisation of the different menu positions (top, bottom, left, right) with configuration 6x8. Right: Online shop interface with menu at top position and configuration 6x8.

information for users. The topic of menu optimisation has been frequently examined in research until today. Thereby, characteristics like menu size or menu position are of common interest. Menu size is described through depth and breadth values, whereby the depth value represents the number of menu levels and the breadth value describes the number of menu items per level. Previous research has demonstrated that deeper menus, i.e. menus with many levels, increase complexity and slow down interaction times and that breadth is usually preferable to depth [21, 31, 36, 57, 59]. For example, Miller [31] conducted an early study investigating how menu breadth and depth affect speed and accuracy. Four menu configurations were tested in a user study:  $2^6$ ,  $4^3$ ,  $8^2$ ,  $64^1$  (*breadth<sup>depth</sup>*). Results indicate the fastest interaction with  $4^3$  and  $8^2$  menus. Interaction with the  $8^2$  menu, which has only two menu levels, results in the fewest error rate. Similar findings are represented by Zaphiris et al. [59] who tested menu configurations of  $2^6$ ,  $4^3$  and  $8^2$ . Their findings reveal that the shallow hierarchies are easier to use, lead to higher levels of orientation and satisfaction and shorter interaction times. Summarised, it is advisable to minimise menu depth but without increasing the breadth to an extreme and on condition that the semantic data allows such a distribution [31]. Research findings concerning the positioning of menus do not reveal a clear recommendation of an optimal menu position but a tendency towards menus at the top position of the screen is recognisable [34].

A very recent research work in the topic of menu optimisation in the retail domain is introduced by Zhang et al. [60]. It provides information about menu performance in online shops, related to the previously discussed characteristics. The researchers investigated the influence of position and configuration of linear menus, where menu items are either located one above the other or next to each other. Four menu positions (top, bottom, left, right) and three configurations (6x8, 8x6, 12x4) were tested. The resulting menu combinations were integrated in twelve different online shop interfaces. In Figure 2.1, the different menu positions and an exemplary interface can be seen. The different menu types were evaluated in a user study. Thereby, participants had to perform several search tasks in order to find products. For each task, the time needed to find and select the target item was measured. Furthermore, a questionnaire about cognitive workload and subjective preference was filled in by the participants. Results revealed that time performance with top-position menus was better than with the other menu positions. The questionnaires showed that top-position menus and left-position menus are preferred over the other menu positions. Preference was higher for the menu configuration of 8x6. Overall, the score of the 8x6 top-position menu is the highest whereas the one of the 12x4 bottom-position menu is the lowest. This confirms similar research findings previously discussed. This evaluation shows the linear menu variants that are recommendable for usage in online shops. In this work, these findings are used to develop an optimal reference menu which best reflects the current online shop situation and which can be used for comparison purposes.

There also exist several approaches which develop new menu representations in order to improve performance and user preference of the traditional linear menu discussed above. Contrary to characteristics like size and position, these changes have a wider impact on the overall menu functionality. For example, the work of Cockburn et al. [9] examines how the visual search process can be supported and facilitated by reallocation of menu space. The researchers compared the following menu designs: standard menu, split menu [47] which displays frequently or recently selected menu items on the top and a new menu design called Morphing Menu. A Morphing Menu gives visualisation priority to frequently used menu items by providing more screen space to them so that they appear more salient to the user (see Figure 2.2, left side). The results of their user study revealed that frequency split menus were the fastest, followed by standard and morphing menu. Recency-based split menus turned out to be the slowest. This demonstrates that visual search can be supported by reallocation of menu space. The use

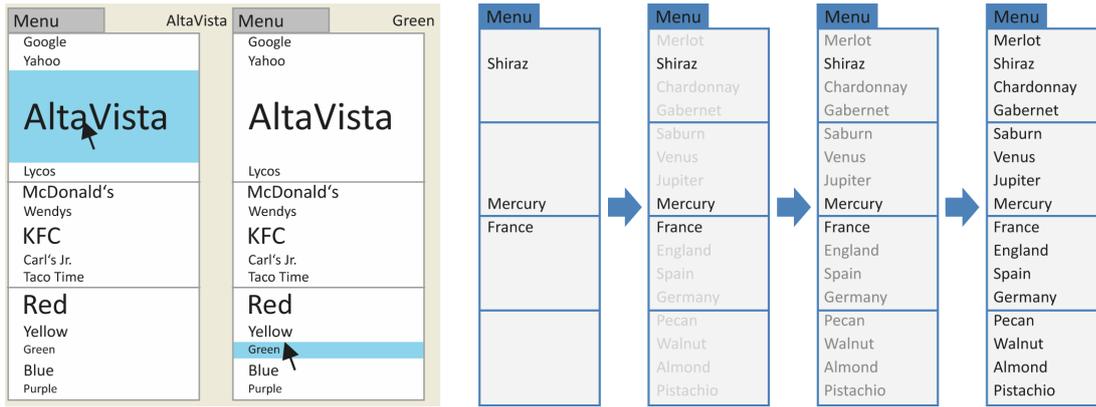


Figure 2.2: From left to right: Morphing Menu with enlarged areas for predicted items [9] and Menu with Ephemeral Adaption which firstly displays predicted items [10].

of frequency split menus, for example, in a shopping site however seems not to be promising. This is because products or categories are often selected to solely gain more information. Therefore, such a selection does not necessarily expresses a future preference towards this product or category. The highlighting of frequently selected but potentially unwanted items would not result in any improvement. Furthermore, menu representation would not be consistent since the set of frequency items changes over time. This could result in confusing instead of the desired support. Difficulties with such dynamic menus are already discussed in research [32].

Another research example which tries to improve the user interaction of standard menus is the one of Findlater et al. [10]. They introduced a new technique for displaying the menus which they call Ephemeral Adaption. This technique uses a prediction algorithm to determine menu items which are likely to be needed by the user. These predicted items are displayed immediately when the menu is opened. The remaining items are gradually faded in. In this way, the predicted items are perceived first by the user. The whole visualisation process can be seen on the right side of Figure 2.2. The technique was compared to a standard menu and a menu using a highlighting technique which highlights predicted items through the use of colour. User results show that Ephemeral Adaption allows faster menu selection when accuracy of prediction is high (79%). Thus, this technique can facilitate the visual search process and reduce interaction time. This positive effect is however regulated by the development of an efficient prediction algorithm. Depending on the web interface, this can be a difficult or even an unsolvable problem. Applied to the domain of web shopping in particular, it seems not

possible to develop an algorithm which can predict desired products precisely enough. Shopping is often a changing process since the range of products as well as shoppers' interests steadily change. Whereas the selection of prioritised items can lead to better menu interaction in general, its use in online shops seems not be promising and is therefore not adopted in this work.

The previous examples adapt only parts of the traditional menu. Another possibility is to completely change the overall structure of the menu. Two examples are given in the following. Ahlström et al. [2] introduced a new menu design by changing the overall shape of the menu. Instead of linear arrangement, the new menu design presents the items in a grid form. The menu therefore looks like a square. In a user study, they tested the new Square Menu (see Figure 2.3, left side) against a standard pull-down menu and a pie menu in which items are ordered circularly. Results show that the new Square Menu is the fastest menu, followed by the standard and the Pie Menu. Participant feedback indicates that Square and Pie Menus seem to be preferred as participants stated that they are faster to use, easier to move through and that they facilitate remembering item position. Summarised, a new spatial arrangement leads to new search and pointing routes. In case of the Square Menu, the items are arranged closer together when compared to a traditional linear menu and therefore reduce pointing and search paths. This approach demonstrates that the modification of the overall menu representation can improve task performance and user preference.

Further, Scarr et al. [43] decided to improve interface interaction with the aid of so-called CommandMaps which flatten the hierarchical structure of menus by presenting all menu levels one upon the other (see Figure 2.3, right side). Like in the previous example menu items are presented in a kind of grid form. Thus, less pointing activities are necessary since the user no longer has to change



Figure 2.3: From left to right: Square Menu [2] and CommandMap by the example of MS Word [43].

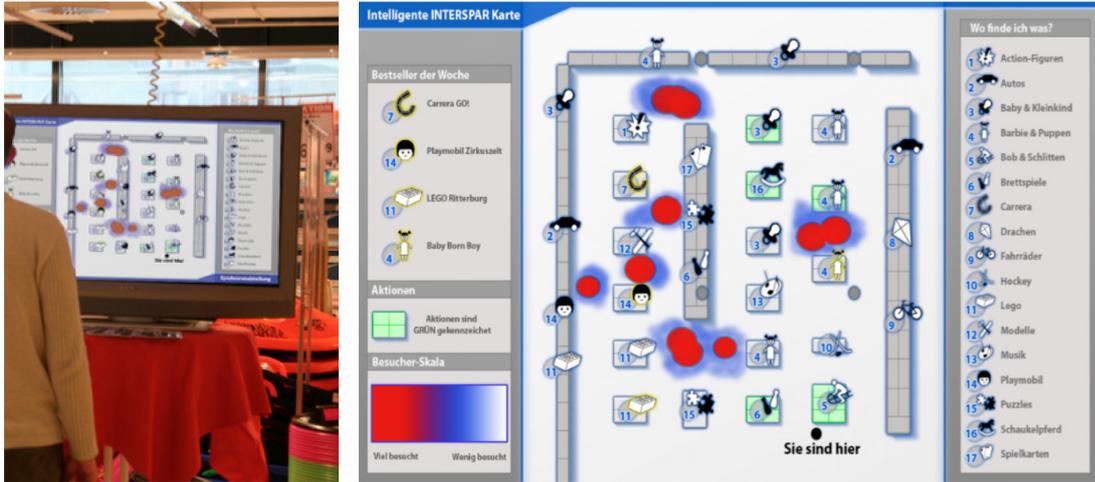


Figure 2.4: From left to right: Installation of the enhanced store map in the appropriate store area and layout of the enhanced store map [29].

the menu levels. The technique of CommandMaps is based on the assumption that expert users have a good spatial memory. The researchers compared it to a standard menu and the Microsoft’s Ribbon interface, known from Microsoft Word. They found out that CommandMaps are significantly faster for experienced users than standard menus and Ribbon interfaces. For novice users, there is no performance difference between the menu designs. Furthermore, user feedback indicates greater ease of use with the new menu design. The representation of the two previous menu examples spreads in two directions: horizontal and vertical. This differs from the traditional menu representation which arranges items either horizontally or vertically. The grid-shaped arrangement is adopted to the new menu representation presented in this work. Contrary to the previous two examples, the newly developed representation in this work is not simply a geometric and schematic arrangement but has a special significance as it is based on a real-world environment.

The following examples already exploited characteristics of real-world environments in order to adapt navigation strategy in online shops. At first, Vrechopoulos et al. [56] investigated how three different brick-and-mortar store layouts can be transmitted into a virtual store environment: Grid, Freeform and Racetrack. To this aim, the navigation characteristics of these three layouts were transferred into virtual layouts which led to different navigation methods. In a user study, the researchers investigated the influence of the layouts on perceived usefulness, ease of use, entertainment and time. Results show that users perceived the freeform layout as more useful and entertaining. The grid layout which is based on a hi-

erarchical tree structure was perceived as easier to use. The latter is additionally supported by the findings of Griffith [11] who tested grid and freeform layout (“tunnel”) against each other. In sum, the researchers adopted characteristics of typical store layouts in local stores and adapted online shop navigation structure appropriately by creating similar interaction processes. Although real-world stores are the source of inspiration, this transformation process is rather abstract since it only reflects specific navigation characteristics instead of suggesting an explicit representation.

In contrast, the research work of Meschtscherjakov et al. [29] uses a more direct transformation and demonstrates how a virtual store map can be used for information retrieval and user orientation. They developed a prototype which displays the floor plan of a store section. Shelves are marked with icons as well as with unique numbers which identify the appropriate product category that is located in them. A legend on the right side of the screen assigns category names to each of the displayed item-number pairs. Additionally, special offers and best sellers are highlighted on the map. The layout can be seen in Figure 2.4. In order to investigate the usefulness of the prototype, the researchers conducted a usability study in the represented store section. Therefore, a screen which displays the map was positioned at the border of the appropriate store section (see Figure 2.4). In this way, the map matched the area behind the screen. In total, 47 customers were interviewed about the prototype. Most of the users stated that the map improved their orientation in the store section. 89.4% of the users successfully completed a search task in which they should find a specific toy. Furthermore, usability findings revealed that the majority of the users found the map easy to understand and that they wished it would be integrated in the whole retail store. These findings demonstrate how a virtual store map can be used to support user orientation and product search. In order to gain this desirable effect in an online shop, the principle of such a virtual floor plan is applied to menu representation in this work. The newly developed menu representation is intended to create a real-world feeling and an intuitive orientation process.

The previous examples are used to compose an own strategy for a novel menu representation. The results of Zhang et al. [60] are used to build a reference menu which depicts the state-of-the-art scenario in present online shops. Based on the real-world figure of a local store used by Meschtscherjakov et al. [29], a map-based menu representation for online shops is developed. The clear representation of a floor plan is intended to guide the user in the virtual environment similar to the

real world. Further, the basis for this representation is a grid-shaped structure, which is an effective way for menu interaction improvement in general [2, 43]. The traditional linear menu and the map-based menu representation are then evaluated against each other in order to compare their influence on task performance and user preference.

## 2.2 Menu Categorisation

Another essential menu characteristic considered in this work is the menu categorisation. Not only the arrangement of the menu items, i.e. the menu representation, is crucial for an easy and effective interaction with menus, but a good information structure and an appropriate naming of categories is an important factor for menu interaction as well. A good categorisation facilitates user comprehension and helps to find products inside the given menu hierarchy. The following research examples demonstrate this context and point out fundamental properties of good categorisations and possibilities for innovative realisations.

The work of Katz and Byrne [20] demonstrates that the choice of menu categories influences user willingness to use a menu in an e-commerce environment. In a first study, they revealed that users take into consideration the expected workload and success of a menu when deciding to use it. If a menu seems not promising, they prefer not to use it. In a second study, the researchers tried to identify which aspects influence this decision. Inspired by results of the first study, they compared two menu properties: First, menu breadth ranging from narrow (9 menu items) to broad (30 menu items) and second, low and high information content (“scent”). Results show that if menus are broad and labels have a high information content, users are more likely to use a given menu. Together with the findings of the first study, this suggests that this configuration results in a better cost-benefit consideration. In sum, the results show that not only the menu representation, but also the quality of the used categories should be taken into account when designing menus. This fact is also confirmed by the work of Tuch et al. [54]. They created two different categorisations for an online shop for clothing. One of them represents a categorisation with a high and one with a low information content. User testing met the researchers’ expectations that a good categorisation with a high information content choice leads to a higher sense of usability. Larson and Czerwinski [21] also recognised the importance of a semantically sound categorisation and integrated this fact into their research on

menu breadth and depth. Furthermore, Miller and Remington [30] emphasizes the need to integrate both aspects, i.e. representation and categorisation, since they are interdependent. The categorisation of menus constitutes therefore a second important menu characteristic and is considered in addition to the menu representation in this research work.

The next work introduces two different methods for realising logical organisation of items and describes important characteristics associated with them. Hearst [16] highlights and explains the differences between hierarchical (faceted) categories and automated clustering, so that the resulting consequences for information exploration in search interfaces become clear. Clustering is a fully automated process which groups items together based on similarity of words or phrases. It represents a possibility to quickly structure information collections, but the automatic process often leads to several logical inaccuracies. Resulting category lists of clustering are frequently incomplete and inconsistent. Usability studies revealed that this affects comprehension of users. In contrast, the studies showed that manually created hierarchies are preferred by users. A good category system represents the relevant concepts of an information set in a coherent and complete manner and therefore has an advantage over the unpredictable results of clustering algorithms. The comparison of the two methods clearly shows the positive characteristics of a good categorisation with a high information content and what should be considered when structuring given information data. A practical example is given by Schwartz and Norman [46] who demonstrate how the distinctiveness of menu items affects task performance of users. They considered two different categorisations, i.e. two different interface menus. While both of them describe the same underlying information set, one of them was optimised in order to realise a higher item distinctiveness at the top-level menu. This means that the menu labels were adapted in order to ensure a coherent organisation by highlighting differences of the individual menu items. Study results meet the researchers' expectations that users perform faster with the optimised menu. The work of Resnick and Sanchez [40] confirms the effect of high quality labels against those with lower quality. In a user study, the researchers examined the influence of different menu labels (high, medium, low) in a health online shop. The results reveal that different levels of label quality lead to significant differences in terms of performance and preference values. The usage of expressive and comprehensive menu labels is thus an essential part of a successful and powerful categorisation. Therefore, the highlighted characteristics of a good categorisation are used in this work when developing a new categorisation for the usage in online shops.

<p><b>LIVING ROOM</b></p> <ul style="list-style-type: none"> <li>Check/Add Appointments</li> <li>Read/Write Calendar Entry</li> <li>Write Letter or email</li> <li>Record from Television</li> <li>Play Music</li> <li>Watch Movie</li> <li>Watch Pictures</li> <li>Read Letter or email</li> <li>User Internet</li> <li>Watch Television</li> <li>Read Newspaper</li> <li>Read TV-Guide</li> <li>Read Fitness-Schedule</li> </ul>	<p><b>HALLWAY</b></p> <ul style="list-style-type: none"> <li>Watch Security Camera</li> <li>Open Front Door</li> <li>Set Alarm Device</li> <li>Use public telephone directory</li> <li>User private telephone directory</li> <li>Make a telephone call</li> <li>Call Police, Firefighter, Doctor</li> </ul>	<p><b>KITCHEN</b></p> <ul style="list-style-type: none"> <li>Check, which groceries are still eatable</li> <li>Check, which groceries are still stocked</li> <li>Check vital dates</li> <li>Read medicine schedule</li> <li>Read the Menu</li> <li>Set up Microwave oven</li> <li>Set up Dishwater</li> <li>Set up Cooker</li> <li>Read Recipe</li> </ul>	<p><b>BATHROOM</b></p> <ul style="list-style-type: none"> <li>Set up Bathtub</li> <li>Set up washing mashine</li> </ul>
	<p><b>BEDROOM</b></p> <ul style="list-style-type: none"> <li>Adjust Bed</li> <li>Set up Alarm Clock</li> </ul>		<p><b>HOUSE</b></p> <ul style="list-style-type: none"> <li>Check, if all Devices are switched off</li> <li>Get actual time</li> <li>Turn Heater on/off</li> <li>Switch Light on/off</li> <li>Check, if door id closed</li> <li>Check, if window is closed</li> <li>Open/close Blinds</li> <li>Open/close Window</li> </ul>

Figure 2.5: Classification based on the Apartment Metaphor, which was developed with a test group during the user study [1].



Figure 2.6: Apartment Metaphor included in a prototype of a smart home control interface [1].

A practical example for the development of a new categorisation in order to provide an intuitive menu interaction is given by Adam et al. [1]. They exploit the intuitive character of metaphors often used in digital environments and introduce a spatial metaphor that they call “Apartment Metaphor” for the navigation in a smart home control interface. The metaphor maps the mental model of a spatial apartment to the structure of the control interface. To reflect the real-world scenario of performing a task by using an appropriate device which is located in a specific room, the categorisation consists of three levels: room, device, task. The concrete mapping of available tasks into this categorisation was developed during a first user study. Thereby, 41 tasks should be assigned into the given room categories: Living Room, Kitchen, Bathroom, Bedroom and Hallway. The set of tasks which, according to the users, do not fit into the given room groups were assigned to a new and more general category: House. Figure 2.5 represents the results of the first study. Afterwards, the device level was added by the researchers and the resulting categorisation was used to implement a prototype of

the smart home control interface (see Figure 2.6). In a second user study, the efficiency and effectiveness of the prototype was tested as well as user satisfaction with it. On average, 86% of the given tasks were successfully completed without help and more than half of tasks needed less than 2.2 clicks (minimum 2 clicks). 94% of the users indicated that the visualisation of the metaphor elements was comprehensible and that they had no problems with selecting them. 83% indicated that the navigation was totally intuitive and 78% of them stated that they had no major problems in finding a device in an expected room. Reactions and statements of consumers furthermore confirm that there is a mental mapping between tasks and corresponding devices as well as between the devices and the rooms where they are typically located. The positive effect of the Apartment Metaphor is also exploited in this work in order to create an intuitive product categorisation which is independent of a specific market organisation. Therefore, the real-world scenario of storing products in specific rooms is used to create an intuitive categorisation.

The previous examples deal with menu categorisation and highlight that not only the representation of a given menu is crucial for a good shopping experience (see Katz and Byrne [20]). It is demonstrated how appropriate categories can enhance the experience and improve user preference values and task performance. Therefore, a second variable is investigated in this work. In addition to the representation of a menu (see chapter 2.1), the underlying categorisation is integrated in the study design as well. Two different categorisations are used. First, a traditional categorisation based on product ranges functions as reference and represents the traditional approach. Second, similar to Adam et al. [1], a

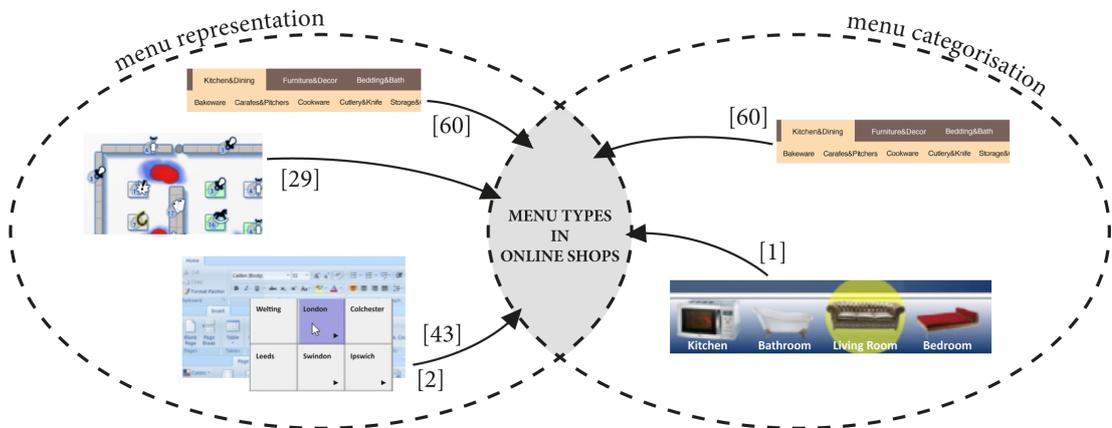


Figure 2.7: Overview of the influences of related work on the concept of this work, divided into representation and categorisation.

categorisation is developed which exploits everyday habits and experiences to create an intuitive categorisation. Therefore, products are assigned to rooms and furniture. The traditional categories and the categories based on the apartment metaphor are evaluated against each other in order to compare their influence on task performance and user preference. Figure 2.7 finally presents an overview of the influences of related work on the concept of this work, including menu representation [2, 29, 43, 60] and categorisation [1, 60].

## 2.3 Interface Evaluation Metrics

Closely connected to the conceptual development and the implementation of new interfaces is an evaluation process, in which they are tested thoroughly. Therefore, this work includes an experiment with users in a controlled setting. In such an experiment, users carry out defined tasks with the aid of the interface in a laboratory environment [26, 48]. During the experiment of this research work, the participants had to perform specific search tasks by using the previously developed menu types. In this context, a certain set of valid evaluation metrics is given in this section. These are used to evaluate the newly developed menu types and to review if they meet expectations. The evaluation metrics introduced in the following capture two different kinds of user feedback: objective and subjective.

### 2.3.1 Objective Feedback

Objective feedback provides information about the task performance of the users. Therefore, different types of performance data are measured during the interaction with the considered interface. This includes task success, duration, errors or similar data and it is strictly connected to the individual task type used for evaluation. Objective feedback provides information about the accuracy or efficiency of the considered interface in achieving the underlying task objective.

#### Task Success

One possible task performance measure constitutes the task success. For each participant and each task, it is captured if the task was concluded successfully. Hence, an overall success rate can be calculated [26]. This performance measure can be used to compare the accuracy of different interfaces or interface elements. In this research work, the accuracy of the considered menu types is compared with the aid of this performance measure. Therefore, it is logged for every search task if the correct product is selected.

## **Errors**

Furthermore, the task performance can be measured by recording and counting of appearing errors [35]. In relation to the use of menus, errors result for example from the selection of wrong menu items. It can be measured whether the task objective is reached directly or only after committing errors. This can be used to find differences in the accuracy of the considered interfaces or interface elements. For this purpose, the number of errors can be considered separately or the complete click stream needed to find and select the target item can be considered. In the latter case, all performed clicks involved in the task finding process are included. A minimum click stream length is given in the optimal case. This works in the same way as the “keystroke per character” technique used for text-entry evaluation [51]. This performance measure is used in this work in order to further evaluate the correct search task trials, which are defined through the previously introduced measure “task success”. Therefore, all clicks on menu items or products are logged during menu interaction, including correct and incorrect clicks.

## **Task Completion Time**

Another possible performance measure is the task completion time [35]. It provides information about how quick tasks can be performed with the different interfaces or interface elements. Therefore, this measure relates to efficiency. In this research work, this performance measure is used to further evaluate the correct search task trials. The time needed for single search tasks is recorded when using the given menu types, i.e. it is measured how long it takes to achieve a desired goal. In this way, the efficiency of the considered menu types can be measured and compared.

### **2.3.2 Subjective Feedback**

Subjective feedback provides information about user preference by capturing the participants’ opinions. This includes their opinion about aspects of usability, user experience, workload or similar aspects concerning the considered interface or the interaction with it. Subjective feedback is often captured through questionnaires which query the impression of the participants by different rating scales, for example the so-called Likert scale [48]. In the following, a selection of well-established and scientifically proven questionnaires is given. Their structure and the related preference aspects are briefly explained.

	1	2	3	4	5	6	7	
easy to learn	<input type="radio"/>	difficult to learn						

Figure 2.8: Extract of the User Experience Questionnaire (UEQ). A 7-point Likert scale is used to query the tendency towards one side of a given contrasting quality pair concerning the perspicuity of the application.

### User Experience Questionnaire (UEQ)

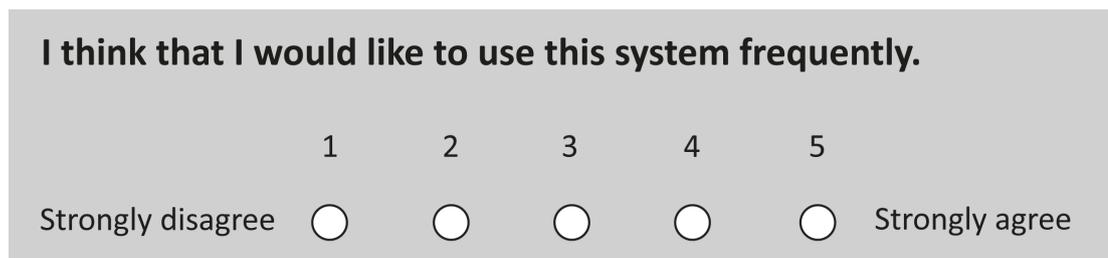
The User Experience Questionnaire (UEQ) investigates the user experience of the participants in terms of attractiveness, efficiency, novelty, stimulation, dependability and perspicuity [22, 39]. A set of contrasting quality pairs represents each of these experience factors. For each of these quality pairs, a 7-point Likert scale serves to express the participants’ tendency towards one side of the pair. In this way, the impression of the participants can be captured in regard of the six factors to form an overall comprehension of the participants’ user experience with a given interface. In total, 26 contrasting quality pairs are listed in the UEQ [39]. One exemplary pair is “easy to learn / difficult to learn” (see Figure 2.8) which belongs to the factor of perspicuity [44]. This questionnaire represents an easy and quick way to get information about the user experience of a considered interface [22, 45]. Additionally, it can be used to compare different interfaces among each other [45]. It is thus used in this research work to individually evaluate the considered menu types and to find out differences between them.

### System-Usability-Scale Questionnaire

The System-Usability-Scale gives information about the usability of the considered interface. In total, the appropriate questionnaire contains ten different usability statements [4, 6]. Each statement has to be rated through a 5-point Likert scale ranging from “Strongly disagree” to “Strongly agree” [25]. The rating therefore indicates the agreement of the participants towards the statement. One statement claims for example that the participant would like to use the interface frequently (see Figure 2.9). The System-Usability-Scale is also referred to as “quick and dirty” and represents a valid possibility to quickly evaluate new interfaces according to its usability [4, 5, 6]. Although the UEQ captures usability aspects as well, the System-Usability-Scale is additionally integrated in this research work due to its popularity and its stability over many years of research. It is used to evaluate the perceived usability of all considered menu types.

## Task Load Index Questionnaire (Nasa-TLX)

The Nasa-TLX Questionnaire investigates the influence on the participants' subjective workload during given tasks [7]. The following six workload characteristics are included in this questionnaire: mental demand, physical demand, temporal demand, effort, performance and frustration level [7, 14]. For each of these characteristics, a 20-point rating scale is presented which ranges from "Low" to "High". In this way, the subjective estimation of the participants concerning the different workload characteristics is captured [13]. Figure 2.10 presents the 20-point rating scale on the example of the characteristic "mental demand". The Nasa-TLX questionnaire represents an easy and validated possibility to evaluate perceived workload [13]. In this research work, it is used to determine the extent of workload resulting from the interaction with all the considered menu types. Their task load indexes are compared among each other in order to define the most and less demanding menu type.

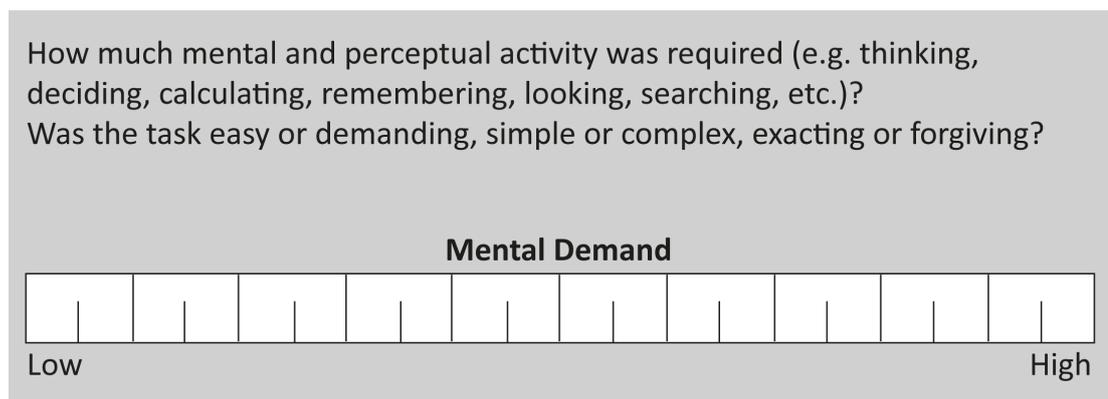


**I think that I would like to use this system frequently.**

1      2      3      4      5

Strongly disagree                  Strongly agree

Figure 2.9: Extract of System-Usability-Scale Questionnaire. One of overall ten statements is displayed. The agreement or disagreement to the given statement is indicated by a 5-point Likert scale.



How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc.)?  
Was the task easy or demanding, simple or complex, exacting or forgiving?

**Mental Demand**

--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--

Low      High

Figure 2.10: Extract of the Nasa-TLX Questionnaire. A 20-point rating scale is used to indicate to which extent the exemplary characteristic "mental demand" is required.

### I had a sense of „being there“ in the shop:

Please rate your sense of being in the shop, on the following scale from 1 to 7, where 7 represents your normal experience of being in a place.

	1	2	3	4	5	6	7	
Not at all.	<input type="radio"/>	Very much.						

Figure 2.11: Extract of the Immersion Questionnaire. A 7-point Likert scale is used to indicate to which extent a feeling of physical presence evolved.

### Immersion Questionnaire (SUS)

Immersion effects arising during the use of an interface are captured through the SUS Questionnaire established by Slater, Usoh and Steed [55]. The questionnaire includes six questions querying the degree to which the participant feels physically present in the virtual environment with the aid of 7-point Likert scales [28, 55]. Figure 2.11 shows an exemplary question of the Immersion Questionnaire. The Immersion Questionnaire is involved in the evaluation process of this research work although no high ratings are expected since the considered menu types are integrated in a two-dimensional browser application. Nevertheless, two different menu representations are investigated from which one is expected to create a more realistic experience. Therefore, the Immersion Questionnaire is used to search for differences between these two menu representations.

# Chapter 3

## Concept

The previously introduced research provides information on how search via menu can be improved and evaluated in order to create a more satisfying search experience. On the basis of different domains, several effective methods could be identified in relation to the representation or the underlying categorisation of menus. This work aims to develop and test different menu types using, refining and combining these methods for their use in online shops. In this chapter, the theoretical concept is introduced and explained in detail. First, this chapter presents the state-of-the-art of online shops in order to compare it with research results and to confirm the impression of common online shop menus. Then, a set of products is introduced which serves as basis for further menu development and evaluation purposes throughout this work. This is followed by the detailed definition of the two menu aspects, which are covered in this work: categorisation and representation. In addition, two realisation strategies are presented for each of these aspects. Finally, the further approach is outlined in terms of implementation and evaluation.

### 3.1 State-of-the-art

One essential activity while using an online shop, is searching for products. Thereby, the menu functionality plays an important role. It offers the possibility to steadily refine the results until the desired item is found. In Table 3.1, a selection of several existing online shops is given which represent the current state-of-the-art. It provides information about the menu types integrated in the respective interfaces. Based on the related work, two aspects are considered: the arrangement of the menu items (the representation of the menu) and the semantic classification of the products (the categorisation). All considered on-

Online Shop	Categorisation	Representation
Amazon <sup>1</sup>	product range, theme	linear (4, 20)
Conrad <sup>2</sup>	product range, theme	linear (4, 8)
Ikea <sup>3</sup>	product range, theme, room	linear (3, 24)
Real <sup>4</sup>	product range, theme	linear (4, 9)
Rewe <sup>5</sup>	product range, theme	linear (3, 12)
Tesco (grocery) <sup>6</sup>	product range, theme	linear (4, 11)
Tesco direct <sup>7</sup>	product range, theme	linear (5, 12)
Zalando <sup>8</sup>	product range, theme, target-group	linear (4, 3)

Table 3.1: Comparison of different online shop interfaces regarding the used menu types. Representation (depth, top-level breadth) and categorisation of the menu types were considered. Example: The shop interface of Rewe includes a linear menu with 3 depth levels and a breadth of 12 at the top-level menu. Categories are based on product ranges and themes.

line shop interfaces use a kind of linear menu representation, in which the menu items are arranged above or beside each other. Some of them also integrate a multi-column menu representation, for example the IKEA interface contains a two-column menu at the top-level. There are huge differences in menu breadth, ranging from 3 to 24 menu items. Depth values at the contrary, which lie between 3 and 5 levels, are close together. This distribution corresponds to previous findings that menu breadth should be generally preferred over menu depth in order to optimise performance [21]. However, in the selected online shop interfaces, the labels used to represent individual menu items are mainly text-based. Research concerning new representation methods is therefore not fully exploited. Only two online shops (Rewe, Ikea) additionally integrate icons, which illustrate the related text label. Three menus (Conrad, Rewe, Tesco direct) indicate the number of subordinated items behind the appropriate text label. In both cases, the additional label information is only available at some menu levels. Besides the menu representation, the logical meaning of the underlying categorisation is examined. All considered online shop interfaces use hierarchical categories reflected in the menu depth. While hierarchies are useful for organising a given set of data, it is essential that the underlying logic is meaningful and comprehensive to make it easy for the user to identify which label to select next in order to achieve his

<sup>1</sup> [www.amazon.com](http://www.amazon.com) (accessed 05.04.2017)

<sup>2</sup> [www.conrad.com](http://www.conrad.com) (accessed 05.04.2017)

<sup>3</sup> [www.ikea.de](http://www.ikea.de) (accessed 05.04.2017)

<sup>4</sup> [www.real.de](http://www.real.de) (accessed 05.04.2017)

<sup>5</sup> [www.rewe.de](http://www.rewe.de) (accessed 05.04.2017)

<sup>6</sup> [www.tesco.com/groceries](http://www.tesco.com/groceries) (accessed 05.04.2017)

<sup>7</sup> [www.tesco.com/direct](http://www.tesco.com/direct) (accessed 05.04.2017)

<sup>8</sup> [www.zalando.de](http://www.zalando.de) (accessed 05.04.2017)

aim. All considered menus in Table 3.1 use intermixed categories. This means that categories follow different sorting strategies within a menu level. Most of the time, categories are based on a combination of product ranges and themes which is well-known from local stores. For example, the category “beverages” refers to a product range whereas the category “baby” refers to a theme. Research has shown that such a mixture of categories can potentially be unclear for users since the labels fail to clearly describe the underlying information space, which is essential in order to give the user an overall impression of the search space [16]. Especially novice users who are not familiar with the specific occurrences of a new online shop could be irritated by this, but experienced users can struggle as well when they search for new products. In the worst case, difficulties like this may lead to shopping attempts being stopped [27]. In sum, the state-of-the-art shows that current online shops do not benefit from previous research in menu optimisation and still rely on already established methods.

## 3.2 Selection of Products

Menu realisation always depends on the data to be displayed. In online shops, the underlying data corresponds to the offered products. Thus, in this work, an adequate set of product data is needed as a basis for the development of menu types. Originating from the selected products appropriate categories can be chosen in order to logically organise them in a menu hierarchy. Since this

<b>Product List</b>		
ball pen	batteries	bedclothes
board game	breakfast bags	chocolate bar
coca cola	coffee filter	college block
computer game	condoms	cutlery
deodorant	dishwasher tabs / powder	DVD / Bluray
electric water kettle	facial tissue	fresh yeast
glue	hot-water bottle	ketchup
laundry detergent	milk	mustard
newspaper / magazine	pea	potato crisps
salt	shoes	socks
swimwear	tabasco	toilet paper
toothpaste	towel	underwear

Table 3.2: Set of products used as basis for the development of the different categorisations and consequently for the creation of the different menu types.

work does not specialise in a particular sub area of the online retail domain, but aims at representing a preferably large section of it, the set of products needed to vary widely over all possible product ranges. Thus, the scope of the resulting categorisations is as wide as possible. However, since this work is restricted in extent and time, the set of products is limited to a set of 36 products. This amount of products yet represents most core areas in online retail. For the purpose of orientation, an exemplary real-world hypermarket is considered. The product selection is mainly based upon a data set of frequently searched products, which was collected during every day activity in this market and was made available for research purposes. Thus, a realistic set of relevant products is given. As already mentioned, it was necessary to chose products that belong to diverse product ranges. This was taken into account when selecting from the list of frequently searched products. The included 36 products belong to various product ranges like for example “food”, “office stuff”, “clothes”, “electronics” and more. The complete product set can be seen in Table 3.2.

### **3.3 Aspects of Menu Types**

Two fundamental aspects were identified in the related work section and are taken into account for further development of menu types: representation and categorisation. The representation of menus concerns the arrangement of related menu items. The logical information structure used to sort product data is described by the categorisation. Based on these aspects, a traditional menu type could be identified through research examples and the state-of-the art. By adjusting one or both aspects, new menu types result. For each of these aspects, the current practice in online shops is presented and a newly developed concept is introduced.

#### **3.3.1 Categorisation**

An important aspect of menu types in online shops is the underlying categorisation which is used to classify the related product data. The categorisation therefore determines the semantic structure of the menu. Usually, categorisations are composed in a hierarchical manner. This means that there exist several levels with a number of category items, which lead to a subordinated level of category items. In this work, categorisations are based on a three-level hierarchy with top-, sub- and product-level. This leads to menus with two levels and follows previous research on menu depth (see Chapter 2). In total, two different categorisations are investigated in this work: traditional and apartment.

## Traditional Categorisation

The traditional categorisation constitutes a reference since it is oriented towards exemplary categorisations used in present online shops [60]. These are usually based on different product ranges and themes. Table 3.1 demonstrates this by means of exemplary web pages (see second column). The traditional categorisation serves as reference for the comparison with the second used categorisation, which is newly developed and is described later. After determining the nature of traditional online shop categories, a real-world market with a typical product classification was used to define a specific and appropriate traditional categorisation on the basis of the previously defined product set. The used market is the same one that has already been used for the selection of the exemplary product set. As already mentioned, the traditional categorisation is based on a three-level hierarchy, which consists of the top-, sub- and product-level. The top-level categories correspond to the product range, which is typically a delimited area in the market. In the exemplary market, this is for example the product area “milk & cheese”. The sub-level categories describe a more precise product type inside this product range. It usually constitutes a specific shelf or several shelves

<b>Product Ranges</b>	<b>Product Types</b>
preserves / ready-to-eat meals	salt / pulses / rice, noodles, delicacies / olives, vegetables / sauerkraut, sour vegetables / pickles
home textiles / lingerie	socks, underwear, bathroom utensils, home textiles, bathroom textiles
sweets & snacks	fruit gum / chocolate bars, sweets, candies / chewing gum, snacks
shoes / leather goods	leather goods / accessories, shoes
chemist's / hygiene / personal hygiene	over-the-counter drugs, facial tissues, soap, plasters / foot care, travel sizes / deodorant, toilet paper, dental care
office supplies / books	PC stuff, media, booklets / writing pads, arts / crafts, office supplies
...	...

Table 3.3: Extract of the traditional categories which result from the exemplary real-world market on the basis of the selected product set. The total count of product ranges is 20.

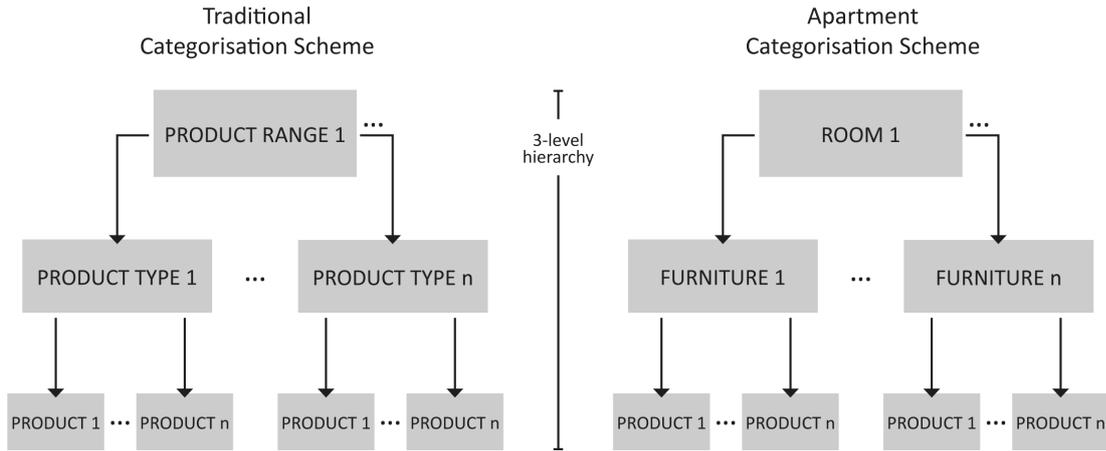


Figure 3.1: Visualisation of the three-level hierarchy of the two categorisations. Left: Traditional Categorisation. Right: Apartment Categorisation.

in the delimited market area, for example “cheese” in the exemplary market. The last level represents the product level, presenting the individual products. A visualisation of the three-level hierarchy of the traditional categorisation can be seen in Figure 3.1 (see left side). Furthermore, an extract of the traditional categories which result from the exemplary real-world market can be seen in Table 3.3. The complete traditional categorisation can be found in Appendix A2, including categories and product assignments.

### Apartment Categorisation

As stated in the related work section (see Chapter 2), the apartment categorisation is based on the Apartment Metaphor [1]. Metaphors can be a useful instrument for an intuitive user interaction [19]. They are used in many software and web applications in order to facilitate usage and learning process for users. For example, see the well-established “desktop metaphor” [15]. The use of an interface metaphor leads to a natural model which meets realistic expectations of the users [3]. Accordingly, the apartment metaphor uses the fact that typically every user is familiar with the structure of an apartment. Due to everyday habits and experiences, they have a general idea of where to search for specific products which are located in an apartment. This is an intuitive process, which is expected to lead to an easy handling of a shopping interface. Just as for the traditional categorisation, it holds that the apartment categorisation is based on a three-level hierarchy. The top-level categories represent the rooms of an apartment, for example the room “kitchen”. The sub-level categories correspond to specific furniture inside this room. On the example of the room “kitchen”, one

exemplary piece of furniture is the “fridge”. The last level is identical to that of the traditional categorisation. It is the product level, where the specific products are located. A visualisation of this three-level hierarchy can be seen in Figure 3.1 (see right side). In order to develop the apartment categories and to define the appropriate product assignments, the previously defined set of diverse products was used as basis. A pilot study was conducted to find out where users expect these products to be located inside an apartment. The apartment categorisation was thus build upon users’ expectations.

### 3.3.2 Representation

Another fundamental aspect of menu types is their representation. Different representations vary in the arrangement of the menu items on screen. This can influence the search time needed to visually find a desired menu item as well as the time needed to point and click on it [2, 9, 53]. In this work, three-level categorisation hierarchies are used as basis for the representations. This leads to menus with two menu levels. The top-level menu provides access to related sub-level menus, which finally provide access to the subordinated products. In total, two different representations are investigated in this work: linear and map-based.

#### Linear Representation

The first representation under investigation is the linear menu representation. The linear menu is widespread in present web interfaces like online shops [60]. In Table 3.1, this is demonstrated by means of exemplary online shop interfaces (see last column). In linear menus, the menu items are ordered one beneath the other or one above the other. Thus, the menu items, which are usually marked with textual labels, form either a horizontal or a vertical line. The linear menu representation can therefore be either a horizontal menu or a vertical menu. The linear menu representation builds the baseline in this research project. It serves as reference for comparison with the second menu representation which is newly developed and introduced subsequently. The chosen linear menu representation is based upon the findings of Zhang et al. [60], who evaluated and compared vertical

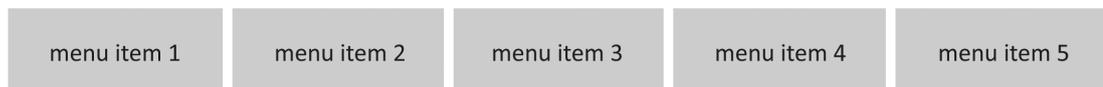


Figure 3.2: General linear menu representation with five menu items which are arranged horizontally (top-level menu).

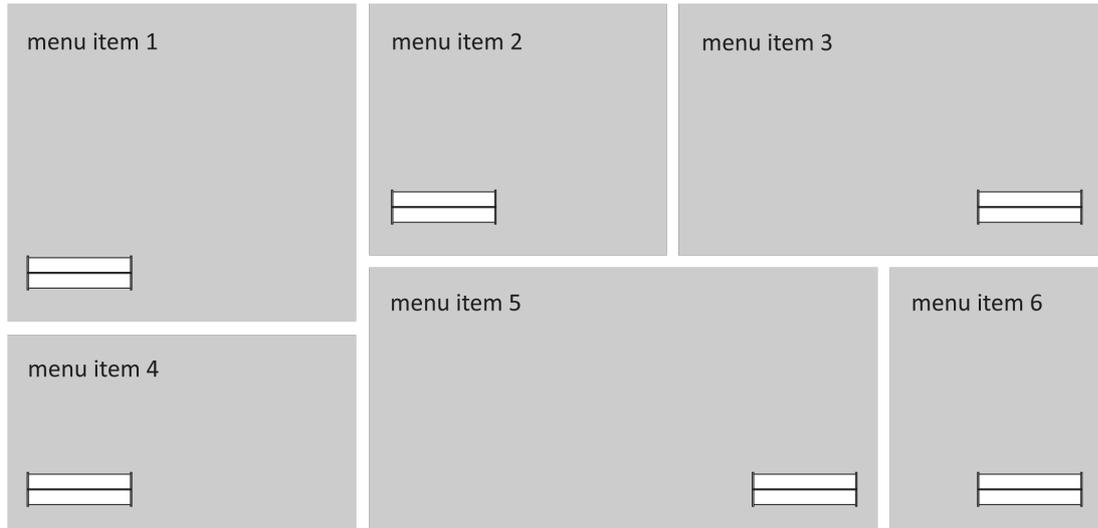


Figure 3.3: General map-based menu representation of a fictive market with six menu items (top-level menu). Supplementary icons, here shelves, illustrate the figure of the market floor plan.

and horizontal menus at different positions. According to that, a horizontal linear menu at top screen position is the most recommendable and is therefore used as reference menu representation. The depth and breadth of a linear menu depend on the underlying categorisation. A general visualisation of a horizontal menu with five menu items can be seen in Figure 3.2.

### Map-Based Representation

The second representation, which is newly developed and investigated in this work, is the map-based menu representation. It is influenced by previous findings concerning grid-shaped arrangement [2, 43] as well as by the idea of in-store floor guides used for orientation purposes. Such in-store guides are often used in shopping malls, where they are printed on signs near the stairways. Moreover, previous findings show that a virtual store map can be an effective tool for user orientation [29]. On the basis of these research findings, the map-based menu representation was developed. This menu representation is not based on an abstract shape, but rather reflects a real-world environment, which is described by the underlying categorisation. The different menu items are arranged according to the position they take in relation to each other in the real world. In this way, a real-world environment is represented virtually. The menu thus functions just as an interactive floor plan. This realistic spatial arrangement is expected to facilitate the creation of a mental model of the menu due to spatial memory capabilities. This usually leads to fast information retrieval and increased

performance [12, 41]. In connection with a general market, the map-based menu represents the floor plan of this market and visualises its market areas on the top-level menu and its shelves on the sub-level menus. Accordingly, if the apartment categorisation builds the basis, the map-based menu represents the floor plan the appropriate apartment with its rooms on the top-level menu and its furniture on the sub-level menus. Since the structure of real-world environments like markets or apartments usually are not linear, a grid-shaped arrangement results for the menu items of a map-based menu. As with the linear menu representation, the size of the map-based menu depends on the underlying categorisation. In addition to the new spatial arrangement of the menu items, the textual labels are supplemented by illustrating icons. These icons are used to strengthen the realistic spatial impression given by the new menu representation. An exemplary map-based menu is visualised in Figure 3.3.

### 3.4 Approach

The theoretical concept is a first step towards the objective of this work, which is to develop and evaluate new menu types for online shops. The conceptual idea of the different menus and their underlying aspects were fully elaborated. Whereas the traditional categories and an appropriate product assignment could be directly derived from a selected real-world market, the apartment categorisation has to be developed from scratch. In order to create realistic apartment categories and an appropriate product assignment, which reflects the expectations of the majority, users are consulted in a pilot study. During this pilot study, the expectations of the individual participants are analysed and evaluated in order to create a general apartment categorisation. A specific model for the newly developed map-based menu representation is then set up for both categorisations as defined before. According to the two different representations and the two categorisations, four menu types result:

1. Linear Menu (Traditional)
2. Map-Based Menu (Traditional)
3. Linear Menu (Apartment)
4. Map-Based Menu (Apartment)

In order to test and compare these menu types, they are integrated in a HTML-based online shop prototype where they can be used to search for products. After the implementation, the main study is prepared. Therefore, the study

design as well as the procedure and the tasks are specified. Then, the main study is conducted accordingly in order to evaluate the four different menu types. Data about task performance and user preference is collected during the study and analysed afterwards. These results finally give information about the task performance and user preference of the different menu types and reveal if the newly developed menu types could be valuable for future use in online shops.

# Chapter 4

## Pilot Studies

This chapter describes two pilot studies which were carried out in advance of the main study in order to complete all necessary preparations. The first pilot study focuses on the systematic development of the apartment categorisation. After the development of the theoretical hierarchy in the conceptual process, specific categories and product assignments had to be developed. Two phases were needed until the categorisation was sufficiently reliable. The aim of the second pilot study was to form two product groups of the same size and approximately the same average difficulty level. Therefore, each of the considered products was classified according to its mean search error rate. In this way, it was possible to establish a comparability of the product data and a logical basis for the study design could be established.

### 4.1 Apartment Categorisation

The aim of the first pilot study was to develop an apartment categorisation based on the “Apartment Metaphor” [1]. This includes the apartment categories (rooms and furniture) as well as the product assignment. In total, two phases were conducted in order to successively create, review and refine the apartment categorisation. During the first phase, a preliminary set of apartment categories was established on the basis of the participants’ demographical data. The second phase was used to review and refine these apartment categories further. In addition, the considered set of products was assigned to these refined categories as part of the second phase. The resulting apartment categorisation was then used to implement two menu types for online shops, which were tested in the subsequent main study. In this section, the procedures of the two phases as well as the evaluation methods and the results are presented.

**Which rooms or areas do belong to your household?**  
Please check all that apply. Furthermore, please list additional areas/rooms under the point 'Other'.

- bathroom
- kitchen
- bedroom
- living room
- corridor / entrance
- balcony
- garden
- cellar
- Other: \_\_\_\_\_

Figure 4.1: Online questionnaire – Question about the apartments' room types.

#### 4.1.1 Phase 1: Apartment Categories

In the first phase, an online survey was conducted. The aim of this survey was to create a first set of apartment categories, including rooms and furniture. These categories represent a fundamental part of the apartment categorisation since they form the basis for product assignment. Figure 4.1 and Figure 4.2 show extracts of the online questionnaire. The questions aimed at capturing information about the participants' apartment situation. More precisely, this includes the room types which belong to the apartment, as well as product storing habits, i.e. which parts of the apartment are used as storage place. In the latter case, the data is based on an exemplary set of products with various product ranges like food, electronics or clothes. Only 30 of the 36 previously selected products (see Chapter 3) were used since six products were held back to test validity later. In order not to restrict the response options, the appropriate questions were partially designed in a qualitative way. Qualitative or open questions leave scope for individual and potentially unexpected answers and offer the possibility to gain a more objective perspective of the research topic which is not restricted by the researcher's opinion [24]. In this way, the actual living situations and habits of the participants form the basis of the resulting apartment categories.

## Participants

The link of the online questionnaire was shared on social media platforms and participation was fully voluntary. In total, 42 participants took part in the online survey. A visualisation of the demographic data can be seen in Figure 4.3. 20 participants were women and 22 were men. The age ranges from 18 to 58 years with about 31 years on average ( $M=31.12$ ,  $SD=12.35$ ). Most of the participants live in a two-room apartment ( $M=2.17$ ,  $SD=0.85$ ) – bathroom, kitchen

1 / 30



**In which room of your apartment the product "salt" is placed or stored?**  
Please check all that apply.

- There is no specific room in which the product is stored.
- kitchen
- bathroom
- bedroom
- living room
- corridor / entrance
- Other: \_\_\_\_\_

**Please describe the place (in the previously named room) where the product "salt" is placed or stored as detailed as you can:**

Your answer \_\_\_\_\_

Figure 4.2: Online questionnaire – Two questions about product storing at the example of the product “salt”. Appropriate rooms are queried as well as a detailed description of the storage place inside these rooms.



Figure 4.3: Demographic data of the N=42 survey participants, including age and gender information.

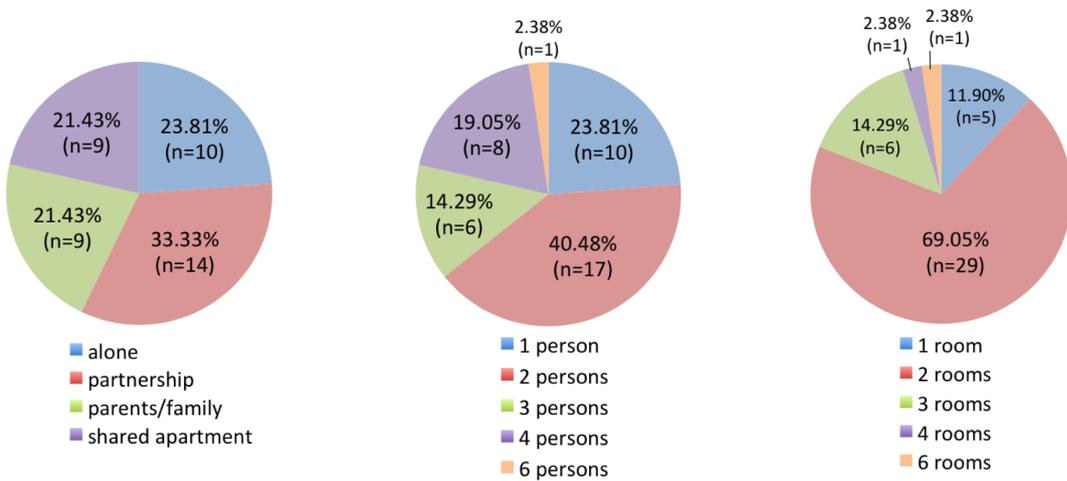


Figure 4.4: Statistical overview of the participants' background (N=42). Left: Apartment type. Middle: Count of inhabitants. Right: Count of rooms.

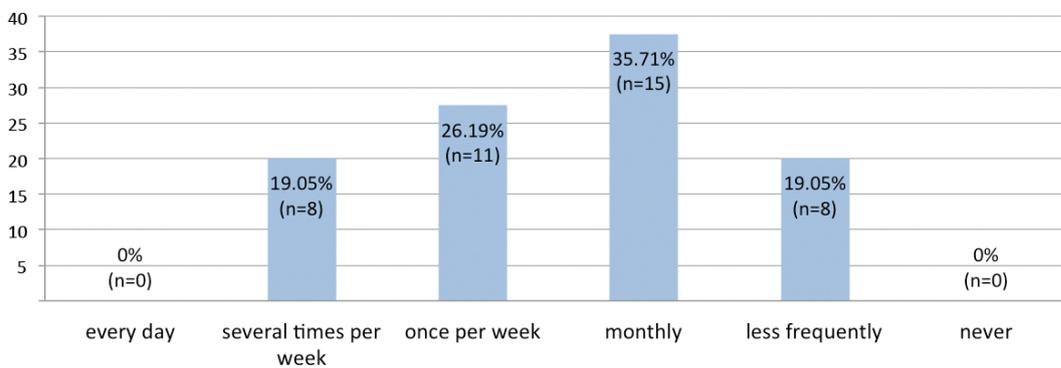


Figure 4.5: Online shopping behaviour of the survey participants (N=42).

or corridor not included – with two inhabitants on average ( $M=2.38$ ,  $SD=1.19$ ). One third of the participants live in a partnership (33.33%,  $n=14$ ), followed by living alone, with parents / family or in a shared apartment with about 20% in each case. Figure 4.4 visualises the complete data, including statistical values. On average, the participants have a well-founded experience with the process of online shopping (see Figure 4.5). All of them have already purchased online. Most of them (80.95%,  $n=34$ ) purchase online at least once per month. Finally, the participants’ feedback revealed that most criticism of online shops relates to unstructured and confusing online shop layouts (35.71%,  $N=14/n=5$ ) as well as malfunctioning search functionality (42.86%,  $N=14/n=6$ ). On the contrary, a good search functionality (60.00%,  $N=50/n=30$ ) and well-structured filters or categories (22.00%,  $N=50/n=11$ ) are the most named positive characteristics.

## Evaluation

Initially, the question about the apartments’ room types (see Figure 4.1) was evaluated. The gathered data was mainly quantitative. It was therefore simply summed up how many times each room had been selected to get the total number of participants who have such a room in their apartment. For example, 35 out of 42 participants have a “living room” (see Table 4.1). Answers given under

Rooms	Owned by (n)	Owned by (%)
<b>bathroom</b>	<b>41</b>	<b>97.6%</b>
<b>kitchen</b>	<b>41</b>	<b>97.6%</b>
<b>bedroom</b>	<b>41</b>	<b>97.6%</b>
<b>corridor / entrance</b>	<b>37</b>	<b>88.1%</b>
<b>living room</b>	<b>35</b>	<b>83.3%</b>
<b>cellar</b>	<b>32</b>	<b>76.2%</b>
garden	20	47.6%
...	...	...
office	5	11.9%
...	...	...

Table 4.1: Ordered statistical results of the online questionnaire concerning the question about room types ( $N=42$ ). The six rooms in bold are added to the first set of room categories since these rooms belong to clearly more than 50% of the considered households. They represent therefore an average standard apartment.

Rare single rooms	Added to
toilet	bathroom
dressing room, guestroom	bedroom
attic, garage, laundry, pantry, storing room, utility room	cellar: storing room / laundry
dining room	living room

Table 4.2: List of room transformations – Rooms on the left side, which rarely occur as separate room, are added to the room of the right side.

the optional point “Other” however led to qualitative data. The rooms stated in these answers had to be sorted first and then summed up accordingly. In this way, additional rooms were added to the set of considered rooms, like for example the room “office”. Subsequently, the whole data set was statistically analysed by calculating average values. The data was interpreted to gain an impression of the rooms which belong to a general apartment and to form a first set of room categories (top-level). In total, six room categories were included since these rooms were selected by clearly more than 50% of the participants (see Table 4.1). In addition, there is a clear percentage gap to the next lower ranked room.

Afterwards, the data gathered through both questions about the product storing habits was evaluated. The aim was to determine which rooms and pieces of furniture are used for storing purposes and which are thus relevant for the apartment categories with regard to later product assignment. Initially, the first question concerning the rooms (see first question in Figure 4.2) was considered for every single product (30 in total). Here again, the gathered data was mainly quantitative, except for the qualitative data stated under the point “Other”. The latter was thus first analysed to collect similar answers and to sum them up accordingly. For example, one resulting room was the “guest room”, which was additionally stated in relation to the product “bedclothes”. Then, the whole data set was statistically analysed in order to get a ranked overview of the rooms, which were used to store the considered product. For example, the rooms “bedroom” (94.00%,  $n=47/N=50$ ), “corridor/entrance” (4.00%,  $n=2/N=50$ ) and “guest room” (2.00%,  $n=1/N=50$ ) are used to store the product “bedclothes”. After the statistical analysis, the resulting data was interpreted and processed

further to get a preferably universal and clear room storing model. First, a room transformation process was conducted. In this process, all rooms which in general rarely occur as separate rooms are combined with more widespread rooms which are often used for the same purpose. For example, the “dining room” is often part of the apartment’s “living room”. The statements for “dining room” are consequently added to the value of the “living room”. At the example of the product “bedclothes”, the “guest room” is transformed into the “bedroom” since they are usually used for similar storing purposes. The complete list of room transformation rules is given in Table 4.2. After the room transformation process, all outliers which made up less than 6% of the total statements were omitted. For example, the room “corridor/entrance” was omitted in the case of the product “bedclothes” since it constitutes only 4% of the total statements ( $n=2/N=50$ ). The complete processing procedure is demonstrated in Figure 4.6 at the example of the product “bedclothes”. It was applied for all the 30 products. The resulting set of rooms used to store the products was then compared with the previously defined room categories. The six previously identified room categories turned out to be sufficient for storing purposes in most of the cases. One additional room however was part of the mostly stated rooms with at least 6% for some products. This was the room “office”, which was therefore added to the previous set of room categories. The resulting seven rooms therefore represent the top-level categories of the apartment categorisation.

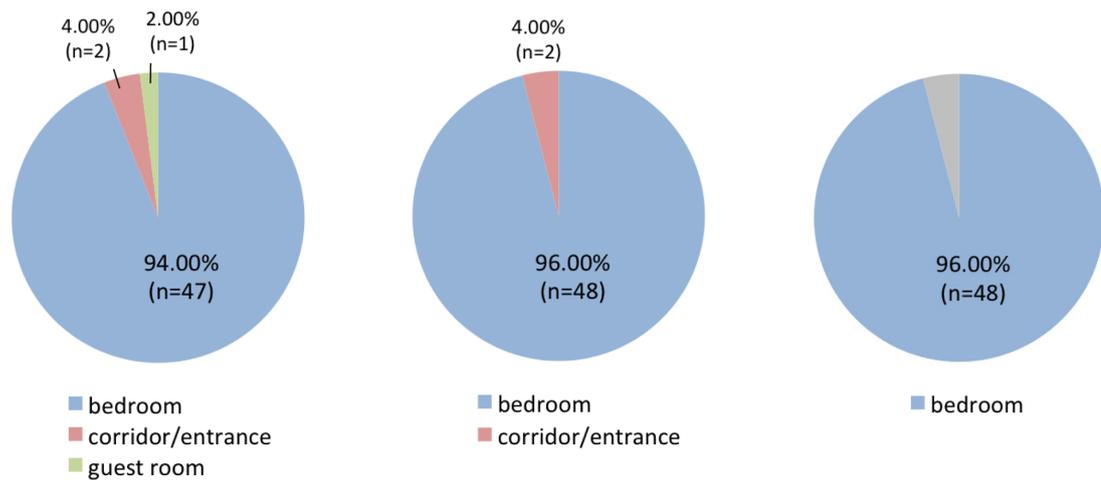


Figure 4.6: Results and evaluation of the online questionnaire at the example of “bedclothes” ( $N=50$ ). Left: Aggregated room data counts. Middle: Room transformation process where “guest room” is added to “bedroom”. Right: Omitting of “corridor / entrance” since it made up less than 6% of total statements.

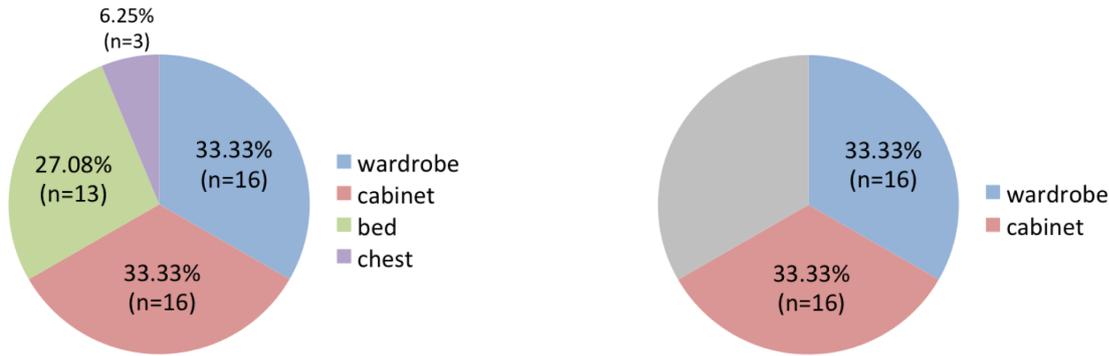


Figure 4.7: Furniture selection on the example of “bedclothes” in the “bedroom” (N=48). Left: Sorted furniture data. Right: Furniture selection process where “wardrobe” and “cabinet” are adopted as storing places since they together cover more than 50% of the total statements.

After determining the set of rooms which were used for product assignment, the furniture/places inside these rooms had to be specified. Therefore, the question concerning the furniture/places (see second question in Figure 4.2) was considered for each product and the related room set which was defined in the previous step. The data gathered through this question was completely qualitative and thus primarily had to be analysed in order to find patterns. Characteristic keywords were chosen to organise the given answers. The answers were then sorted according to these keywords and summed up. Thereby, furniture/places which are highly similar in usage were joined together. Regarding the example “bedclothes” in the “bedroom” (N=48), the “built-in cupboard” (n=1), the “linen cupboard” (n=2), the commode (n=2) and the “cabinet” (n=11) were put together under the keyword “cabinet” which was the most frequently used. Subsequently, the sorted data was statistically analysed, interpreted and processed further in order to get a preferably universal and clear storing model inside the considered rooms. Therefore, only the most frequently stated furniture/places were used as storing locations so that in total at least 50% of the statements were covered. This threshold turned out to be valid in the given data set in order to ensure a sufficiently high degree of accuracy without taking into account subjective outlier statements. Regarding the example of “bedclothes”, the two most frequently stated pieces of furniture “wardrobe” (33.33%) and “cabinet” (33.33%) were thus included in the room “bedroom”. No further rooms were adopted in this example since the first two rooms already cover more than 50% of the total statements. This process is demonstrated in Figure 4.7 at the example “bedclothes” in the room “bedroom”. This final analysis process was applied to all 30 products and the related room sets which were defined in the previous step. Through this final analysis process,

furniture was assigned to the seven previously defined room categories. This furniture corresponds to the sub-level categories of the apartment categorisation. The complete set of apartment categories (rooms and furniture) which resulted from the analysis of the online questionnaire can be seen in Table 4.3.

### Lessons Learned

During the evaluation of the questionnaire data, it became clear that the amount of product mapping information widely varies between the different products. This results from the fact that the actual living situation of the respective participants was queried and not their general assumption. Thus, the participants only had to assign products which are usually located in their apartments. There were consequently some products with only few assignments. For example, all 42 participants provided storing information about the product “salt”, but only 27 participants about the product “hot-water bottle” and even only 12 about the product “potato crisps”. Therefore, a second phase was conducted afterwards in order to use the information of the first phase for further data gathering. In this case, the participants had to assign the products to the apartment categories of the first phase instead of their own rooms and furniture. The results are thus based on the participants’ general expectations. In this way, it could be avoided that several products are classified by a less representative number of participants.

<b>Rooms</b>	<b>Furniture / Places</b>
bathroom	cabinet, floor, sink cabinet, toilet paper holder, washing machine
bedroom	bed, bedside table, cabinet, computer, desk, entertainment center, floor, shoe cabinet, wardrobe
cellar: storing room / laundry	cabinet, hook, washing machine
corridor / entrance	cabinet, shoe cabinet
kitchen	cabinet, drawer, fridge, sink cabinet, table, washing machine, worktop
living room	cabinet, computer, desk, table
office	cabinet, computer, desk

Table 4.3: Apartment categories resulting from the evaluation of the online survey (phase 1). They include seven rooms and their related furniture.

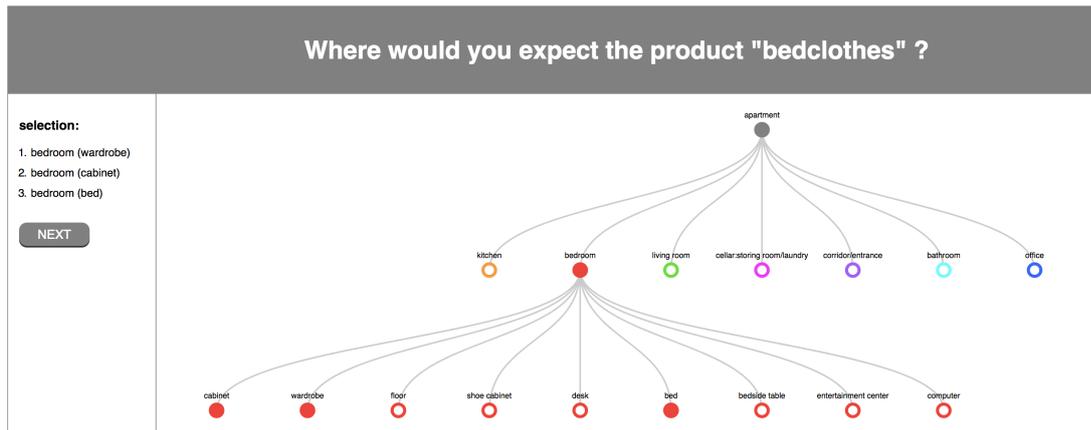


Figure 4.8: Web application used in phase 2 at the example of the product “bedclothes”. The tree visualisation represents the hierarchy of the apartment categories with room nodes on the first level and furniture nodes on the second level. Here, room node “bedroom” is expanded and furniture nodes “bed”, “cabinet” and “wardrobe” are selected. The current selection is displayed on the left.

### 4.1.2 Phase 2: Product Assignment

In the second phase, the first set of apartment categories was integrated in a web application to review and refine it in a user study. The aim of this study was to check the validity of the apartment categories by testing whether there were any room or furniture categories missing. In addition, the second phase was used to establish the product assignments. For this purpose, a basis of 36 products was used, which should be assigned to the apartment categories of the first phase. In addition to the 30 products used in the first phase, six additional products were included to check if the category set is also adequate for new products. The user study took place at the Saarland University and participation was fully voluntary. In total, 20 participants took part in this study, including 9 women and 11 men.

#### Web Application

The web application which was used in the second phase is visualised in Figure 4.8. The application consists of three parts. On the top of the screen, the current question is displayed. On the left side, the current selection is listed and a “NEXT” button is displayed through which the selection can be submitted and the next question can be started. On the right side, the apartment categories are visualised through an interactive hierarchical tree representation. The root of the tree represents the apartment. On the first level are the room nodes and on the second are the furniture nodes (see Figure 4.8). In order to see the furniture of a specific room, the study participants had to click on the appropriate room node.

By clicking on a furniture node, the room-furniture pair was selected and added to the selection list on the left screen side. Every selection could be taken back by a second click on the appropriate node. The participants of the user study could select as many room-furniture pairs as they believed to be necessary to assign a given product. They were instructed to additionally communicate verbally when they thought that any room or furniture was missing.

## Evaluation

The product storing data, which was gathered through the aid of the web application, was quantitative data. It was therefore summed up and statistically analysed. An extract of the resulting values can be seen in Figure 4.9. For example, five different storing places resulted for the product “bedclothes”. In the room “cellar”, the “cabinet” (3.03%,  $n=1/N=33$ ) and the “washing machine” (3.03%,  $n=1/N=33$ ) were selected. The “bed” (30.30%,  $n=10/N=33$ ), the “cabinet” (42.42%,  $n=14/N=33$ ) and the “wardrobe” (21.21%,  $n=7/N=33$ ) were selected in the “bedroom”. Subsequently, the aggregated data results were interpreted and processed further. For each product, the top statements were used to establish the product assignments so that at least 60% of the given state-

SALT (N=32)				
cellar: storeroom/ laundry		kitchen		
cabinet n=3 9.38%		cabinet n=17 53.13%	drawer n=6 18.75%	worktop n=4 12.50%
				table n=2 6.25%

BEDCLOTHES (N=33)				
cellar: storeroom/ laundry		bedroom		
cabinet n=1 3.03%	washing mashine n=1 3.03%	bed n=10 30.30%	cabinet n=14 42.42%	wardrobe n=7 21.21%

POTATO CRISPS (N=29)			
cellar: storeroom/ laundry	kitchen		living room
cabinet n=5 17.24%	cabinet n=16 55.17%	drawer n=3 10.34%	cabinet n=5 17.24%

Figure 4.9: Extent of the study results, including the total number of selections per product, as well as the number of statements per room-furniture pair and related rounded statistical values. Grey highlighting indicates which room-furniture pairs are accepted for the product assignment. Pairs with grey background result from the first evaluation rule and grey shaded pairs result from the second one. The complete study results of the second phase can be seen in Appendix A.1.

<b>Rooms</b>	<b>Furniture/Places</b>
bathroom	cabinet, <b>sink</b> , sink cabinet, <b>hook</b> , toilet paper holder
bedroom	bed, bedside table, cabinet, entertainment center, wardrobe
cellar: storing room / laundry	cabinet, washing machine
corridor/entrance	cabinet, shoe cabinet
kitchen	cabinet, drawer, fridge, sink cabinet, table, worktop
living room	cabinet, computer, <b>entertainment center</b> , table
office	cabinet, computer, desk

Table 4.4: Refined apartment categories resulting from the evaluation of the user study (phase 2). They include seven rooms and their related furniture. Categories resulting from the qualitative evaluation process are given in bold.

ments were covered. This threshold turned out to be valid in the given data set in order to ensure a sufficiently high degree of accuracy without taking into account subjective outlier statements. Based on this evaluation rule, it follows that two storing places were included in the apartment categorisation for the product “bedclothes” (see Figure 4.9). These are the places “bed” and “cabinet” inside the “bedroom” since they are together the most frequently named storing places (72.72%,  $n=24/N=33$ ). In addition to this basic evaluation rule, an additional rule was applied in the evaluation process. According to this rule, all assignments which were stated from at least 6 out of the 20 participants are included in the apartment categorisation as well. This second evaluation rule was included since such an assignment was stated by a large part of the participants (30%,  $n=6/N=20$ ) and represents a high agreement and not an outlier statement. This rule could not stand for itself alone because results would have been too restricted, but omitting the affected assignments could potentially lead to an increased error rate in future applications. Due to this second evaluation rule, seven additional assignments were added to the results from the first evaluation rule. For example, the storing place “wardrobe” in the “bedroom” was added to the two previously defined places since more than 30% (35.00%,  $n=7/N=20$ )

of the participants selected it (see example “bedclothes” in Figure 4.9). Furthermore, all categories which were included in the apartment categories so far, but which were not selected often or not at all, were removed. Besides the evaluation of the quantitative data which was measured through the web application, there was also some qualitative data, which was communicated verbally by some participants and which was noted by the researcher. The evaluation of this data mainly confirmed the previously established and refined apartment categories. There were only few supplement suggestions indicating that there was some room/furniture missing. Most of them were communicated only once and were ignored since they obviously represent individual opinions instead of general expectations. All supplement suggestions which occurred at least four times, i.e. by 20% ( $n=4/N=20$ ) of the participants, were used to adapt or complement the apartment categories since they were a useful addition. In total, three pieces of furniture or places were added. Table 4.4 shows the refined apartment categories, including the supplements resulting from the qualitative analysis (see bold highlighting). The complete apartment categorisation can be seen in Appendix A.3, including room categories, furniture categories and product assignments.

### **Lessons Learned**

Since there were only few correction suggestions and since the apartment categories were positively accepted in general, no further phases were implemented. Therefore, the refined results from this second phase represent the final apartment categorisation, including the apartment categories and the product assignments.

## **4.2 Product Groups**

After the selection of an adequate product set in the conceptual process (see Chapter 3), a difficulty level was assigned to each product in order to provide a better comparability among each other. This was necessary to control learning effects within one categorisation during the main study. A short pre-survey was conducted in order to define the difficulty levels for each of the selected products. Therefore, the total set of 36 products was divided into six subsets with six products. In total, 30 participants took part in this pre-survey on a voluntary basis. A sheet of paper relating to one of the six subsets was handed out to each participant. They had to assign all six products of the given subset according to one of the traditional top categories (product ranges) by ticking off the appropriate box. Since each participant classified six products, each product was



Figure 4.10: Overview of the classification process conducted in order to divide the total set of 36 products into two sub groups of the same size and with an approximately identical difficulty level.

thus classified five times in total. The gathered data was added up and evaluated. For each product, all incorrect answers were identified and statistical values concerning the error rates were calculated. Thereby, error rates can assume the following values: 0% (n=14), 20% (n=15), 40% (n=2), 60% (n=2), 80% (n=1) or 100% (n=2). A total average error rate of 21.67% (M=21.67, SD=27.20) resulted. This finding shows that there really exists potential for improvement since expectations often not meet the reality. The average statistical values resulting from the short classification survey led to the difficulty classification used in the subsequent main study to form two comparable product groups in order to eliminate learning effects concerning the different categorisations. Therefore, the total set of 36 products was divided into two groups of 18 products each. All products were classified according to their level of difficulty so that the average value of both groups is approximately even (see Figure 4.10). In this way, the comparability of the different menu types remains valid. A complete list of the two product groups can be found in Appendix A.6.

# Chapter 5

## Implementation

This chapter introduces the implemented online shop prototype, which is realised as a web application. Initially, the overall architecture is presented and explained, including the prototype structure as well as the interplay with the database. Then, the main parts of the online shop prototype are described in detail: menu area and product area. Considering the menu area, the realisation of the individual menu types is described in detail. For each of the four menu types, their organisation on screen and their functionality are illustrated. Additionally, the underlying technical specifications are briefly explained. Finally, a description of the product area is given. For this purpose, its organisation on screen as well as the visualisation of the individual products is described.

### 5.1 Prototype Architecture

All architecture components were set up with the aid of web server solution stack XAMPP. A simplified overview of the different components and their relation is given in Figure 5.1. The online shop prototype consists of three parts: the header which simply provides information about the shop name and the language, the menu area and the product area. The basis of the online shop prototype is the integrated data set, which is saved and structured in a SQL database. The used database contains a total set of 77 products. Among these are the 36 products, which were used for the development of both categorisations (see Chapter 3) and which will also be used for evaluation purposes during the main study. The remaining products were used to create a more realistic and complex prototype and are never used for product searches in the later main study. In this database, all 77 products as well as their assignment into both categorisations are included. This is the traditional categorisation on the one hand and the

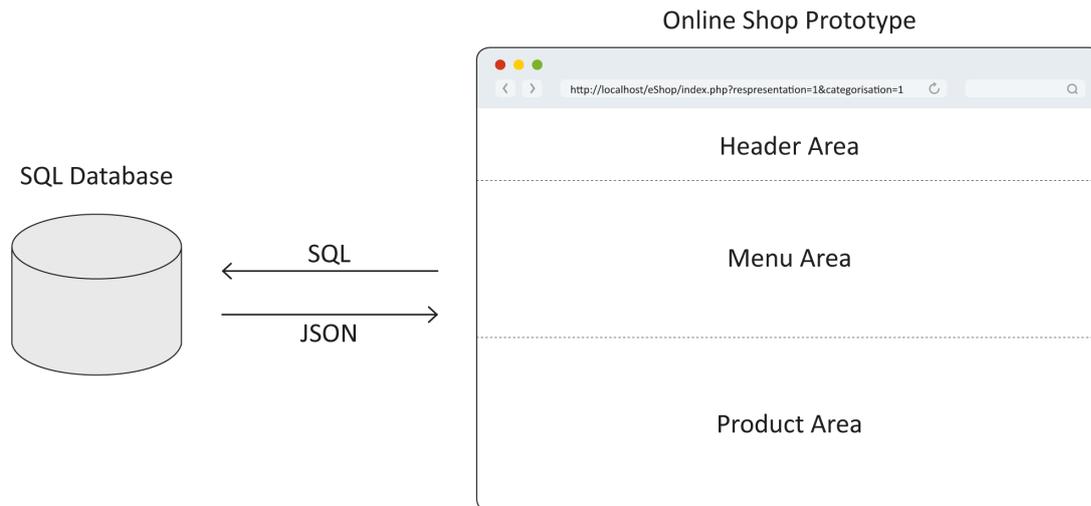


Figure 5.1: Simplified overview of the implementation architecture. The individual components are visualised and their relation is delineated.

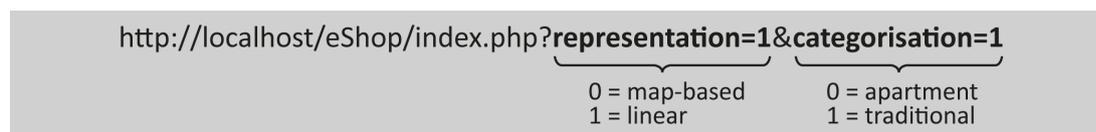


Figure 5.2: Exemplary prototype URL which starts the prototype with the linear menu based on traditional categories.

apartment categorisation on the other hand. Through the use of a database, the online shop prototype is easily expandable by future product storing data. In order to start the prototype, the appropriate URL has to be entered in a browser window. Since only data concerning one specific categorisation is needed, this is determined through the prototype URL. Therefore, the appropriate parameter is adapted accordingly. Thus, either data related to the traditional or apartment categorisation is loaded at the beginning. Additionally, the representation can be specified through a parameter of the URL. Depending on this, the loaded category data is either represented in a linear menu or in a map-based menu. An exemplary prototype URL is shown in Figure 5.2. When the web-based prototype is started through the URL, the categorisation and representation parameters are handed over to a PHP script of the prototype. The appropriate category and product storing data is then requested through a SQL query, which is transferred to the database. Data is transformed into a JSON object, which is transmitted to the JavaScript application where it is used to build the menu type. In the following, the different menu types and their functionality are described more precisely.

## 5.2 Menu Area

The menu area is located below the header area and is the central part of the online shop prototype. It contains one of the four previously developed menu types which differ in the representation (linear/map-based) and/or the categorisation (traditional/apartment). As already mentioned, these settings are specified through URL parameters when the prototype is started. In the following, the two linear menus are presented in detail first and then the two map-based ones.

### 5.2.1 Linear Menus

The linear menu representation used in this research work consists of two menu levels: the top-level and the sub-level. The related menu items of a specific menu level are arranged one beside the other. They have a rectangular background and are visually separated from adjacent items through a fine vertical line. Furthermore, each individual menu item is characterised through a textual label which is associated with the underlying categorisation. Due to the particular categorisations, different amounts of menu items result for the two linear menu types. Therefore, the linear menus are described in more detail in the following.

#### Linear Menu with Traditional Categories

As already mentioned before (see Chapter 3.3.1), the traditional categorisation derived from a real-world market. In total, 20 top-level categories were determined, each with a varying number of related sub-level categories. Due to the high number of top-level categories, the top-level menu with traditional categories is spread out over two rows. In this way, readability of the menu can still be en-

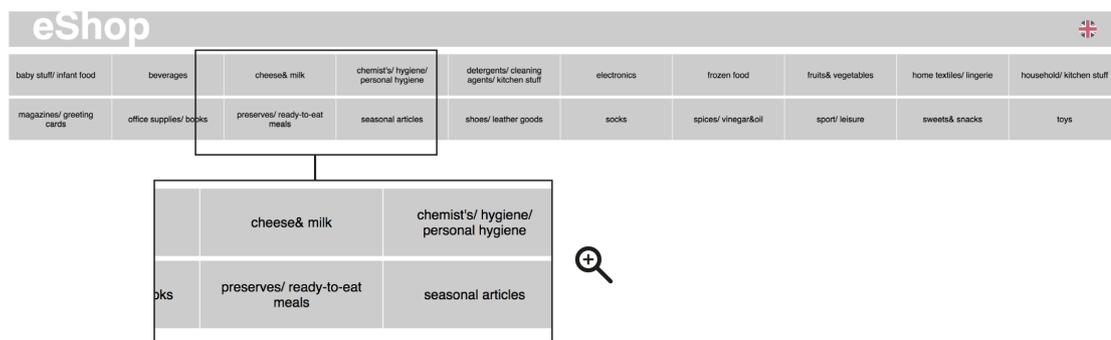


Figure 5.3: Overview of the top-level of the linear menu with traditional categories. For the purpose of better readability, the related 20 top-level menu items are spread out over two rows.

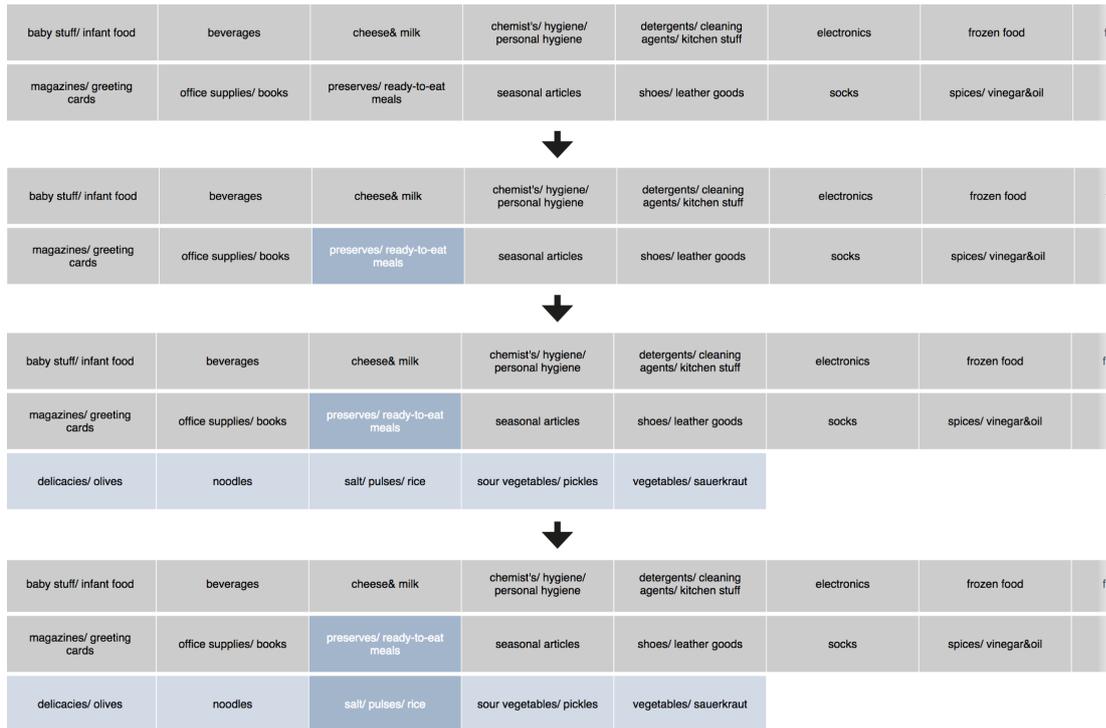


Figure 5.4: Different interaction states of the linear menu with traditional categories. Top: Top-level menu, no selection. Middle: The top-level menu item “preserves / ready-to-eat meals” is selected by first hovering and then clicking on it. The appropriate sub-level menu is then displayed. Bottom: The sub-level menu item “salt / pulses / rice” is hovered and selected.

sured. An overview of the top-level of the linear menu with traditional categories is given in Figure 5.3. As can be seen, all top-level menus have a grey background and a black text label by default. In order to display a specific sub-level menu, one of the available top-level menu items has to be selected by clicking on it. A mouse over functionality is used to indicate that the individual menu items are clickable. As long as the mouse cursor hovers over a menu item, its background colour is changed. If a particular menu item is selected through a click, the colour change remains as long as another item of the same level is selected. Furthermore, the related sub-level menu is displayed beneath the top-level menu. If, for example, the top-level menu item “preserves / ready-to-eat meals” is selected first, its background colour changes from “grey” to “blue”. The colour “blue” was chosen because of its neutrality. In contrast to the colours “green” or “red”, for example, it is not associated with a special meaning. In addition to the colour change of the top-level menu item, the related sub-level menu is displayed which contains all the subordinated menu items. All sub-level menu items have a blue background colour with alpha channel “0.5”. Here too, a mouse over function-

ality triggering a colour change is used to demonstrate that the sub-level menu items are clickable. A click on a sub-level menu item results in the display of all products which relate to the selected top-level and sub-level menu items. If, for example, the sub-level menu item “salt / pulses / rice” is selected afterwards, its background colour changes from “light blue” to “dark blue”. Furthermore, all products are displayed which belong to the selected pair of top-level and sub-level category in the traditional categorisation. Figure 5.4 visualises the different menu states involved in this exemplary selection process based on the linear menu with traditional categories and the top-level menu item “preserves / ready-to-eat meals” and the related sub-level menu item “salt / pulses / rice”.

### Linear Menu with Apartment Categories

The apartment categorisation was developed in a pilot study with two phases (see Chapter 4.1) and is based on the expectations of the participants. It consists of seven room categories in total, each with a varying number of related furniture categories. Therefore, the top-level menu includes seven menu items. One row is sufficient to clearly present all these menu items. An overview of the top-level of the linear menu with apartment categories can be seen in Figure 5.5. The basic layout characteristics of this linear menu is identical to the other linear menu. The same applies for the interaction functionalities like mouse over or item click. Thus, all top-level menus have a grey background and a black text label by default. Colour change is provoked by hovering or clicking a menu item. In order to display a specific sub-level menu, one of the available top-level menu items has to be selected by clicking on it. Besides the colour change of the top-level menu item, the related sub-level menu is displayed beneath the top-level menu. For example, if the top-level menu item “kitchen” is selected, its colour changes from grey to blue and the related sub-level menu is displayed. All sub-level menu items again are provided with a light blue background colour. The subsequent selection of the sub-level menu item “cabinet” changes its background colour to

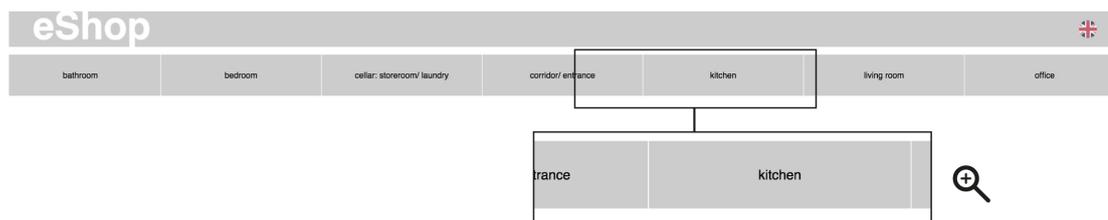


Figure 5.5: Overview of the top-level of the linear menu with apartment categories. In total, seven top-level menu items are integrated.

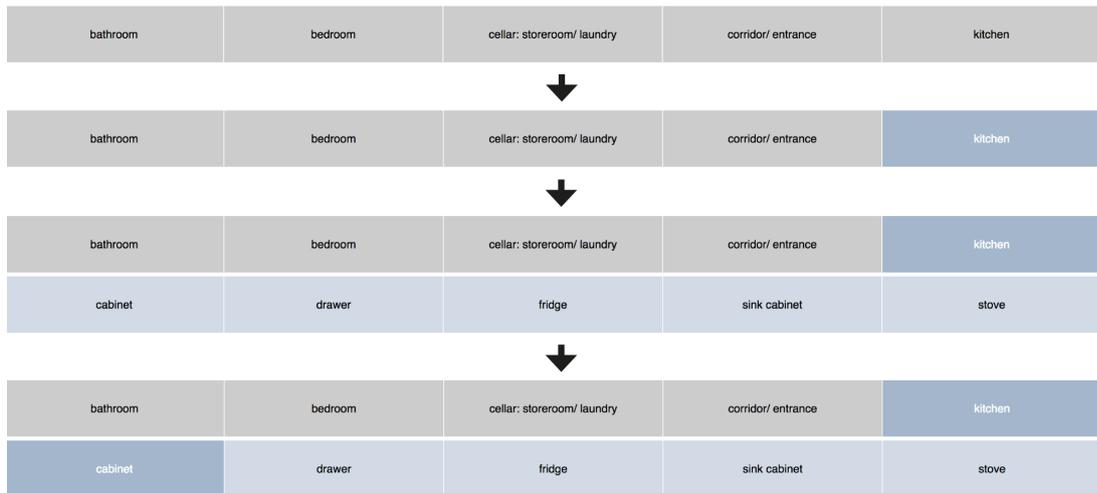


Figure 5.6: Different interaction states of the linear menu with apartment categories. Top: Top-level menu, no selection. Middle: The top-level menu item “kitchen” is selected by first hovering and then clicking on it. The appropriate sub-level menu is then displayed. Bottom: The sub-level menu item “cabinet” is hovered and selected.

“dark blue”. Additionally, all products are displayed which belong to the sub-level category “cabinet” under the top-level category “kitchen” in relation to the apartment categorisation. Figure 5.6 visualises the different states of the linear menu with apartment categories in relation to this exemplary selection process.

### Technical Specifications

Both linear menus are mainly based on textual labels representing the underlying categorisation. Therefore, the linear menus are realised through the HTML tags `<ul>` and `<li>` which show items one by one. In order to create the specific layout characteristic discussed before, several CSS style attributes are indicated. Additionally, JavaScript functions were used to realise the menus’ interactivity, like mouse over or click functionality. The sub-level menus are displayed beneath the top-level menu and are implemented in the same way as the top-level menu.

### 5.2.2 Map-Based Menus

In the map-based menu representation which is newly developed in this research work, the related menu items are arranged according to a real-world environment which is reflected by the used categorisation. The menu therefore either represents a map of a shopping market or an apartment. Each top-level menu item, which corresponds to a specific area of the map-based menu, is charac-

terised through a text label as well as an illustrating icon. Furthermore, all top-level menu items have a rectangular background area and are visually separated from adjacent items through defined spacing between them. Sub-level menu items are represented by furniture icons inside the area of the superordinated top-level menu item. Since the specific categorisations do however result in different overall shapes and different amounts of menu items, the map-based menus are therefore explained individually hereafter.

### Map-Based Menu with Traditional Categories

Since the traditional categories are based on an exemplary real-world market, the representation of the map-based menu with traditional categories is inspired by the floor plan of this market. This includes its separated market areas and the related product shelves. For reason of clarity, the two floors of the market were displayed side by side and are separated by a larger space. The top-level menu items correspond to the market areas and are arranged accordingly. For reasons of simplicity and clarity, each real market area is mapped to a rectangle even if the real shape is more complex and irregular. However, the virtual menu representation is as close to the real one as possible, including area size and position. Figure 5.7 presents an overview of the top-level of the map-based menu with traditional categories. As can be seen in the figure, every top-level menu item is supplemented by a text label as well as an illustrating icon. This icon

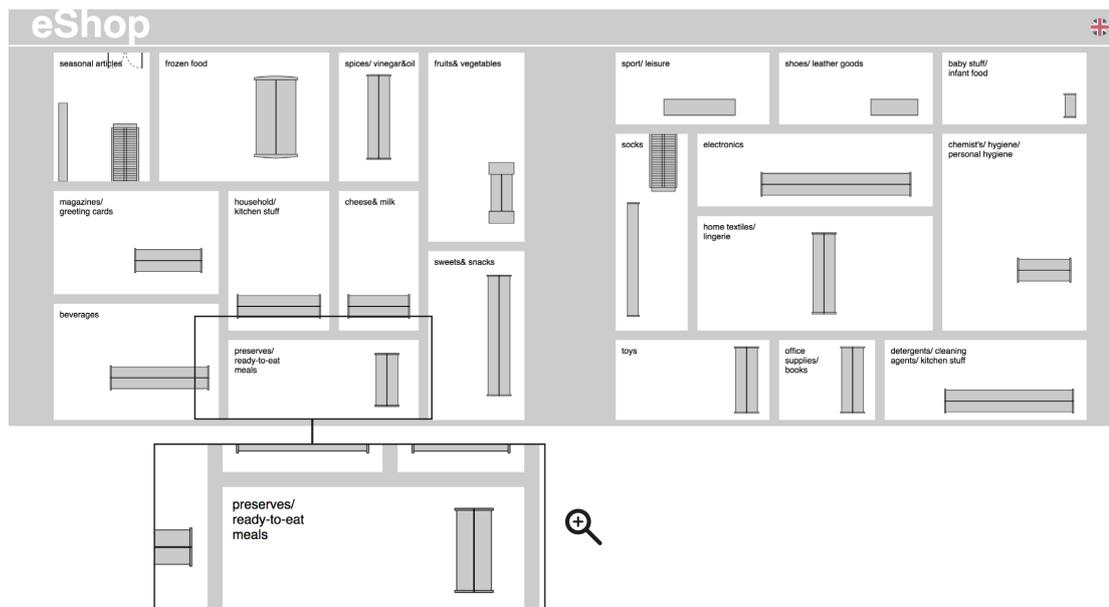


Figure 5.7: Overview of the top-level of the map-based menu with traditional categories. In total, 20 top-level menu items, i.e. market areas, are integrated.

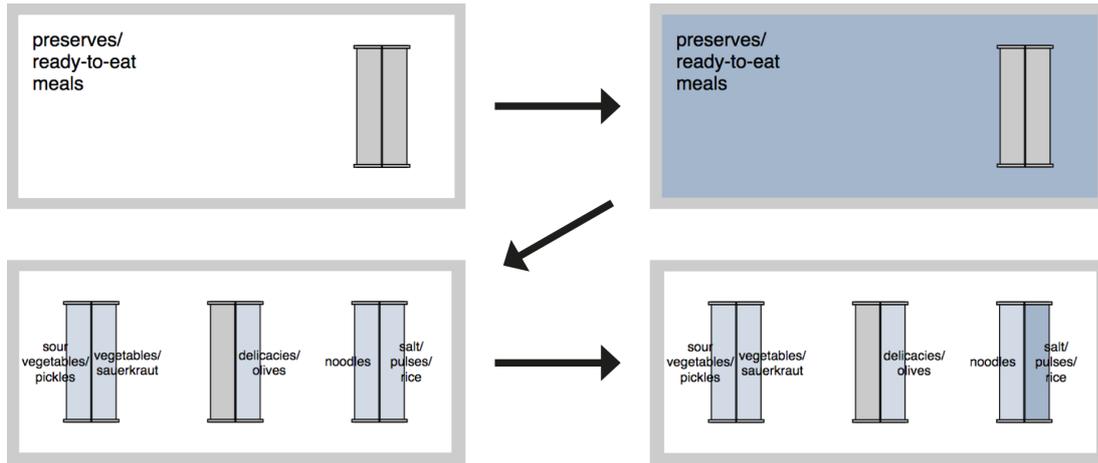


Figure 5.8: Different interaction states of the map-based menu with traditional categories using the example of the top-level menu item “preserves / ready-to-eat meals”. Top left: Standard view of the top-level menu item. Top right and bottom left: The top-level menu item is selected by first hovering and then clicking on it. The subordinated shelves are then displayed. Bottom right: The sub-level menu item “salt / pulses / rice” is hovered and selected.

functions like a preview of the content, i.e. the shelves, of the related market area. The product shelves which are located inside the particular market area depict the sub-level menu items of the appropriate top-level menu item. They are only displayed if the appropriate market area is selected by clicking on the top-level menu item. The operating principle of the map-based menus is similar to that of the linear menus. Here too, a mouse over functionality with colour change is included in order to highlight selectable menu items. For example, a mouse over on the market area “preserves / ready-to-eat meals” (top-level) changes its background colour from “white” to “blue”. If the menu item is clicked, all related market shelves, i.e. the sub-level menu items, are displayed inside this area. All selectable sub-level menu items are presented in a light blue colour. Interactions like hovering or clicking result in a more saturated blue colour. When a sub-level menu item is selected by a mouse click, all products which are associated with the selected top-level and sub-level menu items are displayed below the menu area. For example, if the market shelf “salt / pulses / rice” (sub-level) is selected inside the market area “preserves / ready-to-eat meals” (top-level), all products are displayed which are assigned to this category pair in the traditional categorisation. In Figure 5.8, the resulting states of the map-based menu area “preserves / ready-to-eat meals” are visualised using this exemplary selection process. In Appendix A.4, the map-based menu with traditional categories is visualised unfolded, displaying all market areas and their subordinated product shelves.

## Map-Based Menu with Apartment Categories

The map-based menu with apartment categories represents the floor plan of an apartment, including its rooms and furniture. Since the apartment categorisation reflects an average of general expectations, the floor plan is not simply based on an existing apartment. However, rooms and furniture are arranged in a realistic way so that the overall structure is close to real apartments. Here too, floors are displayed side by side and are visually separated by a larger space. The top-level menu items correspond to the rooms of the apartment. An overview of the top-level of the map-based menu with apartment categories can be seen in Figure 5.9. Just as for the map-based menu with traditional categories, every top-level menu item is supplemented by a text label as well as an illustrating icon which offers a preview of the room content. However, in this case, the icons are more diverse since pieces of furniture in an apartment vary in appearance and functionality. Therefore, preview icons were chosen in order to best reflect the characteristics of the individual rooms. For example, the room “kitchen” is supplemented by a “fridge”-icon and the “living room” by a “couch”-icon. All pieces of furniture, i.e. the sub-level menu items, of a specific room are only visible if the room is selected by clicking on it. Again, a mouse over functionality is used which changes the item’s background colour. An exemplary selection process could for example

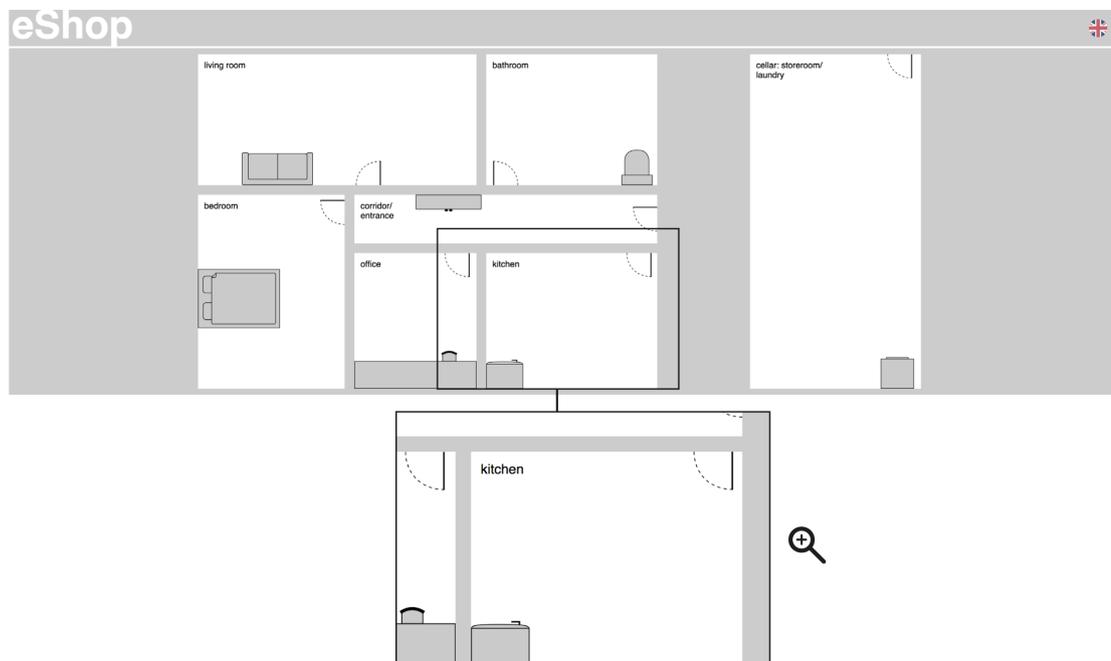


Figure 5.9: Overview of the top-level of the map-based menu with apartment categories. In total, seven top-level menu items, i.e. rooms, are integrated.

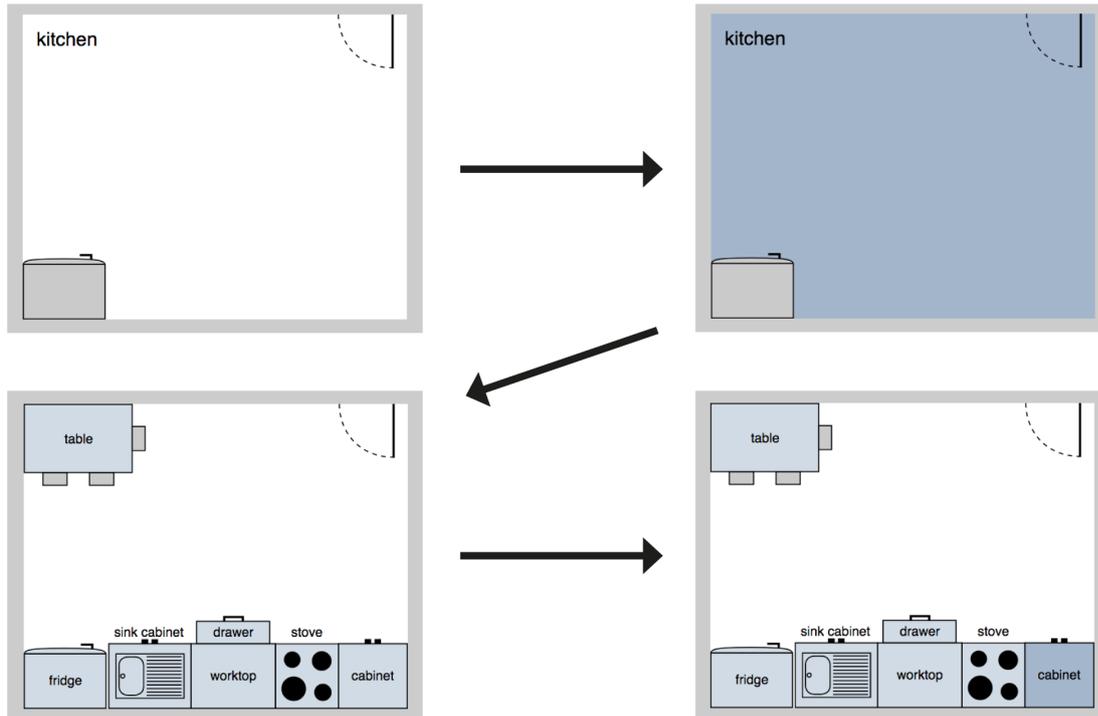


Figure 5.10: Different interaction states of the map-based menu with apartment categories using the example of the top-level menu item “kitchen”. Top left: Standard view of the top-level menu item. Top right and bottom left: The top-level menu item is selected by first hovering and then clicking on it. The subordinated shelves are then displayed. Bottom right: The sub-level menu item “cabinet” is hovered and selected.

start with the selection of the room “kitchen” (top-level). If the mouse cursor hovers over it, its colour changes from “white” to “blue”. Then, if the menu item is clicked, all related kitchen furniture, i.e. the sub-level menu items, is displayed inside the kitchen area. The clickable items are again presented with a light blue colour. Interactions like clicking or hovering result in a more saturated blue colour. If a piece of furniture, i.e. a sub-level menu item, is selected by clicking on it, all related products are displayed beneath the menu area. For example, if the “cabinet” (sub-level) is selected inside the previously selected “kitchen” (top-level), all products are displayed which are associated with this pair of top-level and sub-level category. Additionally, the colour of the “cabinet”, i.e. the sub-level menu item, is changed to a more saturated blue colour in order to visualise its selection. The different states of the top-level menu item “kitchen” of the map-based menu with apartment categories is presented in Figure 5.10. In Appendix A.5, the map-based menu with apartment categories is visualised unfolded, displaying all rooms and their subordinated furniture.

## Technical Specifications

In the map-based menus, the menu items are organised in a grid-form which best reflects the structure of floor maps. Therefore, the CSS style element “display: grid” is used to represent the top-level of both map-based menus. Each of the individual menu items is represented through a HTML `<div>` tag. Additionally, a specific grid-position is defined for each of the top-level menu items. The sub-level menu items are displayed inside the superordinate top-level menu area. This is realised by using SVG files, which are loaded inside these areas. The SVG functionality enables the creation of the individual furniture shapes. The SVG files contain the appropriate furniture objects which can be individually addressed to set them to “visible” or “invisible” in dependency of the menu state. Additionally, dynamic colour change is possible. In this way, the interactivity of the sub-level menu items can be realised.

## 5.3 Product Area

The product area is located beneath the menu area. It is only visible if a pair of top-level and sub-level menu item is selected. As soon as such a pair is selected, regardless of the given menu, the assigned product or products are displayed in the product area. Additionally, the appropriate path through top-level and sub-level is visualised above the product list in order to clarify the connection to the selected menu items. Figure 5.11 displays the product area using the example of the apartment categories in case of the selected menu items “kitchen” (top-

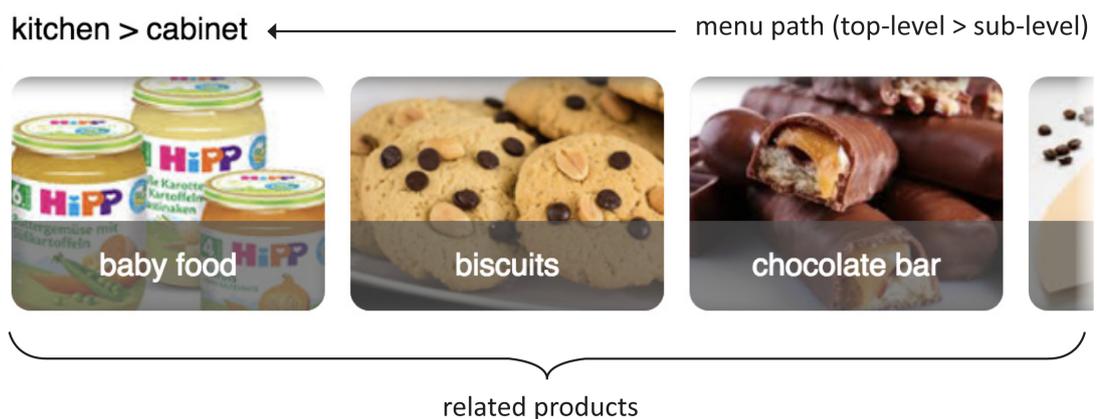


Figure 5.11: Exemplary product area related to the selected menu items “kitchen” and “cabinet” based on the apartment categories. This selection path is shown at the top of the product area. Below it, the related products are listed next to each other. Every product is visualised through its product name and an image.

level) and “cabinet” (sub-level). Each product is visualised by means of an image as well as the product name. The latter is captured in a text layer which is located at the bottom of the image. The individual products are clickable. This functionality is used later in the main study in order to record the selection of the participants. In an online shop, this functionality is necessary in order to load detail information on products or to add them to the shopping cart.

# Chapter 6

## Main Study: Menu Types

This chapter presents the main study of this work, which was conducted in order to evaluate the previously implemented menu types with regard to their representation and categorisation. First, four research hypotheses are presented, which form the basis for the study design. Then, hardware and software specifications are given, followed by a description of the participants. Subsequently, the study design, the task and the study procedure are described in detail. Finally, the study results are presented, statistically examined and discussed with regard to the previously established research hypotheses.

### 6.1 Hypotheses

The objective of the main study was to investigate the effect of the metaphoric apartment categorisation and the map-based menu representation on task performance and user preference. Expectations for the results are based on previous findings concerning categorisation and representation (see Chapter 2) and are expressed by means of hypotheses. The following null hypothesis is given:

**Null Hypothesis.** There are no significant differences of task performance and user preference with regard to the categorisations and the representations.

#### 6.1.1 Hypotheses: Apartment Categorisation

The “Apartment Metaphor” exploited by Adam et al. [1] turned out to be an effective way to support consumers to quickly and easily understand and use the offered information in terms of filtering out desired parts. Since the categorisation used in this work is based on the same metaphor, the same positive effects are expected to arise in an online shop environment. This expectation is further

strengthened by observations and comments made during the pilot study (see Chapter 4). Therefore, two hypotheses are:

**Hypothesis 1-1.** The apartment categorisation is significantly better than the traditional categorisation with regard to task performance (success rate, click count, task completion time).

**Hypothesis 1-2.** The apartment categorisation is preferred by the users regarding user experience, usability and workload ratings.

### 6.1.2 Hypotheses: Map-Based Representation

The findings of Ahlström et al. [2] and Scarr et al. [43] demonstrate that a grid-shaped menu structure can lead to enhanced performance and preference values. Additionally, the work of Meschtscherjakov et al. [29] shows that the principle of a virtual map can be used as an effective tool for user orientation. The map-based menu representation used in this work exploits and combines these properties. It is based on a grid-shaped structure which is adapted to the characteristics of a floor plan in terms of visual cues and arrangement. Therefore, two further hypotheses are:

**Hypothesis 2-1.** The map-based representation is significantly better than the linear representation with regard to task performance (success rate, click count, task completion time).

**Hypothesis 2-2.** The map-based representation is preferred by the users regarding user experience, usability, workload and immersion ratings.

## 6.2 Participants

The call for participants was shared in social media and distributed via flyers at the Saarland University. The participation was fully voluntary. In total, 24 participants took part in the main study. 12 of them were male and 12 female. The age ranged between 20 and 33 years with about 25 years on average ( $M=25.3$ ,  $SD=3.6$ ). A visualisation of the demographic data can be seen in Figure 6.1. Most of the participants live in a two room apartment ( $M=2.04$ ,  $SD=0.86$ ), excluding bathroom, kitchen or corridor, with two inhabitants ( $M=2.6$ ,  $SD=1.3$ ). The participants live with their parents/family in most of the cases (29.17%,

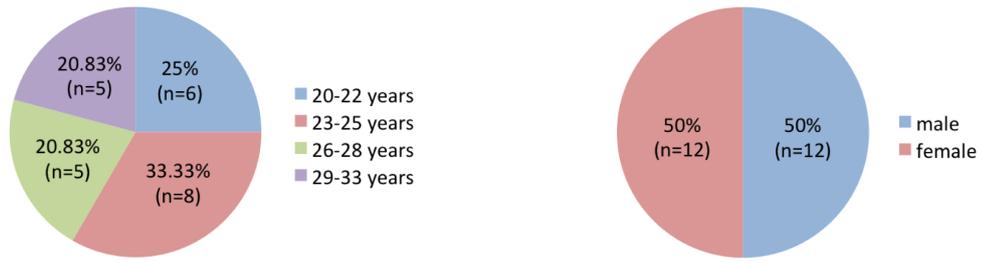


Figure 6.1: Demographic data of the N=24 study participants, including age and gender information.

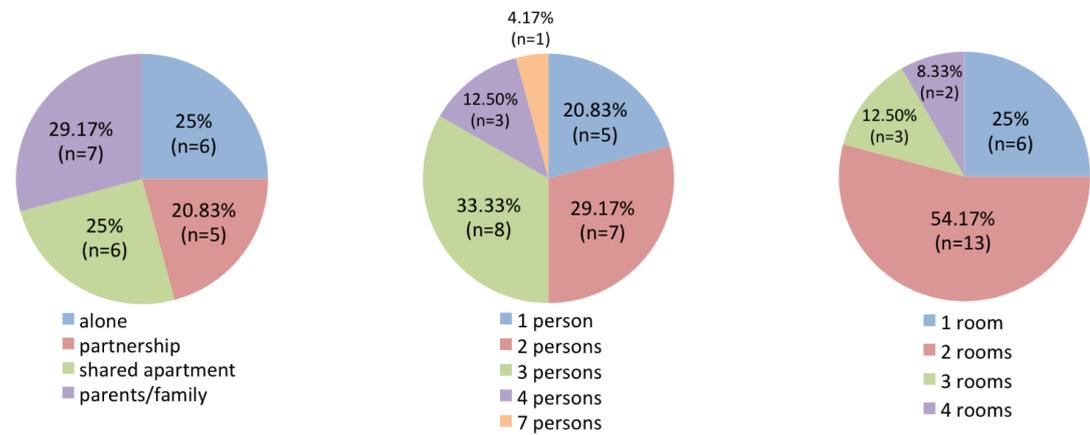


Figure 6.2: Statistical overview of the participants' background (N=24). Left: Apartment type. Middle: Count of inhabitants. Right: Count of rooms.

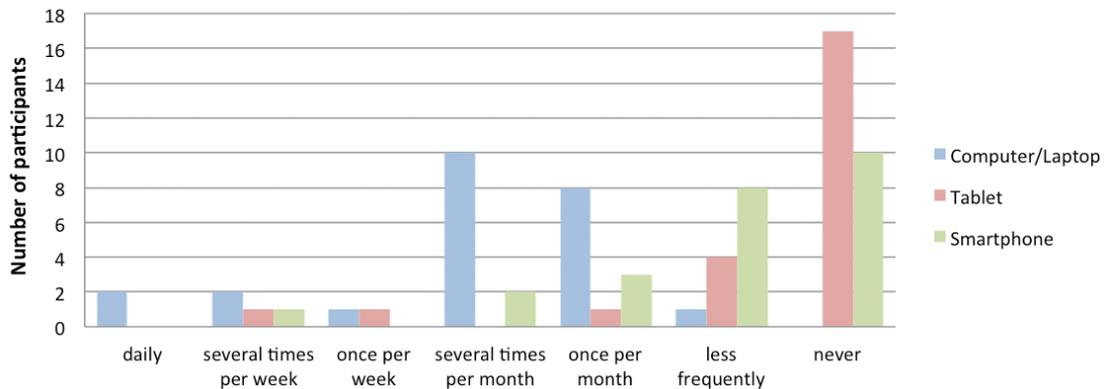


Figure 6.3: Online shopping behaviour of the survey participants (N=24) depending on the used devices.



Figure 6.4: Experimental setup used during the main study.

n=7), followed by living in a partnership or in a shared apartment (25%, n=6) and living alone (20.83%, n=5). Figure 6.2 visualises the complete data, including statistical values. On average, the participants are well experienced in the process of online shopping (see Figure 6.3). All participants regularly purchase online. Thereby, most online purchases are conducted with a computer/laptop, compared to tablets or smartphones. The majority of the participants (62.5%, n=15) purchase online at least several times per month.

### 6.3 Apparatus

The experiment was conducted on a MacBook Pro running Mac OS El Capitan (10.11.6) which was connected to a 24-inch monitor. A standard wireless mouse was used as input device with medium speed settings. The software was displayed in the web browser “Google Chrome” (version 58.0.3029.110, 64-bit). HTML, CSS and JavaScript were used to implement the different prototypes. Additionally, the JavaScript D3 library was used for data visualisation purposes. A database was set up with the aid of the web server solution stack XAMMP (version 7.0.5-0) and therefore, data exchange was realised through the script language PHP. The experimental setup can be seen in Figure 6.4.

## 6.4 Design

Four menu types were tested in the main study, which differ in their representation and/or categorisation. In order to test the previously established hypotheses, two independent variables were integrated in the experiment:

- **Representation** (Linear, Map-Based)
- **Categorisation** (Traditional, Apartment)

In the linear menu representation, the items are arranged in a horizontal row. In the map-based menu representation, the items are arranged in a grid form and represent a virtual map. The traditional categorisation consists of three levels: product range, product type and product. Room, furniture and product form the three levels of the apartment categorisation. The aim of the study was to investigate the impact of the independent variables on the following dependent variables:

- **Task Performance** (Success Rate, Click Count, Task Completion Time)
- **User Preference** (User Experience, Usability, Workload, Immersion)

In order to gain objective feedback on the efficiency and accuracy of the menu types, the performance aspects success rate, click count and task completion time were measured. Appropriate data was logged during the individual search tasks. The preference aspects user experience, usability, workload and immersion were captured through the use of well-established questionnaires (see Chapter 2) in order to gain subjective feedback of the participants.

The experiment was based on a within-subject design. This means that all four menu types were tested by all of the study participants [26, 50]. Since the menu types' purpose is to search for products, a search task is used to test the independent variables. This is a knowledge-based task which means that users gain knowledge while they perform the given tasks. In this case, it is necessary to create different but still comparable search tasks for different search conditions [26]. In order to eliminate learning effects concerning the different categorisations, the total set of 36 products was broken down into two equally difficult groups with 18 products respectively (see Chapter 4). One group was used for product searches with the two linear menu types and the other for product searches with the two map-based menu types. In this way, it could be avoided that the participants search for the same products within one categorisation. Furthermore, the order in which one participant tested the menu types was counterbalanced. In this

way, adverse influences on the results can be avoided [26]. These include learning effects arising from previous menu types as well as fatigue effects that increase at the end of the study procedure. Since there are four menu types in total, a counterbalanced design with four conditions was suitable. Consequently, 24 different sequences of menu types were necessary ( $4!=4 \times 3 \times 2 \times 1$ ). Thus, 24 participants took part in the main study. Each of them conducted 18 product searches per menu type. This approach led to the following number of product searches:

$$\begin{aligned} & \mathbf{24 \text{ participants} \times 2 \text{ representations}} \\ & \mathbf{\times 2 \text{ categorisations} \times 18 \text{ product searches}} \\ & \mathbf{= 1728 \text{ product searches}} \end{aligned}$$

## 6.5 Task

During the main study, each participant had to perform a series of search tasks with the different menu types. The task goal is to find and select a specific product. A single search task consists of selecting one top-level category followed by selecting one sub-level category and finally by selecting a product. The specific selection process is based on the given menu and its representation. The first representation is the linear one (see Figure 6.5). In order to search for a product using a linear menu, the participant has first to select one category of the top-level menu bar. In order to do so, the participant has to click on the menu item with the appropriate textual label which is either a product range or a room depending on the underlying categorisation. As a result, a second menu bar is displayed beneath the top-level menu bar. This sub-level menu bar shows the subordinated categories of the previously selected top-level category. They represent either a product type or a piece of furniture depending on the categorisation. One of these sub-level categories has then to be selected by clicking on the menu item with the appropriate textual label. Afterwards, all products which relate to the pair of selected top- and sub-level category are displayed beneath the menu area (see Figure 6.6). The second representation is the map-based one (see Figure 6.7). First of all, the participant has to select one top-level category. This is done by clicking on the area with the appropriate textual label which either represents a product range or a room depending on the underlying categorisation. As a result, the appropriate furniture icons inside the selected area are displayed. They represent the subordinated categories of the previously selected top-level category. Depending on the underlying categorisation, the sub-level categories

are either shelves or diverse pieces of furniture. The participant has then to select one of these sub categories by clicking on the graphical representation of the appropriate shelf or piece of furniture. After selecting one top- as well as one sub-level category, the set of associated products is displayed in the product area which is located beneath the menu area (see Figure 6.6). This final step is always the same regardless of the underlying menu type. Then, in order to select a product, the participant has to click on it and confirm this decision in the appearing confirmation window. Although multiple storing places are consciously integrated for some products in the apartment categorisation, only one placement is considered for each product in the main study. The selected placement is that in the highest ranked room and the related highest ranked piece of furniture. Thus, there is only one correct solution for a given search task. This means that only one path through top- and sub-level categories leads to the searched product. This

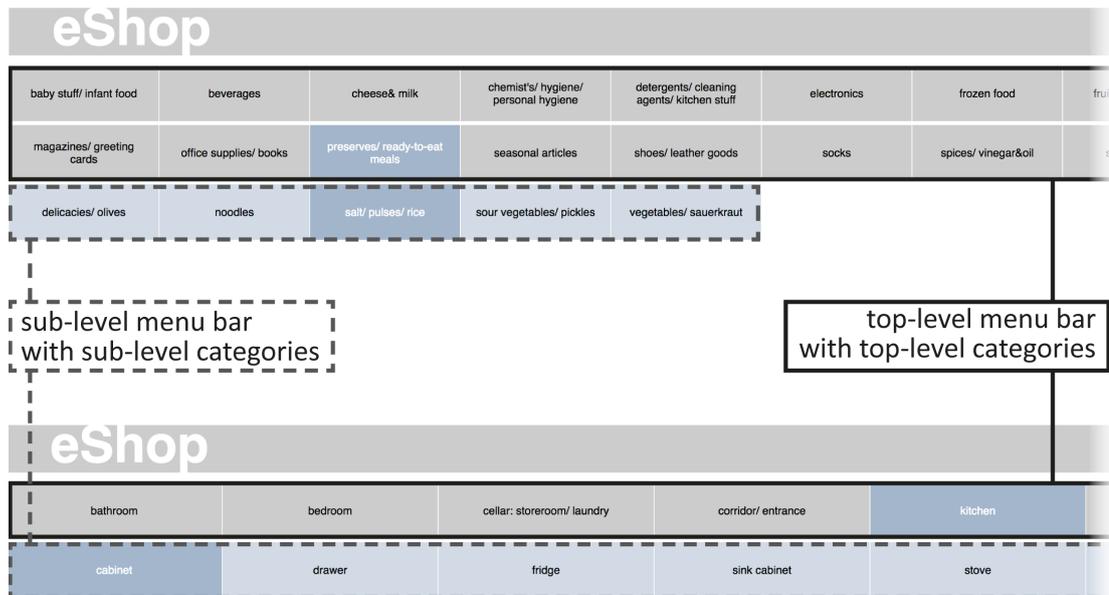


Figure 6.5: Linear menu with traditional categories at the top or apartment categories at the bottom. Menu items provided in the more saturated shade of blue represent selected menu items. Grey or less saturated blue menu items represent unselected menu items at the top- or sub-level menu, respectively.

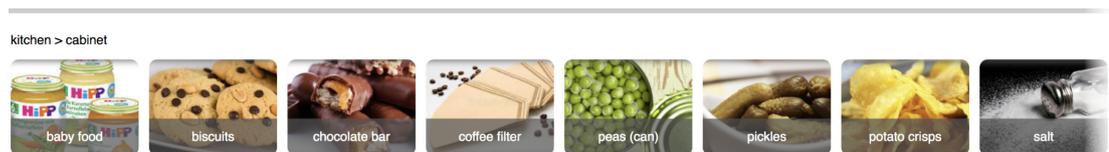
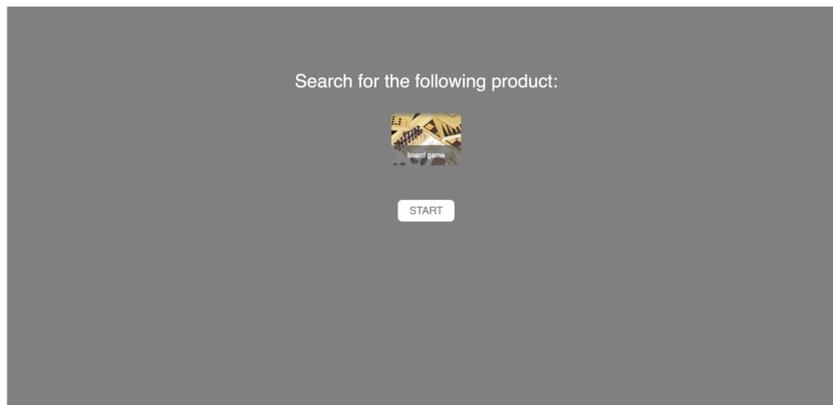


Figure 6.6: Exemplary product area displaying products relating to the sub-level category “cabinet” under the top-level category “kitchen”.



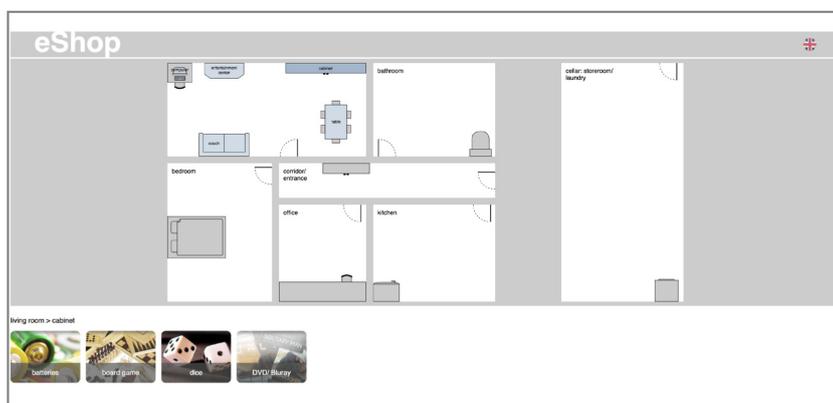
Figure 6.7: Map-based menu with traditional categories at the top or apartment categories at the bottom. As in the linear menu, the more saturated blue colour means that the menu item is selected, whereas less saturated blue menu items represent unselected menu items.

allows comparability between the different search tasks and the categorisation is nevertheless represented, since multiple storing places could only lead to a higher success probability. If the participant selects an incorrect product, the search task is considered as “unsuccessful” in the later evaluation process. Furthermore, a timer was integrated, which automatically stops the current search task after 30 seconds. This time span was defined by analysing the execution times of test runs with three participants. If a search task ends due to time expiration, it is also considered as “unsuccessful”. An exemplary task is visualised in Figure 6.8.



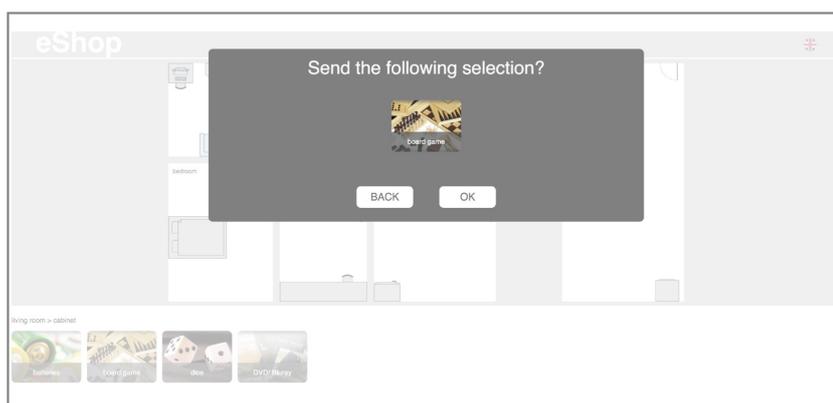
1. Search instruction

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2. Search process

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3. Product selection

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Figure 6.8: Visualisation of an exemplary search task where the product “DVD /Bluray” has to be searched by using the map-based menu with apartment categories. Top: View displaying the search instruction and the START button which starts the search. Middle: View of the online shop with the appropriate menu type. Bottom: Secure view with BACK and OK button, the latter confirms the product click and the former leads back to the view of the prototype.

## 6.6 Procedure

At the beginning of the experiment, the participant was welcomed by the researcher. Then, some general explanations and instructions were given to him in form of an informed consent form [48] (see Appendix A.7). Thereby, a signature was required to confirm that participation was voluntary. Subsequently, the main part of the experiment took place. As already mentioned, every participant used all four menu types one by one in a counterbalanced order. Before using a specific menu type, the participant was given an introduction to its functionality by playing a demonstration video that shows an exemplary search task step by step. Then, 18 search tasks were conducted in a random order. A single product search finished as soon as one product was selected or if the available time of 30 seconds expired. When the 18 product searches were finished, four post-task questionnaires (UEQ, System-Usability-Scale, Nasa-TLX, SUS) were filled in by the participant. In this way, user preference ratings concerning the previously used menu type were captured. The whole process was then repeated for the remaining three menu types. Afterwards, a concluding questionnaire was answered by the participant. This questionnaire included questions about the participants' opinion about the previously used menu types, their general shopping experience and living situation as well as demographical questions (see Figure 6.10). Finally, the researcher expressed his gratitude to the participant and said goodbye. In total, the study procedure took about 50 minutes. An overview of the whole procedure of the main study is presented in Figure 6.9.

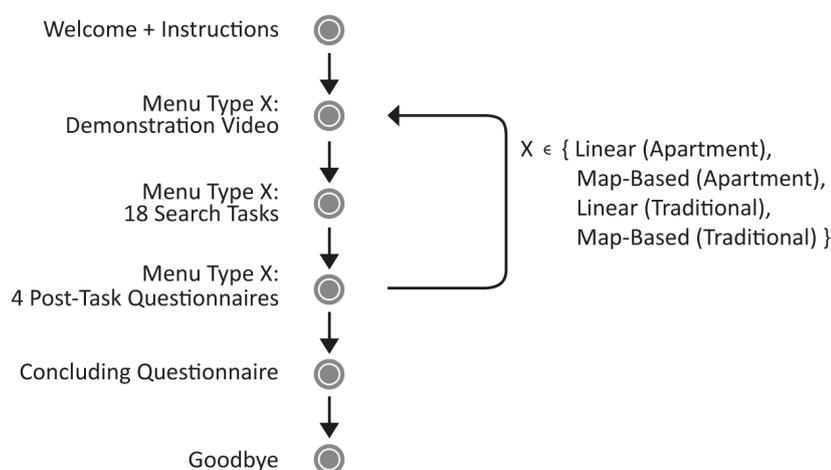


Figure 6.9: Overview of the complete procedure of the main study during which the four menu types were tested one after another.

## I Study Impressions

**Which of the four menus would you prefer to use in the future?**

Please name it (list market, map market, list apartment, map apartment) and describe why.

Your answer

---

## II Living Situation

**I live ...**

- alone
- in a shared apartment
- with parents/ family
- in a partnership

## III Shopping Behaviour

**It is very easy for me to find desired products in online shops.**

	1	2	3	4	5	
Does not apply.	<input type="radio"/>	Applies.				

## IV Personal Details

**Gender:**

- male
- female

Figure 6.10: Extract of the concluding questionnaire used at the end of the main study. The questionnaire is divided into four sections: study impressions, living situation, shopping behaviour and personal details. For each section, one exemplary question is given.

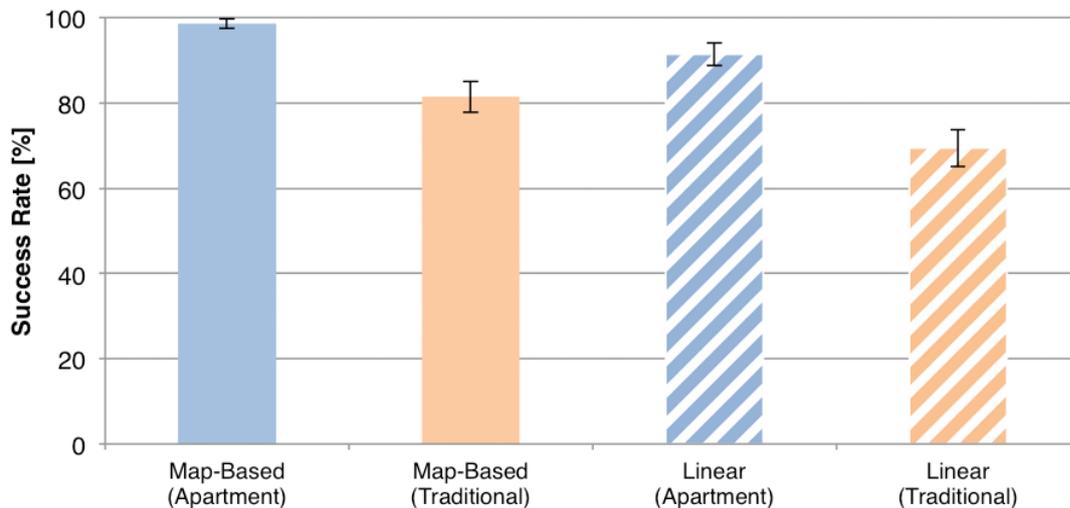


Figure 6.11: Visualisation of the average success rate concerning the different menu types. The values are given as percentages [%]. In addition, the 95% confidence is indicated by error bars.

## 6.7 Results

In this section, the results of the main study are presented and visualised. This includes performance data which was collected during the search tasks as well as the preference ratings from the post-task questionnaires. Furthermore, the findings of a statistical analysis are given, which was conducted by using IBM SPSS Statistics<sup>1</sup>. These findings provide information on the significance of the different average results. An overview of the average values and the results of the statistical analysis is also given in Appendix A.8, A.9 and A.10.

### 6.7.1 Task Performance

In the first section, the task performance data is examined. This includes the success rate, the click count and the task completion time of the product searches. The average values of the respective menu types are visualised and the results of the statistical analysis are presented.

#### Success Rate

The success rate describes the ratio between the number of successful product searches and the total number of product searches. A product search is considered successful if the correct product is selected within the available time of

<sup>1</sup> <https://www.ibm.com/products/spss-statistics> (accessed 19.01.2018)

30 seconds. In total, 1728 product searches were considered. For each menu type, the average success rate is based upon a total set of 432 product searches. This value results from the number of 24 participants and the number of 18 product searches per menu type. Figure 6.11 gives an overview of the average results of the different menu types. The map-based menu with apartment categories was the most successful menu type with an average success rate of about 99% (M=98.61, SD=11.72). It is followed by the linear menu with apartment categories with a success rate of about 91% (M=91.44, SD=28.02) and the map-based menu with traditional categories which obtained an approximate success rate of 81% (M=81.48, SD=38.89). The linear menu with traditional categories has the lowest success rate with about 69% (M=69.44, SD=46.12). An univariate ANOVA (“analysis of variance”) [24] showed significant differences of success rate with regard to the menu type ( $F_{3,1724}=60.71$ ,  $p<0.01$ ,  $\eta^2=0.10$ ). Furthermore, an ANOVA was performed with representation and categorisation as factors and the success rate as dependent variable. There were significant differences of success rate regarding representation ( $F_{1,1724}=34.96$ ,  $p<0.01$ ,  $\eta^2=0.02$ ) as well as categorisation ( $F_{1,1724}=144.94$ ,  $p<0.01$ ,  $\eta^2=0.08$ ). Comparing the representations, the map-based representation has a higher average success rate (M=90.05, SD=29.96) than the linear one (M=80.44, SD=39.69). In relation to the categorisations, the apartment categorisation (M=95.02, SD=21.76) has a higher average success rate than the traditional one (M=75.46, SD=43.06).

### Click Count

The click count refers to the total number of clicks needed to successfully complete the individual product searches. This includes clicks on top- and sub-level menu items as well as product clicks. In total, a minimum of three clicks is necessary to reach a product. A higher click count shows that error clicks occurred during the product search. Only successful product searches are included in the examination of the average click count since the click count of unsuccessful tasks only represents a lower limit and thus would falsify average values. As a result, the average click count is based upon different amounts of product searches for each menu type. In the case of the traditional categories, a total set of 300 product searches is included for the linear menu and 352 for the map-based menu. A total set of 395 and 426 product searches were included in the case of the linear or the map-based menu with apartment categories. The average results of the different menu types are given in Figure 6.12. The linear menu with apartment categories has the highest average click count (M=3.88, SD=1.54). The average

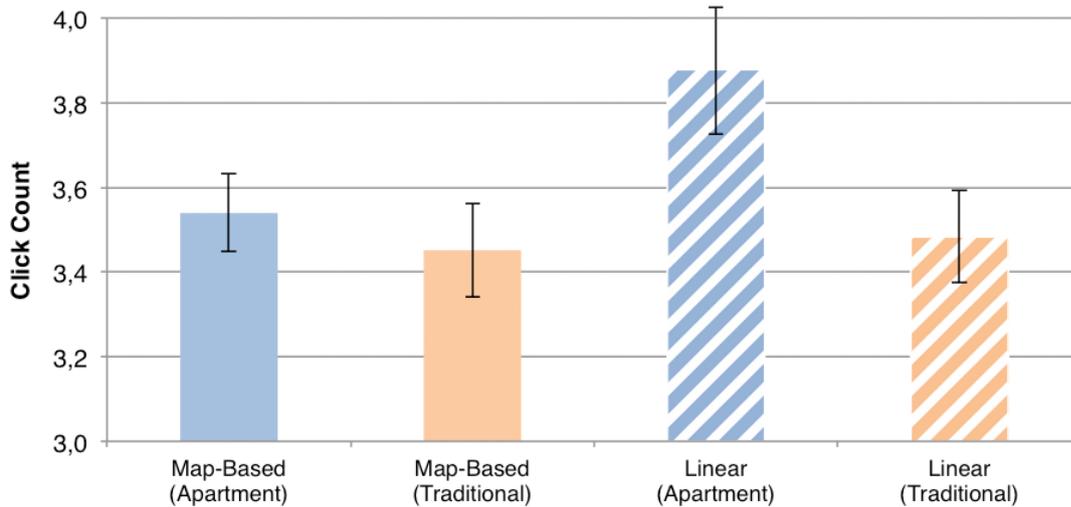


Figure 6.12: Visualisation of the average click count concerning the different menu types. In addition, the 95% confidence is indicated by error bars.

click count of the remaining three menu types are approximately the same: map-based menu with apartment categories ( $M=3.54$ ,  $SD=0.97$ ), linear menu with traditional categories ( $M=3.48$ ,  $SD=0.97$ ), map-based menu with traditional categories ( $M=3.45$ ,  $SD=1.06$ ). An univariate ANOVA showed significant differences of click count regarding the menu type ( $F_{3,1469}=10.68$ ,  $p<0.01$ ,  $\eta^2=0.02$ ). In addition, significant differences of click count with regard to the factors representation ( $F_{1,1469}=9.03$ ,  $p<0.01$ ,  $\eta^2=0.01$ ) and categorisation ( $F_{1,1469}=15.40$ ,  $p<0.01$ ,  $\eta^2=0.01$ ) were found. There was also an interaction between representation and categorisation ( $F_{1,1469}=6.21$ ,  $p<0.05$ ,  $\eta^2=0.00$ ). The map-based representation has a slightly lower click count ( $M=3.50$ ,  $SD=1.01$ ) than the linear one ( $M=3.71$ ,  $SD=1.34$ ). Furthermore, the apartment categorisation has a slightly higher click count ( $M=3.70$ ,  $SD=1.29$ ) than the traditional one ( $M=3.47$ ,  $SD=1.02$ ).

### Task Completion Time

In order to compare the efficiency of the menus, the task completion time was examined. For this purpose, the time needed to successfully complete the individual product searches was measured. As for the number of clicks, only the successful product searches form the basis for the calculation of the average task completion time for each menu type. In the case of the traditional categories, a total set of 300 product searches are included for the linear menu and 352 for the map-based menu. A total set of 395 and 426 product searches result for the linear or the map-based menu with apartment categories. Figure 6.13 shows the average task completion time of the four different menu types. Again,

a univariate ANOVA was conducted. Significant differences were found with regard to the menu type ( $F_{3,1469}=33.96$ ,  $p<0.01$ ,  $\eta^2=0.07$ ). The shortest average task completion time of 7.96 s ( $M=7.96$ ,  $SD=3.80$ ) was achieved by the map-based menu with apartment categories, followed by its linear version which has an approximate task completion time of 9.68 s ( $M=9.68$ ,  $SD=5.58$ ). The average task completion time of the two menus with traditional categories is the same: linear menu with traditional categories ( $M=11.31$ ,  $SD=5.89$ ), map-based menu with traditional categories ( $M=11.31$ ,  $SD=6.17$ ). Furthermore, an univariate ANOVA shows significant differences of task completion time regarding the factors representation ( $F_{1,1469}=9.35$ ,  $p<0.01$ ,  $\eta^2=0.01$ ) and categorisation ( $F_{1,1469}=78.12$ ,  $p<0.01$ ,  $\eta^2=0.05$ ). The ANOVA also showed an interaction between this two factors ( $F_{1,1469}=9.49$ ,  $p<0.01$ ,  $\eta^2=0.01$ ). The linear representation has a higher average task completion time ( $M=10.38$ ,  $SD=5.77$ ) than the map-based one ( $M=9.47$ ,  $SD=5.28$ ). Comparing the categorisations, the apartment categorisation has a shorter average task completion time ( $M=8.79$ ,  $SD=4.82$ ) than the traditional one ( $M=11.31$ ,  $SD=6.04$ ).

### 6.7.2 User Preference

The second section deals with the user preference data which results from the questionnaires used. This includes data about user experience, usability, workload and immersion. The average values of the respective menu types are visualised and the results of the statistical analysis are presented.

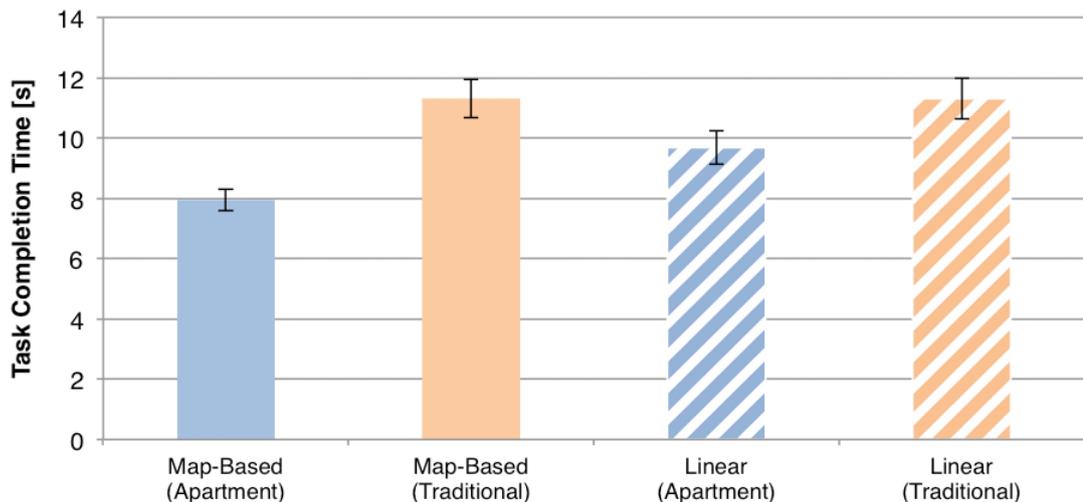


Figure 6.13: Visualisation of the average task completion time concerning the different menu types. Values are given in seconds [s]. In addition, the 95% confidence is indicated by error bars.

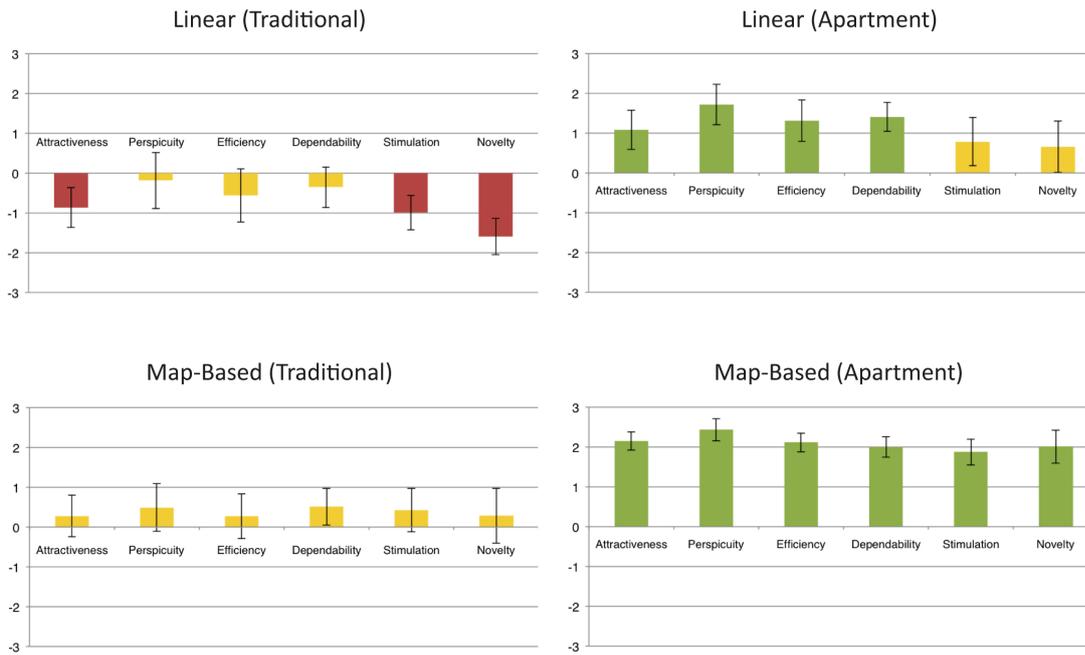


Figure 6.14: Average results of the UEQ sub scores with regard to the different menu types. Value range goes from -3 to +3. Values below -0.8 represent a negative evaluation (red), values above +0.8 represent a positive evaluation (green) and the remaining values represent a neutral evaluation (yellow). In addition, the 95% confidence is indicated by error bars.

	<b>Menu Type</b> ( $F_{3,92}$ , $p$ , $\eta^2$ )	<b>Representation</b> ( $F_{1,92}$ , $p$ , $\eta^2$ )	<b>Categorisation</b> ( $F_{1,92}$ , $p$ , $\eta^2$ )
Attractiveness	(30.40, <0.01, 0.50)	(22.87, <0.01, 0.20)	(68.31, <0.01, 0.43)
Perspicuity	(18.03, <0.01, 0.37)	(6.27, <0.05, 0.06)	(47.80, <0.01, 0.34)
Efficiency	(19.41, <0.01, 0.39)	(9.44, <0.01, 0.09)	(48.80, <0.01, 0.35)
Dependability	(24.46, <0.01, 0.44)	(12.23, <0.01, 0.12)	(60.72, <0.01, 0.40)
Stimulation	(22.35, <0.01, 0.42)	(25.20, <0.01, 0.22)	(41.43, <0.01, 0.31)
Novelty	(26.84, <0.01, 0.47)	(31.64, <0.01, 0.26)	(48.04, <0.01, 0.34)

Table 6.1: Results of the multivariate ANOVA with regard to the menu type as well as representation and categorisation and the UEQ sub scores as dependent variables: Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, Novelty.

## User Experience

The User Experience Questionnaire (UEQ) is used to quickly evaluate the perceived user experience in relation to the different menu types. Regarding the overall score, which ranges from -3 to +3, the map-based menu with apartment categories was rated best with an average of 2.10 (M=2.10, SD=0.53), followed by its linear version (M=1.16, SD=1.18). The map-based menu with traditional categories has an average score of 0.38 (M=0.38, SD=1.27) and its linear version achieved the lowest score (M=-0.76, SD=1.15). An univariate ANOVA showed significant differences of the overall UEQ score regarding the menu type ( $F_{3,92}=30.61$ ,  $p<0.01$ ,  $\eta^2=0.50$ ) as well as the representation ( $F_{1,92}=22.46$ ,  $p<0.01$ ,  $\eta^2=0.20$ ) and the categorisation ( $F_{1,92}=69.17$ ,  $p<0.01$ ,  $\eta^2=0.43$ ). The map-based representation achieved a higher overall score (M=1.24, SD=1.30) than the linear one (M=0.20, SD=1.50) and the score of the apartment categorisation (M=1.63, SD=1.02) is higher than that of the traditional one (M=-0.19, SD=1.33). However, the results of the UEQ are usually divided into 6 sub scores: Attractiveness (A), Perspicuity (P), Efficiency (E), Dependability (D), Stimulation (S), Novelty (N). An overview of the average sub score values is given in Figure 6.14 for each of the menu types. The map-based menu with apartment categories obtained the best user experience results regarding all six sub scores: A (M=2.15, SD=0.58), P (M=2.44, SD=0.70), E (M=2.11, SD=0.60), D (M=2.00, SD=0.63), S (M=1.88, SD=0.81), N (M=2.01, SD=1.04). It is followed by the linear menu with apartment categories and the map-based menu with traditional categories. The lowest user experience results are achieved by the linear menu with traditional categories: A (M=-0.87, SD=1.25), P (M=-0.19, SD=1.76), E (M=-0.56, SD=1.68), D (M=-0.35, SD=1.28), S (M=-0.99, SD=1.09), N (M=-1.59, SD=1.13). Accordingly, the apartment categorisation achieved higher sub scores than the traditional one. The same holds for the map-based representation in comparison with the linear one. A multivariate ANOVA showed significant differences or effects of all six sub scores regarding the factors menu type, representation and categorisation (see Table 6.1).

## System-Usability-Scale

With the aid of the System-Usability-Scale Questionnaire, each participant rated the experienced usability in relation to each menu type. Thus, 24 usability scores were used as basis for each of the four menus. The resulting average score values of the different menu types are visualised in Figure 6.15. The map-based menu with apartment categories achieved the best usability score on av-

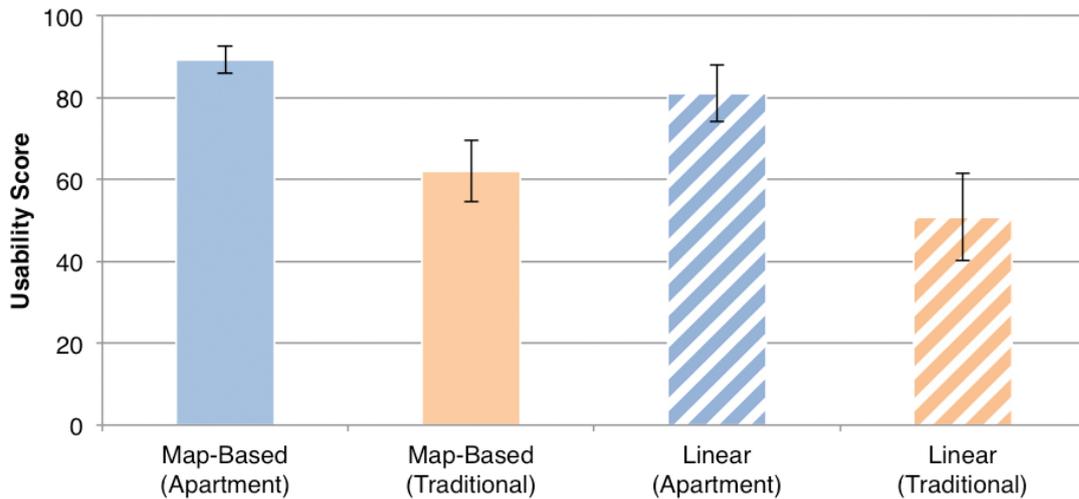


Figure 6.15: Visualisation of the average usability scores concerning the different menu types. Value range goes from 0 to 100. Higher usability scores represent a better usability. In addition, the 95% confidence is indicated by error bars.

erage (M=89.17, SD=8.16), followed by its linear version (M=80.94, SD=17.19) and the map-based menu with traditional categories (M=61.98, SD=18.87). Finally, the linear menu with traditional categories achieved the lowest usability score (M=50.73, SD=26.66). An univariate ANOVA revealed significant differences with regard to the menu type ( $F_{3,92}=20.62$ ,  $p<0.01$ ,  $\eta^2=0.40$ ). Furthermore, significant differences of the usability score in regard to the categorisation ( $F_{1,92}=55.34$ ,  $p<0.01$ ,  $\eta^2=0.38$ ) and a significant effect for the representation ( $F_{1,92}=6.37$ ,  $p<0.05$ ,  $\eta^2=0.07$ ) were found. Comparing the categorisations, the apartment categorisation has a higher average usability score (M=85.05, SD=13.95) than the traditional one (M=56.35, SD=23.54). The comparison of the representations shows that the map-based representation has a higher average usability score (M=75.57, SD=19.89) than the linear one (M=65.83, SD=26.93).

## Workload

With the aid of the Nasa-TLX Questionnaire, the experienced workload of the participants was measured for each of the different menu types. The questionnaire consists of six sub scores: Mental Demand (MD), Physical Demand (PD), Temporal Demand (TD), Performance (PF), Effort (EF) and Frustration (FR). The map-based menu with apartment categories achieved the lowest average workload ratings in all six sub scores: MD (M=26.04, SD=16.01), PD (M=12.50, SD=8.34), TD (M=26.67, SD=20.41), PF (M=28.13, SD=25.32), EF (M=22.08, SD=17.56), FR (M=15.00, SD=15.39). It is followed by its linear version and

the map-based menu with traditional categories. The highest average sub scores were achieved by the linear menu with traditional categories: MD (M=62.50, SD=21.32), PD (M=23.54, SD=24.38), TD (M=67.71, SD=22.65), PF (M=63.13, SD=22.98), EF (M=58.13, SD=21.51), FR (M=61.04, SD=23.59). Accordingly, the apartment categorisation achieved lower workload ratings than the traditional one regarding all sub scores. The same holds for the map-based representation in comparison with the linear one. A multivariate ANOVA was performed with the six sub scores of the Nasa-TLX and the factors menu type, representation and categorisation. Considering the menu types, there were significant differences regarding MD, TD, PF, EF and FR, but not for PD (see Table 6.2). Furthermore, the ANOVA showed significant differences of FR and a significant effect of TD and EF regarding the representation. In relation to the categorisation, a significant effect of PD as well as significant differences of MD, TD, PF, EF and FR were found (see Table 6.2). In addition, the overall workload score was calculated which includes a weighting of the different factors of the Nasa-TLX questionnaire. For this purpose, each participant compared all factors pairwise in order to capture the individual importance of each factor. The overall workload score ranges from 0 to 100, whereby high values represent high workload. Figure 6.16 shows an overview of the average workload scores of the different menu types. The map-based menu with apartment categories has the lowest overall workload score on average (M=22.10, SD=10.78), followed by its linear version (M=30.88, SD=19.48), the map-based menu with traditional cat-

	<b>Menu Type</b> ( $F_{3,92}, p, \eta^2$ )	<b>Representation</b> ( $F_{1,92}, p, \eta^2$ )	<b>Categorisation</b> ( $F_{1,92}, p, \eta^2$ )
Mental Demand	(17.49, <0.01, 0.36)	(no significance)	(49.02, <0.01, 0.35)
Physical Demand	(no significance)	(no significance)	(4.70, <0.05, 0.05)
Temporal Demand	(17.34, <0.01, 0.36)	(4.41, <0.05, 0.05)	(47.51, <0.01, 0.34)
Performance	(11.01, <0.01, 0.26)	(no significance)	(29.01, <0.01, 0.24)
Effort	(15.13, <0.01, 0.33)	(4.73, <0.05, 0.05)	(40.65, <0.01, 0.31)
Frustration	(20.11, <0.01, 0.40)	(8.66, <0.01, 0.09)	(50.96, <0.01, 0.36)

Table 6.2: Results of the multivariate ANOVA with regard to the factors menu type, representation and categorisation and the Nasa-TLX sub scores as dependent variables: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, Frustration.

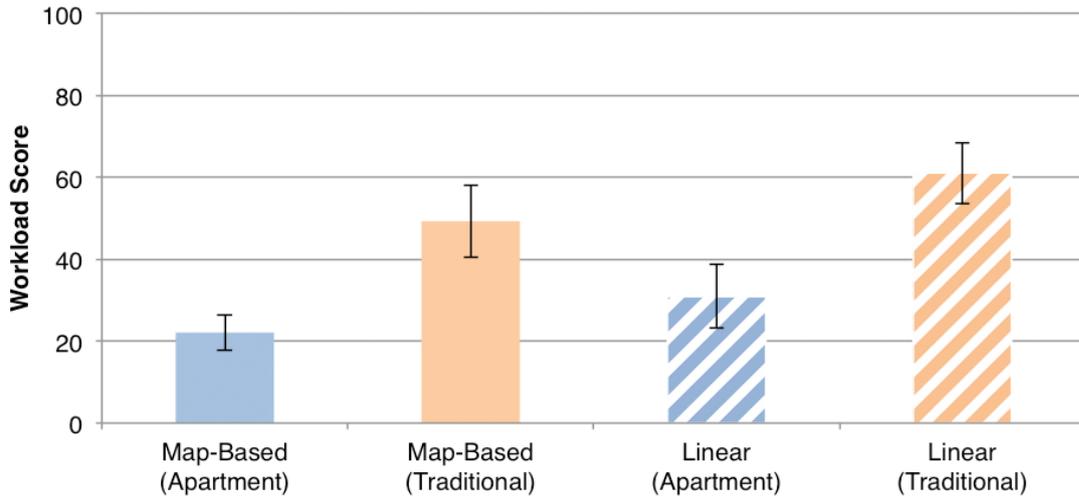


Figure 6.16: Visualisation of the average workload scores concerning the different menu types. Value range goes from 0 to 100. Higher values represent a higher overall workload. In addition, the 95% confidence is indicated by error bars.

egories ( $M=49.26$ ,  $SD=22.22$ ) and the linear menu with traditional categories with the highest score ( $M=61.04$ ,  $SD=18.69$ ). An univariate ANOVA showed significant differences of the overall workload score with regard to the menu type ( $F_{3,92}=22.22$ ,  $p<0.01$ ,  $\eta^2=0.42$ ). There were also significant differences regarding the factors representation ( $F_{1,92}=7.58$ ,  $p<0.01$ ,  $\eta^2=0.08$ ) and categorisation ( $F_{1,92}=58.93$ ,  $p<0.01$ ,  $\eta^2=0.39$ ). With regard to the representations, the map-based representation has a lower workload score on average ( $M=35.68$ ,  $SD=22.06$ ) than the linear one ( $M=45.96$ ,  $SD=24.27$ ). The comparison of the categorisations shows that the apartment categorisation achieved a lower workload score ( $M=26.49$ ,  $SD=16.19$ ) than the traditional one ( $M=55.15$ ,  $SD=21.17$ ).

## Immersion

The SUS Questionnaire was used to measure the immersion feeling in relation to the different menu types, with special interest in the representation. Two different overall immersion scores can be calculated upon the six involved questions: SUS Mean and SUS Count. The SUS Mean uses the mean score over all questions and the SUS Count is the number of answers with rating “6” or “7” (highest ratings). Figure 6.17 shows the average results of the SUS Mean and the SUS Count in relation to the menu types. An univariate ANOVA showed that there were significant differences between the menu types concerning SUS Mean ( $F_{3,92}=25.15$ ,  $p<0.01$ ,  $\eta^2=0.45$ ) and SUS Count ( $F_{3,92}=5.51$ ,  $p<0.01$ ,  $\eta^2=0.15$ ). Regarding the SUS Mean, the map-based menu with apartment categories has the highest score ( $M=4.29$ ,  $SD=1.10$ ), followed by the map-based menu

with traditional categories ( $M=3.69$ ,  $SD=1.38$ ), the linear menu with apartment categories ( $M=2.76$ ,  $SD=1.44$ ) and the linear menu with traditional categories ( $M=1.53$ ,  $SD=0.56$ ). The same order results with regard to the SUS Count: map-based menus with apartment categories ( $M=1.63$ ,  $SD=1.76$ ) or traditional categories ( $M=0.96$ ,  $SD=1.73$ ), followed by the linear menus with apartment categories ( $M=0.54$ ,  $SD=1.44$ ) or traditional categories ( $M=0$ ,  $SD=0$ ). Furthermore, an univariate ANOVA was conducted with representation and categorisation as factors and the SUS Mean or the SUS Count as dependent variable. Regarding the representation, significant differences were found in relation to the SUS Mean ( $F_{1,92}=59.07$ ,  $p<0.01$ ,  $\eta^2=0.39$ ) and the SUS Count ( $F_{1,92}=12.20$ ,  $p<0.01$ ,  $\eta^2=0.12$ ). There were also significant differences of SUS Mean ( $F_{1,92}=14.66$ ,  $p<0.01$ ,  $\eta^2=0.14$ ) and a significant effect of SUS Count ( $F_{1,92}=4.28$ ,  $p<0.05$ ,  $\eta^2=0.04$ ) with regard to the categorisation. In relation to the categorisations, the apartment categorisation achieved a better SUS Mean and a better SUS Count than the traditional one. Regarding the two representations, the map-based representation achieved a higher SUS Mean ( $M=3.99$ ,  $SD=1.27$ ) than the linear one ( $M=2.15$ ,  $SD=1.25$ ). The same holds for the SUS Count: map-based representation ( $M=1.29$ ,  $SD=1.76$ ) and linear representation ( $M=0.27$ ,  $SD=1.05$ ).

## 6.8 Discussion

In this work, the effects of linear and map-based representations as well as traditional and apartment categorisations were investigated in an online shop environment. In this chapter, the results of the main study are discussed in detail with regard to the performance data and the preference data. In this context, the validity of the previously established hypotheses is checked. Finally, a selection of participant comments is reviewed and the limitations of this work are discussed.

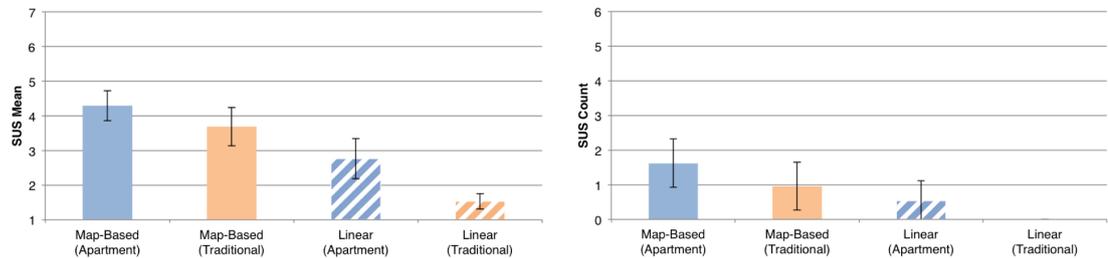


Figure 6.17: Visualisation of the average values of SUS Mean (left) and SUS Count (right) concerning the different menu types. Values of SUS Mean range from 1 to 7 and values of SUS Count range from 0 to 6. Higher values suggest a higher immersion feeling. In addition, the 95% confidence is indicated by error bars.

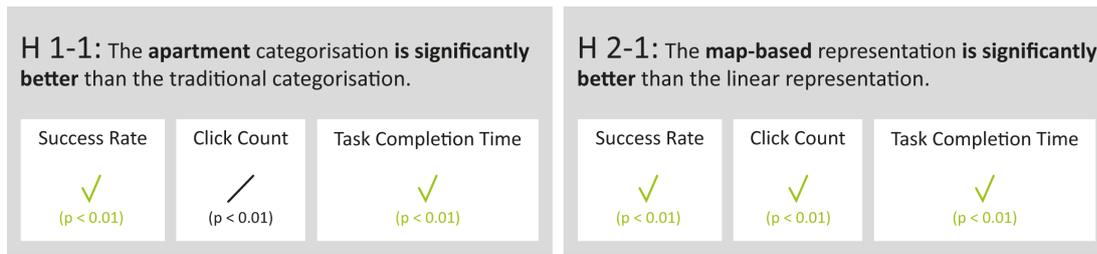


Figure 6.18: Overview of the task performance results with regard to the research hypotheses. For each performance aspect, it is indicated whether the related hypothesis is met (checkmark) or not met (stroke). Additionally, p-values are given, which show statistical significance.

### 6.8.1 Task Performance

First and foremost, the results of the *success rate* are especially important with regard to task performance, since they are based on the complete set of conducted product searches and make a fundamental statement about the effectiveness of the methods. The results show clear differences with regard to representation and categorisation. Both menus with apartment categories have a higher success rate than the two menus with traditional categories (H 1-1). Furthermore, the map-based menu with apartment categories has a higher success rate than its linear version. The same holds when comparing the map-based and linear menu with traditional categories (H 2-1). Summarised, the most successful menu type combines the map-based representation and the apartment categorisation, which seem to make it easier to find desired products. It achieved an average success rate of about 99%. Since the menu with the lowest average success rate of about 69% is the commonly used menu type in today’s online shops, the results show a remarkable potential for improvement.

Regarding the average *click count*, it can be noticed that the menus with apartment categories have no advantage over the menus with traditional categories. In fact, the linear menu with apartment categories has the highest number of average clicks. These results do not match the expectation that the apartment categorisation outperforms the traditional categorisation in all aspects. One possible explanation for this significant difference could be the unfamiliarity with the used furniture terms. If the participants were unclear about the difference between furniture terms, e.g. “cabinet” and “sink cabinet”, they had to try the different menu options, which results in a higher click count. This is also in line with the result that the map-based representation in general has a significant lower click count (H 2-1). Accordingly, the map-based menu with apartment categories has no increased average click count. Here, the used furniture terms are

additionally illustrated by a graphical representation of the corresponding furniture. This visual cue can help participants in understanding the differences between the used furniture. However, all average click counts are very close to the minimum click count of 3 clicks. Therefore, none of the considered menu types has a remarkably high click count and there is no noticeable disadvantage.

The results of the *task completion time* again show clear differences. The apartment categorisation leads to a shorter average search time. This suggests that the intuitive categorisation helps users in understanding the underlying information space. Furthermore, it seems that the visual cues given in the map-based menus and their realistic spatial arrangement actually facilitate the visual search process. The target items can thus be found more quickly. These results confirm the expectations and the hypotheses made in advance (H 1-1, H 2-1).

Overall, it can be concluded that the apartment categorisation generally has a positive influence on the considered performance aspects and that it can be enhanced even more in combination with the map-based representation. Figure 6.18 visualises which performance aspects are fulfilled with regard to the related hypotheses. Since the hypotheses H 1-1 and H 2-1 are largely met, they are accepted and the considered null hypothesis is rejected.

## 6.8.2 User Preference

Considering the results of the *user experience*, there is a clear advantage of the apartment categorisation and the map-based representation. The map-based menu with apartment categories achieved the highest ratings in all six sub scores. The high ratings for the sub scores “Perspicuity”, “Efficiency” and “Dependability” in particular point to increased understanding and reliability. It seems that the apartment categorisation is easier to understand and that the visual cues of the map-based representation facilitate the search process. Further, high ratings in the sub scores “Attractiveness”, “Stimulation” and “Novelty” indicate that the more realistic and illustrating representation of the categories seems to lead to a new and appealing experience. Overall, the results of the UEQ completely confirm the given hypotheses (H 1-2, H 2-2).

Regarding the *usability* results, similar tendencies can be observed. Again, the two menus with apartment categories achieved better results than the two menus with traditional categories. Additionally, map-based menus achieved higher usability scores than linear menus within the respective categorisation. Values around 68 are considered as average rating<sup>2</sup>. Accordingly, the apartment cate-

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<sup>2</sup> [www.measuringu.com/sus](http://www.measuringu.com/sus) (accessed December 15, 2017)

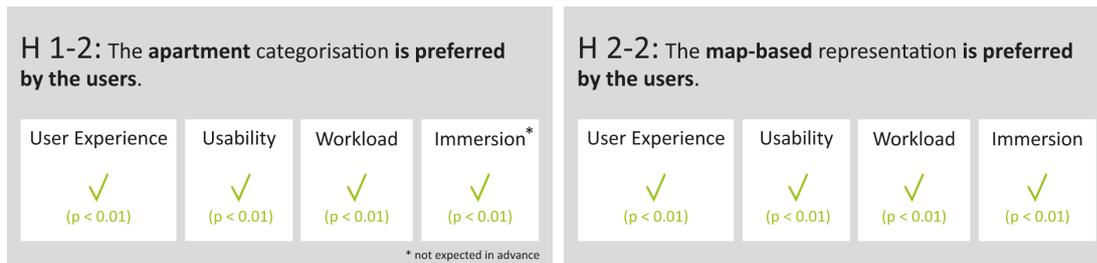


Figure 6.19: Overview of the user preference results with regard to the research hypotheses. For each preference aspect, it is indicated whether the related hypothesis is met (checkmark). Additionally, p-values are given, which show statistical significance.

gorisation’s overall usability score of 85.05 is well above the average score. This suggests that the categorisation is easy to understand and helps users to find desired products. The map-based menu with apartment categories achieved especially good usability results with an average value of 89.17, which shows that the comprehensibility is further enhanced by the illustrative character of the map-based representation. Overall, the results clearly indicate that the new menu characteristics lead to easy-to-use menus. Therefore, the hypotheses are also met in relation to the usability (H 1-2, H 2-2).

The *workload* results show that the apartment categorisation perceived a low overall workload score of 26.49 on average. In contrast, the workload score of the traditional categorisation is more than twice as high (55.15). This indicates that the classification according to rooms and furniture is less demanding than the traditional one. Furthermore, the map-based menus achieved a lower workload evaluation than the linear menus. Regarding the individual sub scores, the map-based representation leads to lower effort, frustration and temporal demand, which indicates that the visual cues facilitate and accelerate the orientation process. The apartment categorisation additionally minimises the mental demand, which demonstrates that there is no need for complex and strenuous considerations. Overall, it shows that the new categorisation and representation are less demanding and frustrating to use. This is in line with expectations and confirms the hypotheses (H 1-2, H 2-2).

The results of the SUS questionnaire show that the *immersion* effect of the map-based representation is higher than the one of the linear representation (H 2-2). As expected, the illustrating character of the map-based representation leads to a more realistic shopping experience. In addition, a difference between both categorisations could be determined. The apartment categorisation receives a higher average immersion score (H 1-2). This is probably due to the fact that

the apartment categories rather describe physical objects and spaces instead of simply describing the content. This fact probably addresses the user's spatial imagination automatically and thus leads to a higher immersion. However, as expected, none of the menus received particularly high immersion scores, i.e. immersion effect is not particularly high. The highest average score, which is achieved by the map-based menu with apartment categories, is 4.29 regarding the SUS Mean and 1.63 regarding the SUS Count. This result is not surprising, since all implementations are two-dimensional. But the map-based menus show a clear advantage over the linear ones, which corresponds to the desired effect.

In sum, taking into account the results of the user preference, it can be concluded that there is a significantly higher preference for the apartment categorisation. In addition, the map-based menus are preferred to linear menus. The hypotheses H 1-2 and H 2-2 are accepted since they are met in all considered aspects (see Figure 6.19). These results also clearly show that the considered null hypothesis has to be rejected.

### 6.8.3 Comments

The user comments additionally confirm the overall impression of the previously discussed results. In the concluding questionnaire, the participants were explicitly asked for their opinion on the tested menus. One question asks to state the menu they would prefer to use in future. Results are very clear. 23 out of 24 participants named the map-based menu with apartment categories and one named the linear menu with apartment categories. The answers of the participants clearly show the positive impression made by the apartment categories as well as by the map-based representation. The reasons for this choice were given in terms such as "intuitive", "easy", "entertaining", "clear" or "fast". This is fully in line with previous expectations and impressions during the execution of the study. Additionally, a pairwise comparison of the different menus was part of the concluding questionnaire. Thereby, each participant had to select his preferred menu type in six pairwise comparisons, where each menu was included in three of them. Considering the answers of the 24 participants, 72 evaluations result for each menu type. The results of this pairwise comparison also show that apartment categories and map-based menus are preferred by the participants. Accordingly, the map-based menu with apartment categories is selected the most (98.61%,  $n=71/N=72$ ). It is followed by its linear version (59.72%,  $n=43/N=72$ ) and the map-based menu with traditional categories (26.39%,  $n=19/N=72$ ). The least selected menu is the linear menu with traditional categories (15.28%,  $n=11/N=72$ ). This matches

the verbal comments made during the study execution. For example, when faced with the linear menu with traditional categories, one participant stated “this was so hard” and another one stated “this will take a long time” after he saw the appropriate demonstration video. In contrast to this, participants made positive statements in relation to the apartment categorisation. For example, “this was cool”, “this was great” or “very intuitive”. One participant further expressed the wish that this categorisation should be integrated in online shops. The participants’ comments confirm the task performance and user preference results and are in line with the previously established research hypotheses.

#### **6.8.4 Limitations**

Since all results are based on a limited product set, the results should not simply be generalised. This especially holds for the remarkably high ratings of the preference questionnaires (UEQ, System-Usability-Scale, Nasa-TLX, SUS), which are often close to the optimal rating. Such outstandingly good results rarely occur in practice and presumably have to be attributed to the limited test conditions. The scope of real online shops is usually much larger. Current online shops are based on a clearly more extensive product set. Furthermore, they include a larger functionality range. Therefore, the implemented prototype can surely not reflect the complexity of a real online shop. Additionally, the selected products are mainly based on a list of frequently searched products of an exemplary market. Even if this leads to a relevant product set, there exist several reasons why products belong to this list. For example, a product is frequently searched for because it is either frequently bought or because it is difficult to be found due to the used categorisation. Since the list as well as the traditional categorisation refer to the same market, it cannot be completely ruled out that other products might be found more easily with the traditional categorisation. In sum, the preference ratings are likely to be realistically downsized in an online shop with full functionality range. Similar adjustments to the performance results are likely. However, it can be assumed that the general tendencies will be maintained and that the new categorisation and representation would still show clear positive effects.

# Chapter 7

## Conclusion

Menus in current online shops rarely benefit from new technologies and previous research findings. Inconsistent and overlapping categorisations as well as simple text-based representations often make it difficult to understand and to use the menus successfully. Therefore, this work used unexploited research potential to create new intuitive menu types for online shops. Basic research findings were used to develop new methods for menu categorisation and representation. For example, the apartment categorisation was created on the basis of the “Apartment Metaphor” [1] which classifies products into rooms and furniture. This natural and intuitive metaphor takes advantage of the users’ everyday experiences to facilitate menu interaction. Furthermore, research shows that grid-shaped representations lead to new search and pointing patterns and can thus simplify and/or accelerate the search for specific menu items [2, 43]. The principle of a virtual map furthermore facilitates the orientation process [29]. These two characteristics were used to create the map-based menu representation. It acts like an interactive floor plan and offers a natural way of orientation. A user study was conducted in order to investigate these new methods in comparison with appropriate reference methods which are usually used in current online shops. Four menu types result, which differ in their categorisation (traditional, apartment) and/or their representation (linear, map-based). In total, 24 participants tested and evaluated the different menu types and results largely confirmed expectations. These results clearly indicate that the illustrating and realistic character of the map-based representation improves user orientation. Map-Based menus significantly perform better in terms of success rate, click count and task completion time. For example, the success rate of the map-based representation is about 12% higher than that of the linear one. Furthermore, usability and user experience results indicate that the map-based menus are easier to use and more

appealing. As expected, they additionally lead to significantly higher immersion feelings than the linear menus even though there is still enough room for further improvement. Regarding the categorisation, it seems that the natural and well-known principle of the apartment categorisation leads to an easy and intuitive search process. Menus with apartment categories perform significantly better in terms of success rate and task completion time. The success rate of the apartment categorisation is about 26% higher than that of the traditional one and the average search time is significantly reduced by about 29%. Furthermore, high usability and user experience results indicate that the apartment categorisation increases understanding and reliability. The experienced workload additionally shows that the intuitive apartment categories are less demanding and lead to a lower frustration level. Overall, the map-based menu with apartment categories obtained the best results. Compared to the reference menu, its success rate is about 42% higher and it leads to 42% faster search times. Furthermore, 23 out of 24 participants explicitly stated that they prefer the map-based menu with apartment categories. They described the new menu type as “easy”, “intuitive” and “clear”. Therefore, the map-based menu with apartment categories seems to be the best option for menus in online shops.

In sum, this work identifies two menu characteristics which offer the potential to improve menu interaction and shopping experience in online shops. The intuitive apartment categorisation and the illustrating map-based representation specifically address the identified weaknesses of menus in current online shops and show first positive results. Overall, it is worth pursuing this topic and carrying out additional tests to further develop the methods and test them under real, more extensive test conditions. This should be done with a special focus on setting up general guidelines for menus in online shops in order to provide common and proved strategies.

# Chapter 8

## Future Work

The work presented here shows two menu characteristics that are likely to improve menu interaction in present online shops. However, since this work is based on a limited amount of data, further tests should be carried out before the menus are actually integrated in real online shops. For example, further investigations should include a full shop functionality and a realistic amount of product data. Current online shops usually offer a huge amount of product data, which clearly exceeds the number of 36 products used here. Therefore, it should be tested whether a large and realistic amount of data would lead to changes in the results. In the case of apartment categorisation, further online surveys could be conducted to classify the new products into the already established apartment categories. Another promising approach is the use of machine learning algorithms. Based on the previous set of apartment categories and product classifications, an automatic classification process could be realised. By using this approach, further product assignments can be added more quickly and effortlessly. With regard to the apartment categorisation, further tests with multiple placements could be conducted to investigate whether this would lead to a further increase in success and preference. In addition, further stores could be used to create appropriate categorisations. Since most stores use their own categorisation, it would be interesting to investigate their differences with regard to the apartment categorisation. Even though, store categorisations are based on the same concept, they often differ in their actual realisation, for example in terms of category naming or product classification. Furthermore, it would be interesting to know whether the map-based representation of a well known store might result in an easier interaction than that of an unknown store. In this case, the mental model of the spatial environment should already be established, which could lead to a more effortless and quicker search process. Besides these fundamental investigations, there are



Figure 8.1: Virtual reality based shopping inside an apartment where individual products can be selected to get product information or to put them into the shopping cart [17].

also some possibilities for further development. Although the immersion effect of the map-based menus is higher than that of the linear menus, there is still enough room for further improvement. For example, an improvement could be achieved by using new technologies like 360° videos or virtual reality (VR). When 360° videos are used to represent the spatial environment, the user can look around in the virtual environment. In contrast to looking at a floor plan, this is a more realistic interaction with an environment. In addition, furniture can be depicted in more detail. The user has the possibility to consider them from different perspectives, which offers more placement possibilities. For example, products can be stored in a cabinet or above, which could not be distinguished in the implemented representation. All these improvements can also be realised through the use of a VR application. A further advantage of VR is that a three-dimensional environment can be implemented. Since the implemented map-based representation is two-dimensional, a three-dimensional representation could increase the feeling of immersion. For example, this allows for a more realistic depiction of furniture and products. There are also more realistic interaction possibilities, such as moving in the virtual environment and picking up individual objects. This usually makes it easier to create a feeling of being inside a real environment. Various providers have already taken up the topic, for example eBay<sup>1</sup> or IKEA<sup>2</sup>. In addition, the use of VR applications has already been scientifically investigated with regard to shopping environments [52]. One work has even already integrated and tested the apartment categorisation developed here inside a virtual reality apartment [17] (see Figure 8.1). Results are promising, since product searches

<sup>1</sup> <https://vr.ebay.com.au> (accessed 08.01.2018)

<sup>2</sup> [http://www.ikea.com/ms/en\\_US/this-is-ikea/ikea-highlights/Virtual-reality](http://www.ikea.com/ms/en_US/this-is-ikea/ikea-highlights/Virtual-reality) (accessed 08.01.2018)

could in general successfully be completed and user feedback was positive. In addition to improvements in terms of representation, the apartment categorisation could also be improved and developed further. Its intuitiveness could for example be enhanced by using customised apartment categories. In this way, the users can create their own categories, which completely correspond to their own living situation and storing habits. It would be advisable to offer the standard apartment categorisation as a basis and to additionally give the possibility to change some aspects of it that do not correspond to the user's own expectations and habits. Regarding the map-based representation, the spatial arrangement of the own home would be represented, be it in 2D or 3D. The use of augmented reality could even directly transform the own apartment into the shopping environment. Individual pieces of furniture could be recognised and selected in order to shop for assigned products. The apartment categorisation focuses on online shops, which are based on a broad range of products. Nevertheless, it could also be used in specialised online shops. For this purpose, menu items that are not needed could simply be disabled. However, a more recommendable approach would be to reduce the apartment categorisation to one area. For example, in the case of an online grocery shop, only the room "kitchen" could be considered. A further level could be added to the individual pieces of furniture. For example, the "fridge" could serve as a top-level category which leads to the subcategories "crisper" or "door", among other possibilities. In this way, the metaphor is maintained and a similar positive effect can be assumed. In addition to the use in online shops, it would also be possible to use the apartment categorisation in local stores, be it for actual product organisation inside the market or for integration in product search terminals.

In sum, this work opens a large new research field concerning menu realisation in online shops. New methods for an enriched and facilitated shopping experience were introduced. While the new menu types generally have the potential to improve menu interaction in online shops, more research is needed in order to ensure that this result is maintained in a complete and extensive shop system. The findings gained here should also be taken into account with regard to future VR or local shopping experience.



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# Appendix

## A.1 Pilot Study (Phase 2) – Evaluation

SALT (N=32):

cellar: storeroom/ laundry		kitchen			
cabinet n=3 9.38%		cabinet n=17 53.13%	drawer n=6 18.75%	worktop n=4 12.50%	table n=2 6.25%

BEDCLOTHES (N=33):

cellar: storeroom/ laundry		bedroom		
cabinet n=1 3.03%	washing mashine n=1 3.03%	bed n=10 30.30%	cabinet n=14 42.42%	wardrobe n=7 21.21%

POTATO CRISPS (N=29):

cellar: storeroom/ laundry		kitchen		living room
cabinet n=5 17.24%		cabinet n=16 55.17%	drawer n=3 10.34%	cabinet n=5 17.24%

SHOES (N=25):

corridor / entrance		living room	cellar: storeroom / entrance		bedroom	
cabinet n=1 4.00%	shoe cabinet n=19 76.00%	cabinet n=1 4.00%	cabinet n=2 8.00%		floor n=1 4.00%	shoe cabinet n=1 4.00%

TOOTHPASTE (N=28):

bathroom		
cabinet n=9 32.14%	holder n=1 3.57%	sink cabinet n=18 64.29%

SOCKS (N=24):

bedroom				cellar: storeroom / laundry	
floor n=1 4.17%	bedside table n=1 4.17%	cabinet n=3 12.50%	wardrobe n=18 75.00%	washing mashine n=1 4.17%	

TOWEL (N=30):

bathroom			bedroom		cellar: storeroom / laundry		
washing mashine n=1 3.33%	sink cabinet n=4 13.33%	cabinet n=16 53.33%	wardrobe n=2 6.67%	cabinet n=4 13.33%	washing mashine n=1 3.33%	hook n=1 3.33%	cabinet n=1 3.33%

BALL PEN (N=44):

office			kitchen			living room			bedroom	corridor / entrance
cabinet n=1 2.27%	computer n=1 2.27%	desk n=17 38.64%	worktop n=2 4.55%	drawer n=4 9.09%	table n=5 11.36%	desk n=4 9.09%	cabinet n=1 2.27%	desk n=6 13.64%	desk n=2 4.55%	cabinet n=1 2.27%

 Rule 1: Most frequent answers which together cover at least 60%.

 Rule 2: Selected by at least 30% of the participants.

SWIMWEAR (N=25):

bedroom		bathroom	cellar: storeroom / laundry
cabinet n=2 8.00%	wardrobe n=19 76.00%	cabinet n=3 12.00%	cabinet n=1 4.00%

HOT-WATER BOTTLE (N=32):

bedroom				cellar: storeroom / laundry	bathroom	corridor / entrance	kitchen			living room
bedside table n=1 3.13%	wardrobe n=1 3.13%	bed n=3 9.38%	cabinet n=10 31.25%	cabinet n=5 15.63%	cabinet n=6 18.75%	cabinet n=1 3.13%	drawer n=1 3.13%	worktop n=1 3.13%	cabinet n=2 6.25%	cabinet n=1 3.13%

DVD / BLURAY (N=34):

living room			bedroom				office		
computer n=2 5.88%	table n=1 2.94%	cabinet n=16 47.06%	desk n=1 2.94%	computer n=2 5.88%	cabinet n=1 2.94%	entertainment center n=7 20.59%	desk n=1 2.94%	computer n=1 2.94%	cabinet n=2 5.88%

MUSTARD (N=29):

kitchen			cellar: storeroom / laundry
drawer n=1 3.45%	cabinet n=5 17.24%	fridge n=19 65.52%	cabinet n=4 13.79%

ELECTRIC WATER KETTLE (N=22):

kitchen		
cabinet n=3 13.64%	table n=3 13.64%	worktop n=16 72.73%

BOARD GAME (N=26):

living room	corridor / entrance	bedroom	cellar: storeroom / laundry	office
cabinet n=18 69.23%	cabinet n=2 7.69%	cabinet n=3 11.54%	cabinet n=2 7.69%	cabinet n=1 3.85%

DEODORANT (N=29):

bathroom		bedroom		
sink cabinet n=12 41.38%	cabinet n=13 44.83%	wardrobe n=1 3.45%	bedside table n=2 6.90%	cabinet n=1 3.45%

UNDERWEAR (N=25):

bedroom				cellar: storeroom / laundry
floor n=1 4.00%	bedside table n=1 4.00%	cabinet n=4 16.00%	wardrobe n=18 72.00%	washing machine n=1 4.00%

 Rule 1: Most frequent answers which together cover at least 60%.

 Rule 2: Selected by at least 30% of the participants.

**BREAKFAST BAGS (N=28):**

kitchen		cellar: storeroom / laundry
cabinet n=8 28.57%	drawer n=17 60.71%	cabinet n=3 10.71%

**CUTLERY (N=25):**

kitchen		living room	cellar: storeroom / laundry
cabinet n=2 8.00%	drawer n=20 80.00%	cabinet n=2 8.00%	cabinet n=1 4.00%

**GLUE (N=31):**

office		kitchen	living room		bedroom	cellar: storeroom / laundry
cabinet n=7 22.58%	desk n=13 41.94%	cabinet n=2 6.45%	desk n=3 9.68%	cabinet n=3 9.68%	desk n=1 3.23%	cabinet n=2 6.45%

**COLLEGE-BLOCK (N=34):**

kitchen	office		cellar: storeroom / laundry	living room		bedroom
worktop n=1 2.94%	cabinet n=10 29.41%	desk n=14 41.18%	cabinet n=1 2.94%	table n=1 2.94%	desk n=4 11.76%	desk n=3 8.82%

**CONDOMS (N=23):**

bedroom		bathroom	living room
cabinet n=4 17.39%	bedside table n=16 69.57%	cabinet n=2 8.70%	cabinet n=1 4.35%

**LAUNDRY DETERGENT (N=28):**

cellar: storeroom / laundry		bathroom			kitchen		
washing machine n=11 39.29%	cabinet n=6 21.43%	sink cabinet n=1 3.57%	washing machine n=4 14.29%	cabinet n=3 10.71%	washing machine n=1 3.57%	sink cabinet n=1 3.57%	cabinet n=1 3.57%

**DISHWASHER TABS / POWDER (N=26):**

kitchen				cellar: storeroom / laundry
drawer n=1 3.85%	cabinet n=4 15.38%	washing machine n=1 3.85%	sink cabinet n=18 69.23%	cabinet n=2 7.69%

**COMPUTERSPIEL (N=35):**

office			living room			bedroom	
cabinet n=3 8.57%	desk n=3 8.57%	computer n=14 40.00%	cabinet n=3 8.57%	table n=1 2.86%	computer n=9 25.71%	entertainment center n=1 2.86%	computer n=1 2.86%

 Rule 1: Most frequent answers which together cover at least 60%.

 Rule 2: Selected by at least 30% of the participants.

TOILET PAPER (N=41):

bathroom				cellar: storeroom / laundry		corridor / entrance	
sink cabinet n=3 7.32%	floor n=1 2.44%	cabinet n=10 24.39%	toilet paper holder n=17 41.46%	cabinet n=9 21.95%		cabinet n=1 2.44%	

FACIAL TISSUES (N=41):

bathroom		bedroom			office	corridor/ entrance	cellar: storeroom/ laundry	living room		kitchen			
sink cabinet n=2 4.88%	cabinet n=4 9.76%	bed n=1 2.44%	cabinet n=5 12.20%	bedside table n=6 14.63%	desk n=3 7.32%	cabinet n=2 4.88%	cabinet n=7 17.07%	cabinet n=2 4.88%	table n=2 4.88%	drawer n=1 2.44%	cabinet n=2 4.88%	table n=2 4.88%	worktop n=2 4.88%

NEWSPAPER/MAGAZINE (N=35):

living room			office		kitchen	bedroom		bathroom	corridor / entrance	
cabinet n=1 2.86%	desk n=2 5.71%	table n=15 42.86%	desk n=5 14.29%	cabinet n=2 5.71%	table n=1 2.86%	desk n=1 2.86%	bedside table n=5 14.29%	floor n=1 2.86%	cabinet n=2 5.71%	

COFFEE FILTER (N=25):

kitchen				cellar: storeroom / laundry	
worktop n=1 4.00%	drawer n=4 16.00%	cabinet n=18 72.00%		cabinet n=2 8.00%	

FRESH YEAST (N=23):

kitchen		
drawer n=3 13.04%	cabinet n=3 13.04%	fridge n=17 73.91%

BATTERIES (N=29):

office		kitchen		corridor / entrance		living room		cellar: storeroom / laundry		bedroom
desk n=1 3.45%	cabinet n=7 24.14%	cabinet n=2 6.90%	drawer n=3 10.34%	cabinet n=3 10.34%		desk n=2 6.90%	cabinet n=7 24.14%	cabinet n=3 10.34%		cabinet n=1 3.45%

COCA COLA (N=32):

kitchen			cellar: storeroom / laundry		corridor / entrance	
cabinet n=2 6.25%	worktop n=2 6.25%	fridge n=16 50.00%	cabinet n=11 34.38%		cabinet n=1 3.13%	

TABASCO (N=32):

kitchen					cellar: storeroom / laundry	
table n=1 3.13%	worktop n=4 12.50%	drawer n=4 12.50%	fridge n=7 21.88%	cabinet n=15 46.88%	cabinet n=1 3.13%	

Rule 1: Most frequent answers which together cover at least 60%.

Rule 2: Selected by at least 30% of the participants.

MILK (N=30):

kitchen			cellar: storeroom / laundry
cabinet n=3 10.00%	table n=1 3.33%	fridge n=20 66.67%	cabinet n=6 20.00%

PEAS (N=29):

kitchen			cellar: storeroom / laundry
drawer n=2 6.90%	cabinet n=13 44.83%	fridge n=6 20.69%	cabinet n=8 27.59%

KETCHUP (N=30):

kitchen			cellar: storeroom / laundry
drawer n=2 6.67%	fridge n=18 60.00%	cabinet n=7 23.33%	cabinet n=3 10.00%

CHOCOLATE BAR (N=29):

kitchen				living room	corridor / entrance	cellar: storeroom / laundry
worktop n=1 3.45%	drawer n=3 10.34%	fridge n=5 17.24%	cabinet n=12 41.38%	cabinet n=6 20.69%	cabinet n=1 3.45%	cabinet n=1 3.45%

 Rule 1: Most frequent answers which together cover at least 60%.

 Rule 2: Selected by at least 30% of the participants.

Furthermore, the following storing places were included due to verbal feedback:

1. bathroom – hook – towel
2. bathroom – sink – toothpaste
3. living room – entertainment center – DVD / Bluray

## A.2 Traditional Categorisation

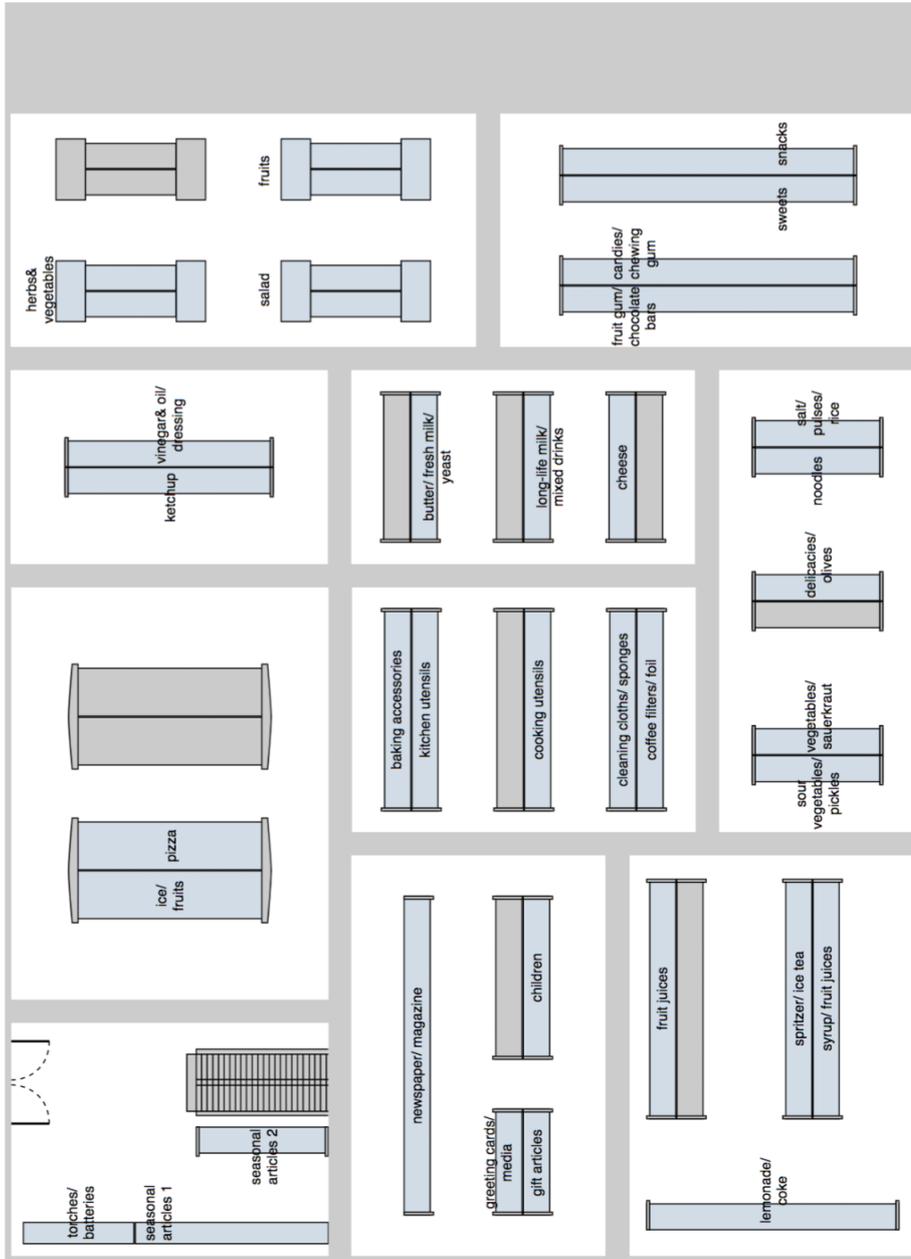
TOP-LEVEL	SUB-LEVEL	PRODUCT-LEVEL
baby stuff / infant food	change me	bedclothes, underwear
	feed me	cutlery
	nurse me (1)	socks, towel
	nurse me (2)	toothpaste
	play with me	socks, underwear
beverages	lemonade / coke	coca cola
cheese & milk	butter / fresh milk / yeast	fresh yeast
	long-life milk / mixed drinks	milk
chemist's / hygiene / personal hygiene	dental care	toothpaste
	deodorant	deodorant
	facial tissues	facial tissues
	over-the-counter drugs	condoms
	plasters / foot care	hot-water bottle
	toilet paper	toilet paper
detergents / cleaning agents / kitchen stuff	clean washing	laundry detergent
	dishwasher detergents / dishwashing liquids	dishwasher tabs / powder
electronics	kitchen electronics	electric water kettle
home textiles / lingerie	bathroom textiles	towel
	home textiles	bedclothes
	underwear	underwear
household / kitchen stuff	coffee filters / foil	breakfast bags, coffee filters
	kitchen utensils	cutlery
magazines / greeting cards	newspaper / magazine	newspaper / magazine
office supplies / books	arts / crafts	glue
	booklets / writing pads	college block
	media	computer game, DVD / Bluray
	office supplies	ball pen
preserves / ready-to-eat meals	delicacies / olives	tabasco
	salt / pulses / rice	salt
	vegetables / sauerkraut	peas
seasonal articles	torches / batteries	batteries
shoes / leather goods	shoes	shoes
socks	socks	socks
spices / vinegar&oil	ketchup	ketchup, mustard
sport / leisure	swimwear	swimwear
sweets&snacks	fruit gum / chocolate bars	chocolate bar
	snacks	potato crisps
toys	board games / card games	board game

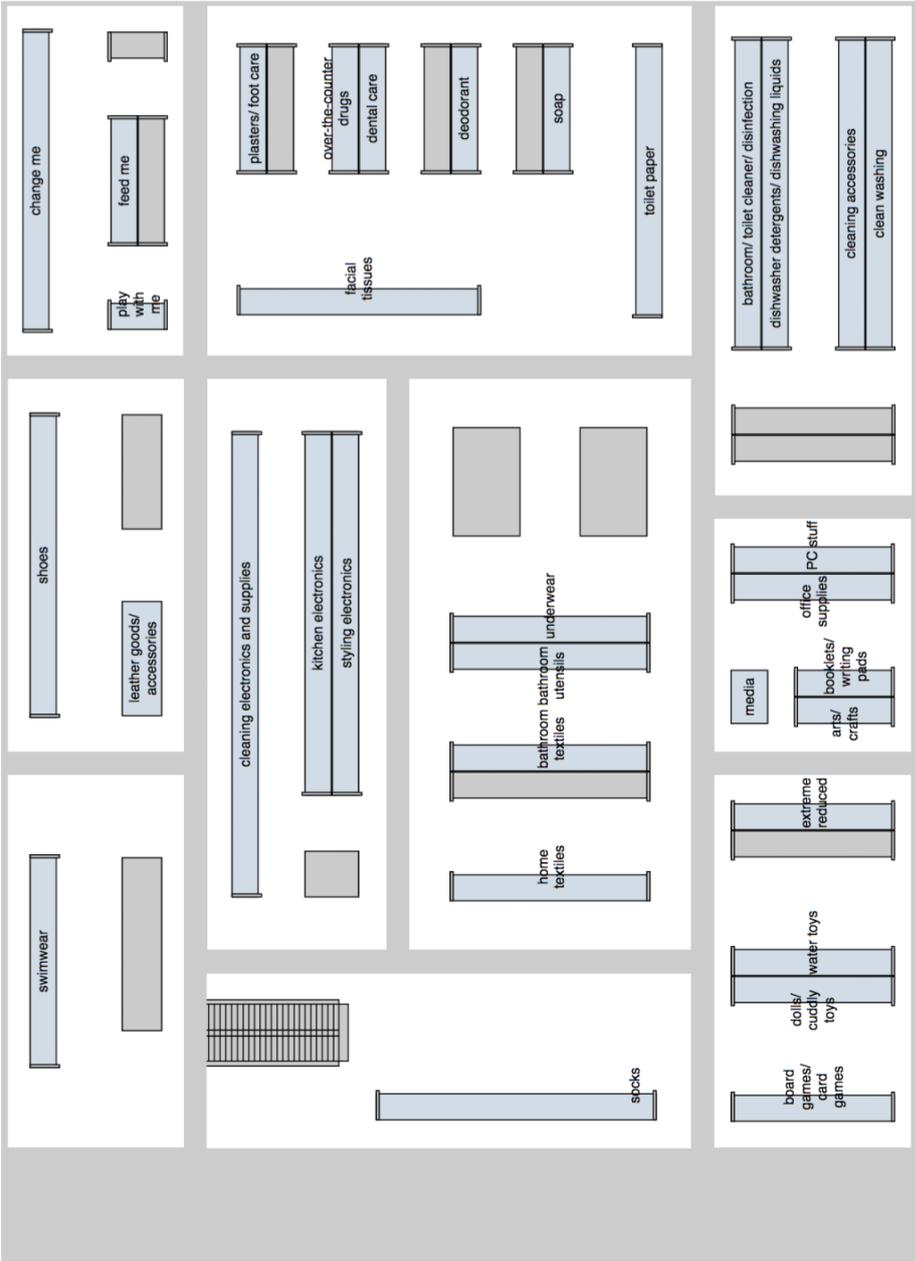
## A.3 Apartment Categorisation

TOP-LEVEL	SUB-LEVEL	PRODUCT-LEVEL
bathroom	cabinet	deodorant*, facial tissue, how-water bottle, toilet paper, toothpaste, towel*
	sink	toothpaste
	sink cabinet	deodorant, toothpaste*, towel
	hook	towel
	toilet roll holder	toilet paper*
bedroom	bed	bedclothes
	bedside table	condoms*, facial tissue*, newspaper / magazine
	cabinet	bedclothes*, facial tissue, hot-water bottle*, towel
	entertainment center	DVD / Bluray
	wardrobe	bedclothes, socks*, swimwear*, underwear*
cellar: storing room / laundry	cabinet	batteries, coca cola, facial tissue, hot-water bottle, laundry detergent, milk, peas, potato crisps, toilet paper
	washing mashine	laundry detergent*
corridor / entrance	cabinet	batteries
	shoe cabinet	shoes*
kitchen	cabinet	breakfast bags, chocolate bar*, coffee filter*, ketchup, peas*, potato crisps*, salt*, tabasco*
	drawer	batteries, breakfast bags*, cutlery*, salt
	fridge	coca cola*, fresh yeast*, ketchup*, milk*, mustard*, peas, tabasco
	sink cabinet	dishwasher tabs / powder*
	table	ball pen
	worktop	electric water kettle*
living room	cabinet	batteries*, board game*, chocolate bar, DVD / Bluray*, potato crisps
	computer	computer game
	entertainment center	DVD / Bluray
	table	ball pen, newspaper / magazine*
office	cabinet	batteries, college block, glue
	computer	computer game*
	desk	ball pen*, college block*, facial tissue, glue*, newspaper / magazine

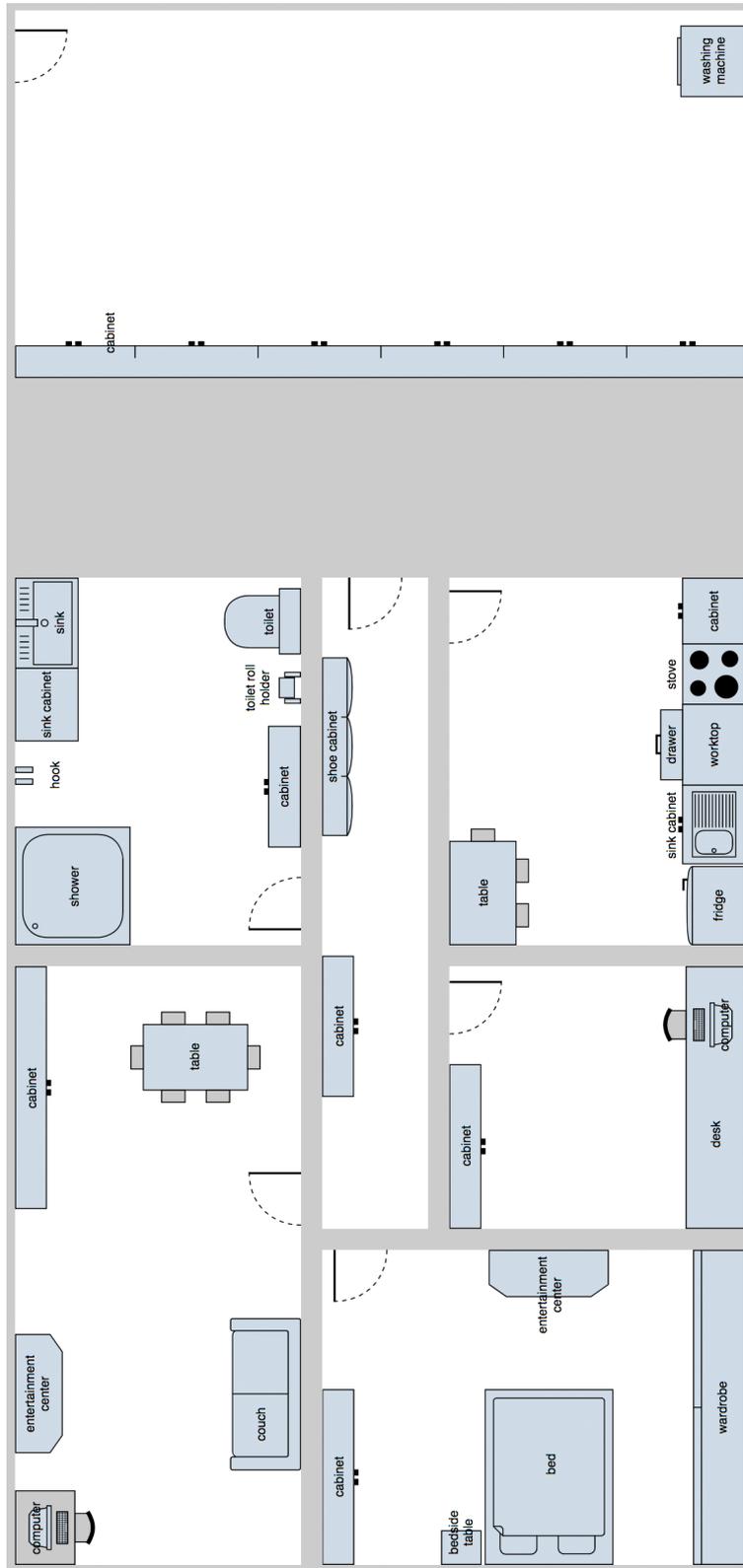
\* Storing places used during the conducted main study.

# A.4 Market Map (unfolded)





## A.5 Apartment Map (unfolded)



## A.6 Product Groups

Product Group 1 (Used for search tasks with the map-based menus.)	Product Group 2 (Used for search tasks with the linear menus.)
salt DVD / Bluray swimwear potato crisps ball pen mustard hot water kettle underwear breakfast bag glue bedclothes shoes toothpaste socks towel board game deodorant cutlery  error rate = ~21.1%	tabasco coffee filter hot water bottle fresh yeast laundry detergent dishwater tabs / powder computer game toilet paper facial tissues newspaper / magazine batteries ketchup college block condoms coca cola milk peas chocolate bar  error rate = ~22.2%

## A.7 Informed Consent Form

Title of this study	study for evaluating different menu types in online shops
Who is carrying out this study?	The study is carried out by the student <b>Nadja Rutsch</b> as part of her master thesis in the area of media informatics.
Why is this study carried out?	The purpose of this study is to evaluate and compare four menu types for online shops by collecting information on <b>speed, error rate and subjective preferences</b> .
What has to be done by the participants?	During this study, every participant uses <b>four online shops with different menu types</b> in order to <b>search 18 products</b> . Additionally, a few <b>questionnaires</b> have to be filled in.
How long does the study take?	The study takes <b>about 50 minutes</b> .
What are the risks of this study?	There are <b>no known risks</b> arising through the participation in this study.
How obligatory is this study?	The participation in this study is completely <b>voluntary</b> . If you decide to take part in this study, you are free to stop participating at any time.
What happens if I have a question?	If you have any questions, you can contact the responsible researcher at any time.
Confidentiality obligation	The data which is recorded during this study are kept <b>confidential</b> . This means that your <b>data</b> always stays <b>anonymous</b> .  In the thesis as well, all your statements will be anonymous by <b>removing all identifying characteristics</b> from them.
Consent	With your signature, you confirm that you are <b>at least 18 years old</b> that the study has been explained to you, meaning that all your questions have been answered in every detail and that you have decided <b>voluntarily</b> to participate in this study.
Name, Date	
Signature	

## A.8 Descriptive Results – Menu Types

	<b>Map-Based Apartment</b> (M, SD)	<b>Map-Based Traditional</b> (M, SD)	<b>Linear Apartment</b> (M, SD)	<b>Linear Traditional</b> (M, SD)
Success Rate	(98.61, 11.72)	(81.48, 38.89)	(91.44, 28.02)	(69.44, 46.12)
Click Count	(3.54, 0.97)	(3.45, 1.06)	(3.88, 1.54)	(3.48, 0.97)
Task Compl. Time	(7.96, 3.80)	(11.31, 6.17)	(9.68, 5.58)	(11.31, 5.89)
User Experience	(2.10, 0.53)	(0.38, 1.27)	(1.16, 1.18)	(-0.76, 1.15)
Attractiveness	(2.15, 0.58)	(0.28, 1.31)	(1.08, 1.24)	(-0.87, 1.25)
Perspicuity	(2.44, 0.70)	(0.49, 1.50)	(1.72, 1.27)	(-0.19, 1.76)
Efficiency	(2.11, 0.60)	(0.27, 1.40)	(1.31, 1.29)	(-0.56, 1.68)
Dependability	(2.00, 0.63)	(0.51, 1.16)	(1.41, 0.90)	(-0.35, 1.28)
Stimulation	(1.88, 0.81)	(0.43, 1.36)	(0.78, 1.52)	(-0.99, 1.09)
Novelty	(2.01, 1.04)	(0.28, 1.71)	(0.66, 1.61)	(-1.59, 1.13)
Usability	(89.17, 8.16)	(61.98, 18.87)	(80.94, 17.19)	(50.73, 26.66)
Workload	(22.10, 10.78)	(49.26, 22.22)	(30.88, 19.48)	(61.04, 18.69)
Mental Demand	(26.04, 16.01)	(53.33, 22.78)	(31.88, 20.31)	(62.50, 21.32)
Physical Demand	(12.50, 8.34)	(22.08, 22.74)	(16.46, 15.36)	(23.54, 24.38)
Temporal Demand	(26.67, 20.41)	(56.67, 22.15)	(34.79, 24.07)	(67.71, 22.65)
Performance	(28.13, 25.32)	(51.04, 22.84)	(34.38, 22.76)	(63.13, 22.98)
Effort	(22.08, 17.56)	(48.33, 22.15)	(30.63, 21.08)	(58.13, 21.51)
Frustration	(15.00, 15.39)	(43.75, 26.63)	(24.58, 22.36)	(61.04, 23.59)
SUS Mean	(4.29, 1.10)	(3.69, 1.38)	(2.76, 1.44)	(1.53, 0.56)
SUS Count	(1.63, 1.76)	(0.96, 1.73)	(0.54, 1.44)	(0, 0)

Descriptive statistical performance and preference results including mean (M) and standard deviation (SD) with regard to the four different menu types.

## A.9 Descriptive Results – Menu Characteristics

	<b>Map-Based</b> (M, SD)	<b>Linear</b> (M, SD)	<b>Apartment</b> (M, SD)	<b>Traditional</b> (M, SD)
Success Rate	(90.05, 29.96)	(80.44, 39.69)	(95.02, 21.76)	(75.46, 43.06)
Click Count	(3.50, 1.01)	(3.71, 1.34)	(3.70, 1.29)	(3.47, 1.02)
Task Compl. Time	(9.47, 5.28)	(10.38, 5.77)	(8.79, 4.82)	(11.31, 6.04)
User Experience	(1.24, 1.30)	(0.20, 1.50)	(1.63, 1.02)	(-0.19, 1.33)
Attractiveness	(1.22, 1.38)	(0.11, 1.58)	(1.62, 1.10)	(-0.30, 1.39)
Perspicuity	(1.46, 1.52)	(0.77, 1.80)	(2.08, 1.08)	(0.15, 1.65)
Efficiency	(1.19, 1.42)	(0.38, 1.76)	(1.71, 1.08)	(-0.15, 1.59)
Dependability	(1.26, 1.19)	(0.53, 1.41)	(1.70, 0.83)	(0.08, 1.28)
Stimulation	(1.15, 1.33)	(-0.10, 1.58)	(1.33, 1.32)	(-0.28, 1.41)
Novelty	(1.15, 1.65)	(-0.47, 1.79)	(1.33, 1.51)	(-0.66, 1.72)
Usability	(75.57, 19.89)	(65.83, 26.93)	(85.05, 13.95)	(56.35, 23.54)
Workload	(35.68, 22.06)	(45.96, 24.27)	(26.49, 16.19)	(55.15, 21.17)
Mental Demand	(39.69, 23.87)	(47.19, 25.76)	(28.96, 18.33)	(57.92, 22.31)
Physical Demand	(17.29, 17.62)	(20.00, 20.47)	(14.48, 12.39)	(22.81, 23.34)
Temporal Demand	(41.67, 25.96)	(51.25, 28.48)	(30.73, 22.46)	(62.19, 22.85)
Performance	(39.58, 26.51)	(48.75, 26.89)	(31.25, 24.02)	(57.08, 23.47)
Effort	(35.21, 23.81)	(44.38, 25.24)	(26.35, 19.67)	(53.23, 22.16)
Frustration	(29.38, 25.96)	(42.81, 29.26)	(19.79, 19.60)	(52.40, 26.38)
SUS Mean	(3.99, 1.27)	(2.15, 1.25)	(3.53, 1.48)	(2.61, 1.51)
SUS Count	(1.29, 1.76)	(0.27, 1.05)	(1.08, 1.69)	(0.48, 1.30)

Descriptive statistical performance and preference results including mean (M) and standard deviation (SD) with regard to the two representations and the two categorisations.

## A.10 ANOVA Results

	Menu Type	Representation	Categorisation
	$(F_{3,1724}, p, \eta^2)$	$(F_{1,1724}, p, \eta^2)$	$(F_{1,1724}, p, \eta^2)$
Success Rate	(60.71, <0.01, 0.10)	(34.96, <0.01, 0.02)	(144.94, <0.01, 0.08)
	$(F_{3,1469}, p, \eta^2)$	$(F_{1,1469}, p, \eta^2)$	$(F_{1,1469}, p, \eta^2)$
Click Count	(10.68, <0.01, 0.02)	(9.03, <0.01, 0.01)	(15.40, <0.01, 0.01)
Task Compl. Time	(33.96, <0.01, 0.07)	(9.35, <0.01, 0.01)	(78.12, <0.01, 0.05)
	$(F_{3,92}, p, \eta^2)$	$(F_{1,92}, p, \eta^2)$	$(F_{1,92}, p, \eta^2)$
User Experience	(30.61, <0.01, 0.50)	(22.46, <0.01, 0.20)	(69.17, <0.01, 0.43)
Attractiveness	(30.40, <0.01, 0.50)	(22.87, <0.01, 0.20)	(68.31, <0.01, 0.43)
Perspicuity	(18.03, <0.01, 0.37)	(6.27, <0.05, 0.06)	(47.80, <0.01, 0.34)
Efficiency	(19.41, <0.01, 0.39)	(9.44, <0.01, 0.09)	(48.80, <0.01, 0.35)
Dependability	(24.46, <0.01, 0.44)	(12.23, <0.01, 0.12)	(60.72, <0.01, 0.40)
Stimulation	(22.35, <0.01, 0.42)	(25.20, <0.01, 0.22)	(41.43, <0.01, 0.31)
Novelty	(26.84, <0.01, 0.47)	(31.64, <0.01, 0.26)	(48.04, <0.01, 0.34)
Usability	(20.62, <0.01, 0.40)	(6.37, <0.05, 0.07)	(55.34, <0.01, 0.38)
Workload	(22.22, <0.01, 0.42)	(7.58, <0.01, 0.08)	(58.93, <0.01, 0.39)
Mental Demand	(17.49, <0.01, 0.36)	(3.29, >0.05, 0.04)	(49.02, <0.01, 0.35)
Physical Demand	(1.77, >0.05, 0.06)	(0.50, >0.05, 0.01)	(4.70, <0.05, 0.05)
Temporal Demand	(17.34, <0.01, 0.36)	(4.41, <0.05, 0.05)	(47.51, <0.01, 0.34)
Performance	(11.01, <0.01, 0.26)	(3.65, >0.05, 0.04)	(29.01, <0.01, 0.24)
Effort	(15.13, <0.01, 0.33)	(4.73, <0.05, 0.05)	(40.65, <0.01, 0.31)
Frustration	(20.11, <0.01, 0.40)	(8.66, <0.01, 0.09)	(50.96, <0.01, 0.36)
SUS Mean	(25.15, <0.01, 0.45)	(59.07, <0.01, 0.39)	(14.66, <0.01, 0.14)
SUS Count	(5.51, <0.01, 0.15)	(12.20, <0.01, 0.12)	(4.28, <0.05, 0.04)

Results of the ANOVA with menu type, representation, categorisation as factors and task performance and user preference aspects as dependent variables.