User Acceptance of 'Smart Products': An Empirical Investigation

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ABSTRACT

Smart Products pose a new class of IT artifacts based on sensors, ID-tags, haptic user interfaces, and other technologies usually subsumed under the notion of 'ubiquitous computing'. Such devices differ in many ways from traditional computers, e.g., with regard to their physical shape, computing power, and interaction paradigms. While a substantial body of literature already exists on underlying technological design challenges, only few researchers have attempted to quantitatively explore factors influencing user acceptance of Smart Products. Against this background, the present study is concerned with the use of Smart Products in a kitchen environment. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), we develop and empirically test a structural model of technology acceptance including five moderating factors. Our results indicate high overall acceptance of the proposed scenarios, corroborate the applicability of the UTAUT model for smart home environments, and confirm significant effects for two moderators.

Keywords

Smart Products, UTAUT, Pervasive computing/ubiquitous computing, Moderating Effect, Technology acceptance model

1. INTRODUCTION

'Ubiquitous Computing' [47], 'Pervasive Computing' [38], 'Things that think' [23], 'Ambient Intelligence' [1], 'Silent Commerce' [16] – a plethora of novel terms has evolved in recent years that propagate the coming of a new paradigm shift in information processing. Common to all these concepts is the shared vision of a future world of everyday physical objects equipped with digital logic, sensors, and networking capabilities [18]. Drivers behind the ongoing trend towards this vision are both miniaturization of microelectronic components and price decline as well as various new technologies reaching mass-market maturity, e.g., in the area of polymer electronics or wireless networks. On the one hand, these so-called 'Smart Products' allow manufacturing companies to differentiate themselves from their competitors by enriching

physical items with digital functionality. On the other hand, the linkage of products with services in the Internet allows for the creation of novel product-service bundles that not only generate a continuous stream of additional revenues but also hold the potential to support new product development by providing companies with valuable information on their products' usage and to strengthen customer relationships.

Smart Products have become a fruitful research area on the interface of electrical engineering, computer science, and information systems. While a substantial body of literature on the associated design challenges (e.g., middleware architectures, multi-modal user interfaces, ad-hoc networking protocols) already exists, only few authors have so far conducted behaviorist research on the factors influencing user acceptance of this new class of IT artifacts. Smart Products differ in many ways from traditional computers, be it desktop PCs or mobile devices, which makes transferability of results from prior technology acceptance research seem questionable. For example, haptic user interfaces on the basis of gesture detection or acceleration sensors provide product owners with an entirely different user experience than the classical desktop environments known from today's graphical user interfaces. On the other hand, computing devices that merge with the physical world – and thus become 'invisible' to certain degree – might also lead to entirely different perceptions of IT than their classical counterparts and even evoke negative reactions to the point of fears from technology paternalism and ubiquitous surveillance [42].

It is against this background that the present study is concerned with the acceptance of Smart Products by end users. For this purpose, we consider the example of a 'smart kitchen' environment that encompasses a number of household appliances and associated digital services that are supposed to support their owner in everyday activities, such as preparing a meal. Based on the 'Unified Theory of Acceptance and Use of Technology' (UTAUT) proposed by Venkatesh et al. [46] and other prior research on technology acceptance, we develop and empirically test a structural model for the explanation and prediction of the users' intention to use a Smart Product. Our sample includes 166 responses to an online questionnaire covering five distinct application scenarios. This research contributes to the IS literature in two ways. First, we investigate the applicability of the UTAUT model to the domain of Smart Products and confirm its explanatory power for this new class of IT artifacts. Second, we extend the base model by five moderating factors and show that two of these play a significant role in varying acceptance behavior between different user groups. From a practical perspective, our

results indicate a generally positive perception of Smart Products by potential users and allow for drawing a number of managerial implications.

The remainder of the paper is organized as follows. We first provide an overview of the concept and the technologies underlying Smart Products. We continue with a review of related works on technology acceptance in general and smart products adoption in particular. Based on this review, we then develop our research model and formulate a set of hypotheses to be tested. Fourth, we describe our research methodology including survey design, data collection, and statistical analysis. The paper closes with a discussion of theoretical and managerial implications, limitations, and suggestions for further research.

2. Technological Background

Research on Smart Products is still scattered across different research streams covering aspects of technology and management. As a consequence, there is no unified definition of the term 'Smart Product' and different notions exist depending on the respective research perspective or application area. What can be said is that Smart Products denote an emerging class of products, which integrate different facets of Ubiquitous Computing technologies in order to provide a richer user experience particularly through connectivity to other products and proactive behavior. Smart Products possess capabilities to act jointly, complement each other, and thus establish a smart environment that goes beyond the isolated functionalities provided by conventional products. Motivated by various technological advances, a number of researchers have already considered this upcoming research issue in the past 20 years. An early proponent was Dhebar [15] who defines Smart Products as "physical products that have IT incorporated in them". In a similar way, Maass and Janzen [30] describe them as "hybrids of physical products and information products". However, as most electronic products today incorporate some kind of IT (e.g., microprocessors embedded in several household devices or cars), this definition is not sufficient for delimiting the scope of Smart Products. Allmendinger and Lombreglia [5] extend this conception by introducing the similar concept of "built-in product intelligence" as a combination of awareness and connectivity, which allows for creating a smart services portfolio around a product, particularly in an industrial setting. Examples for such services are remote maintenance, feature upgrades, or pay-per-use business models.

Smart Products are characterized by the fact that they make use of specific technologies and design principles mainly from the Ubiquitous Computing domain, in order to sense and communicate information about themselves, their condition, and the environmental context around them [18]. This real-time context awareness grants them the capability to act proactively with regard to internal state and context, adapt to different situations, interact with other Smart Products, and convey information across lifecycle boundaries. With respect to prior research on Ubiquitous Computing, Smart Products can be regarded as real-world manifestations of 'calm technologies' as formulated by Weiser [47], who envisioned "a physical world richly and invisibly interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly in the everyday objects of our lives and connected through a continuous network".

Aitenbichler et al. [4] summarize the idea of Smart Products by stating that "Smart Products are real-world objects, devices, or software services bundled with knowledge about themselves, others, and their embedding". This definition sets the focus on the knowledge dimension and emphasizes the capability of autonomous behavior depending on context information. Other contributions define Smart Products by listing a number of characteristic constituents. Rijsdijk and Hultink [35], for instance, postulate that seven dimensions determine the smartness of a product: autonomy, adaptability, reactivity, multi-functionality, the ability to cooperate, humanlike interaction, and personality. They also point out that the smartness of products is a broad continuum that is determined by the extent to which the seven dimensions are fulfilled, which leads to physical objects that "share the ability to collect, process, and produce information and can be described as 'thinking' for themselves".

From a technological perspective three aspects constitute Smart Products: First, network technologies such as Wi-Fi, Bluetooth, UMTS, and Auto-ID technologies such as RFID enable Smart Products to communicate with each other so that a smart environment can emerge. Second, sensors are required to capture the user context, which enables Smart Products to adapt to the user situation and act proactively and in a smart way. Third, sufficient computing power is required to execute smart behavior. To achieve smart behavior with limited computational resources, a number of research programs and initiatives have recently been started, which majorly focus on three aspects [4][6][40]: a first technology-oriented research stream explores the application of semantic modeling of context, product behavior, and interaction. A second stream is concerned with new techniques for superior human-computer interaction as not all smart products will be able to include conventional screen-based user interfaces. Third, researchers are exploring new middleware architectures that are tailored to the specific needs of Smart Products development. Such middleware is designed to connect the Smart Product to internal and external sensors and actuators, to establish communication to other Smart Products and back-end services, and to establish a programming platform that hides the details of a plethora of existing embedded technology stacks.

3. Related Work

Our study focuses on Smart Products in home environments. Strictly speaking, we investigate user acceptance towards a smart kitchen environment that consists of five functional scenarios. In this section we shortly review the literature on the theoretical foundations of our research as well as academic and industrial activities that relate to applications in the home appliances domain.

Research on user acceptance of information technology originates from different theoretical disciplines such as psychology, sociology, and information systems. Various alternative approaches have been proposed to analyze the acceptance and use of a new technology. The majority of technology acceptance models are based on the Theory of Reasoned Action (TRA) [17]. TRA posits that an individual behavioral intention towards a specific behavior can be considered as a proxy of the behavior itself [46]. The Technology Acceptance Model (TAM) [14] has become the most prevalent model for studying user acceptance in the field of information technology. TAM includes two major predictors of the dependent variable *Behavioral Intention*, which

TRA assumes to be closely linked to actual behavior: *Perceived Ease of Use* and *Perceived Usefulness*. More recently, the Unified Theory of Acceptance and Use of Technology (UTAUT) [46] has been proposed, which integrates TAM and the more advanced TAM2 with other technology acceptance research streams. UTAUT represents a parsimonious but still comprehensive framework to provide an understanding of factors that affect technology acceptance, and could be confirmed in a large number of research works (see [43] for a review).

Regarding empirical acceptance studies, there is only a relatively small number of prior studies investigating user acceptance of Ubiquitous Computing and related concepts. Garfield [21] presents results from a longitudinal, qualitative study of the acceptance of Tablet PCs based on interview data from four industries. Main findings include a list of factors that influence the predictors of *Behavioral Intention* in the UTAUT model as well as the identification of the technology's impact on work processes. Sheng et al. [41] studied interaction effects of personalization and context on intention to adopt. They conclude that increasing personalization raises privacy concerns, and the degree of this relationship is moderated by situational context.

Whereas these studies analyze various manifestations of the Smart Product concept, contributions on smart home environments in particular are rather scarce. Vastenburg [44] investigate in a simulated environment, to which degree consumers appreciate home automation applications. They conclude that, in general, consumers have a positive attitude towards home automation. Key success factors for home automation applications are *Ease of Use* and *Predictability*, the latter meaning that consumers understand and foresee the behavior of the system. After evaluating user acceptance of an intelligent thermostat control, Freudenthal and Mook [20] conclude that users carefully weigh benefits and drawbacks of new technologies. Major drawbacks are the difficulty to operate, the insufficient level of control, and privacy concerns, whereas usability is of utmost importance for user acceptance.

With regard to smart kitchen environments, previous studies focused only on a limited number of constituents. So far, research in the kitchen environment has mainly focused on nutrition [24], recipe planning [26], or communications [8]. Although having tested early prototypes with users, these studies are not based on the analysis of larger samples. The only exception we are aware of is a user acceptance study by Rothensee [37] concerning a simulated 'smart fridge', which offers various assistance functions (product information, automatic replenishment, recipe planner). The results indicate that *Perceived Usefulness* is the strongest predictor to *Behavioral Intention*, followed by emotional response to the product. The role of moderating factors (gender, technological competence, sense of presence in a simulation) could not be supported.

4. Research Model

In this section, we describe the research model underlying the study as depicted in Figure 1. Our research

objective is to analyze the user acceptance of a 'smart kitchen' as an example of a Smart Product environment in the home appliance domain. The most obvious choice regarding the theoretical framework for a study like ours seems to be the classical TAM, which has been used as the foundation for several IT acceptance studies in recent years. For the present study however, TAM may have only limited ability to explain smart products acceptance because it neglects the social context in which a technology is being adopted. We consider the social context to be highly important, because smart kitchen appliances are targeting at the consumers' kitchens and homes. For this reason, we decided to construct and test a research model on the foundation of the more advanced UTAUT framework and its constructs as proposed by Venkatesh et al. [46].

Whereas UTAUT has served as the theoretical foundation to many analyses, particularly in industrial settings, it has not yet been applied specifically to smart environments in the domestic domain. Further, moderator variables proposed in the original model are not specifically targeted to the typically voluntary use of the investigated application in the private domain. While basic technology acceptance models have largely matured, the investigation of moderating effects to understand external factors that influence adoption decisions is still under-developed and needs to be further elaborated [13][43]. We intend to fill this two-fold research gap by applying the UTAUT model to the case of a smart kitchen environment and by introducing additional moderating variables to capture consumer traits and external factors that may influence adoption decisions.

The original UTAUT model posits that four independent variables determine an individual's intention to use a technology: *Performance Expectancy*, *Effort Expectancy*, *Social Influence*, and *Facilitating Conditions*. *Performance Expectancy* is defined as the degree to which an individual believes that using a particular technology will help him or her to attain performance gains. *Effort Expectancy* is defined as the degree of ease associated with the use of a particular technology. *Social Influence* is defined as the degree to which an individual perceives that important others believe he or she should use the new technology. *Facilitating Conditions* are defined as the degree to
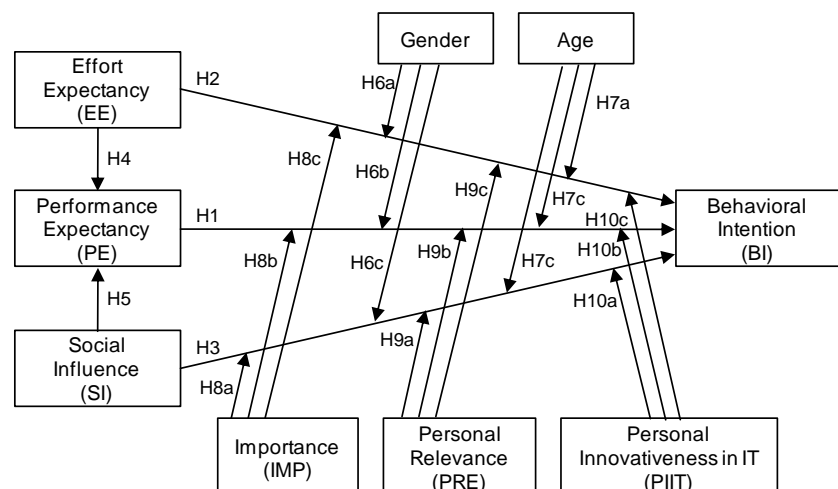

Figure 1: Research Model

which an individual believes that an organizational and technical

infrastructure exists to support use of the new technology. *Gender*, *Age*, *Experience*, and *Voluntariness of Use* moderate the key relationships in this model.

To adjust the UTAUT model to our research setting, we made the following modifications to the original model. First, we eliminated the constructs *Use Behavior* and *Facilitating Conditions* because due to the lack of a working prototype, *Use Behavior* cannot be observed. However, *Behavioral Intention* has shown to be a good predictor of actual behavior as posited by the TRA and could be confirmed in many studies [48]. Second, we added indirect relationships from *Effort Expectancy* and *Social Influence* on *Performance Expectancy* because this relationship was supported by the results from many prior technology acceptance studies [28][29][39]. Third, we eliminated two moderators from the original UTAUT model: *Voluntariness of Use* was eliminated, because the adoption of the proposed smart kitchen environment will, in contrast to workplace settings, always occur on a voluntary basis. *Experience* was eliminated, because in the original UTAUT study *Experience* was examined using a cross-sectional analysis from the time of the artifact's introduction to later stages of greater experience. Due to the early stage of development, and the unavailability of a commercial product, asking respondents at different points in time was not feasible. Fourth, we decided to introduce three additional moderating variables (*Importance*, *Personal Relevance,* and *Personal Innovativeness in IT*), which will be motivated below.

With regard to the direct and indirect relationships between the independent and the dependent variable, we therefore hypothesize the following:

H1: *Performance Expectancy* has a positive effect on *Behavioral Intention*.

H2: *Effort Expectancy* has a positive effect on *Behavioral Intention*.

H3: *Social Influence* has a positive effect on *Behavioral Intention*.

H4: *Effort Expectancy* has a positive effect on *Performance Expectancy*.

H5: *Social Influence* has a positive effect on *Performance Expectancy*.

Prior studies observed a high variability in the corresponding correlations, which suggests that moderator variables may exert a significant influence (e.g., [29][39][43]. Moderation occurs when the relationship between two variables depends on a third variable such as gender or age. As a consequence, the introduction of moderating factors can improve the often limited explanatory power and inconsistencies in existing technology acceptance studies. Therefore we introduce five moderating variables, which we regard as important in the proposed application setting.

First, we consider the differences in acceptance behavior between men and women [31][45]. Men have shown to be usually more pragmatic and task-oriented than women. Moreover, men usually

feel more comfortable using new technologies. On the other hand, women compared to men have been found to have a higher awareness of other's feelings, and, in turn, are more influenced by others. Therefore, it seems likely that men are more driven by *Performance Expectancy*, whereas women are more driven by *Effort Expectancy* and *Social Influence*. Compared with *Gender*, *Age* has received less attention in the existing literature. Young users have been found to be more driven by *Performance Expectancy*, while older users are more driven by *Effort Expectancy* [32][46]. It has also been proposed that older users are more influenced by social factors, because affiliation increases with age and older people are more likely to conform to others' opinions [43]. In accordance with the original UTAUT model, we therefore hypothesize that *Gender* and *Age* play a moderating role in our research model.

H6a: For women the effect of *Effort Expectancy* on *Behavioral Intention* is higher than for men.

H6b: For men the effect of *Performance Expectancy* is higher than for women.

H6c: For women the effect of *Social Influence* on *Behavioral Intention* is higher than for men.

H7a: For older people the effect of *Effort Expectancy* is higher than for younger people.

H7b: For younger people the effect of *Performance Expectancy* is higher than for older people.

H7c: For older people the effect of *Social Influence* is higher than for younger people.

Beyond the logic of the original UTAUT model, we introduce additional hypotheses regarding the moderating influences of *Importance*, *Personal Relevance*, and *Personal Innovativeness in IT*. Prior work has investigated the role of involvement on consumer decisions [49]. Barki and Hartwick [7] investigated its role in the context of information systems development. They define involvement as "a subjective psychological state, reflecting the importance and personal relevance of an object or event". We argue that, following this definition and subsequent applications of the construct, involvement encompasses two different but important factors that influence technology adoption, namely *Importance* and *Personal Relevance*. In the context of our kitchen scenario, *Importance* denotes the extent of intrinsic desire or personal need for support throughout the preparation of a meal. In contrast to that, *Personal Relevance* denotes an individual's general dedication and interest in the application domain. The construct reflects to which extent cooking in general is relevant to an individual. As such it clearly differentiates from the *Importance* construct. For example, cooking can be very relevant for a person when he or she is often preparing food. At the same time, getting help in the kitchen may not be important for the same person because he or she is already very skilled. We therefore decided to split the originally proposed involvement construct into the two aspects *Importance* and *Personal Relevance* by introducing separate constructs.

One of the objectives behind the concept of a 'smart kitchen' is to help users to select and prepare healthier and more tasteful dishes. We theorize that the more a potential user feels that it is important for him to get support in the kitchen the more important becomes *Performance Expectancy* as a predictor, whereas the importance of *Effort Expectancy* and *Social Influence* will diminish.

H8a: The effect of *Effort Expectancy* decreases with higher *Importance*.

H8b: The effect of *Performance Expectancy* increases with higher *Importance*.

H8c: The effect of *Social Influence* decreases with higher *Importance*.

We further theorize that higher *Personal Relevance* increases the strength of the effect that *Performance Expectancy* exerts on *Behavioral Intention* because functional aspects will be more important than usability or social aspects. Consequently, the significance of *Effort Expectancy* and *Social Influence* should diminish.

H9a: The effect of *Effort Expectancy* decreases with higher *Personal Relevance*.

H9b: The effect of *Performance Expectancy* increases with higher *Personal Relevance*.

H9c: The effect of *Social Influence* decreases with higher *Personal Relevance*.

Finally, we add the construct *Personal Innovativeness in the domain of Information Technology* (*PIIT*) as a moderating factor to our model. Agarwal and Prahad [2] introduced this construct as a moderating variable into technology acceptance research. In the context of a novel technology that only few people are familiar with, it could be expected that innovativeness plays an important role in an individual's acceptance behavior. We therefore theorize that in the home domain, people with different levels of *Personal Innovativeness* show different adoption behavior.

H10a: The effect of *Effort Expectancy* decreases with higher *PIIT*.

H10b: The effect of *Performance Expectancy* increases with higher *PIIT*.

H10c: The effect of *Social Influence* decreases with higher *PIIT*.

Table 1: Validation of the measurement model

Construct	Item	Loading	Mean	SD	α	CR	AVE
Behavioral Intention (BI)	BI1	0.96	4.24	1.77	0.95	0.97	0.91
	BI2	0.95					
	BI3	0.94					
Effort Expectancy (EE)	EE1	0.90	5.01	1.47	0.82	0.89	0.74
	EE2	0.88					
	EE3	0.79					
Social Influence (SI)	SI1	0.78	3.69	1.74	0.82	0.89	0.74
	SI2	0.91					
	SI3	0.88					
Performance Expectancy (PE)	PE1	0.88	4.68	1.68	0.85	0.91	0.77
	PE2	0.88					
	PE3	0.88					
Importance (IMP)	IMP1	0.76	4.21	1.9	0.73	0.84	0.64
	IMP 2	0.88					
	IMP 3	0.76					
Personal Relevance (PRE)	PRE1	0.91	5.01	1.69	0.83	0.89	0.73
	PRE2	0.86					
	PRE3	0.79					
Personal Innovativeness in IT (PIIT)	PIIT1	0.76	5.40	1.69	0.77	0.87	0.77
	PIIT2	0.98					

5. Data Collection

5.1 Instrument Development

To test the research model and the associated hypotheses proposed above, we designed a questionnaire on the basis of existing scales from the technology acceptance literature (a list of questionnaire items can be requested from the authors). The measurement scales for the main constructs were operationalized by adopting items from [46] and adapting them to the specific context of our smart kitchen environment. For constructing measurement scales for *Importance* and *Personal Relevance*, we referred to [7] and [49]. *Personal Innovativeness in Information Technology* was operationalized using the scale developed by [2].

The focus of our study is on a complex smart kitchen environment, which incorporates different Smart Products that interact with each other and show context-aware behavior. It is constituted of the following functional blocks: A *Smart Kitchen Interaction Pad*, a Tablet-PC-like device, is the central user interface for the smart kitchen. It provides meal recommendations based on available ingredients and kitchen utensils as well as personal preferences. To guide users in their preparation process, textual and visual presentations provide step-by-step instructions that are synchronized with the actual preparation progress. Smart kitchen utensils can be parameterized according to recipe information, and they give feedback on ongoing activities and status information (e.g. temperature, weight, processing times). A recipe memorization function allows for recording preparation processes including sensorial information from the smart kitchen

tools. Once a recipe is chosen, the user can retrieve a shopping list either as a print-out or on a mobile phone. The shopping list considers which ingredients are already available in the household. Finally, the user can monitor his or her nutrition habits. Consumption in the smart kitchen is automatically recorded, and a mobile application enables users to track non-domestic consumption.

As the described smart kitchen environment is not yet physically available, we have taken a scenario-based approach. For each of the five functional blocks, we developed a detailed textual scenario description, which was complemented by a graphical illustration created by a professional graphics designer. For each scenario, interviewees were asked the same set of questions with minor adaptations to the specific context. All items were measured using a seven-point Likert scale. All constructs were formulated in a reflective mode. To further assure content validity, we followed a two-step process. First, each item was reviewed by three industry experts from a home equipment manufacturer and three academic experts in the area of Smart Products research. This resulted in a small number of changes to the wording and the overall structure of the questionnaire. The revised questionnaire was then circulated among the same group of experts and was then consistently rated as comprehensive and complete. In a pre-test, we then asked ten persons to fill in the questionnaire and provide us with feedback, which led to minor changes for reasons of clarity and comprehensiveness.

5.2 Sample and Descriptive Statistics

The data for the present study were gathered via an online survey, which was accessible for two months starting from September 2009. The participation was anonymous, voluntary, and there were no rewards for participation, which can be interpreted to mean that there should be no confounding effects from coercing subjects into participation or due to subjects that are just after some reward. The survey took about 25 minutes to complete.

600 people in different European countries were contacted by email, of which 175 completed the survey. The survey was designed in a way that participants had to answer all questions before they were able to submit the questionnaire. After an initial screening of the data, nine cases were removed from the sample, because of certain patterns that suggested unreliable responses (e.g., the same response category was checked for all questions). The resulting sample comprised 166 subjects corresponding to a final response rate of 28%. The proportion of gender is almost balanced with 46% of the respondents being female. 39% of respondents were younger than 30 years, 30% were between 31 and 40, 22% between 41 and 50, and 9% older than 51 years.

6. Data Analysis

6.1 Measurement Model

The questionnaire presented five partial scenarios, which were rated separately applying the same scales. This approach allowed for investigating a complex environment consisting of several different technological artifacts on a detailed level. To test whether the five scenarios had been rated in a consistent way, we applied t-tests on construct level to compare each scenario with each other. The results revealed that there were no significant differences at $p < 0.05$ between construct means across all scenarios. Consequently, each scenario can be regarded as *pars pro toto* so that we could aggregate the five scenarios on item level for our further analysis instead of analyzing each scenario separately. As a consequence, we were able to use a questionnaire on a fine-grained functional level and at the same time investigate the smart kitchen environment as a whole.

We applied Partial Least Squares Path Modeling (PLS) as a Structural Equation Modeling (SEM) technique to test the research model. We favored PLS over first generation regression techniques because of its ability to model relationships among different constructs simultaneously and to handle measurement errors [10]. Furthermore, we favored PLS over the covariance-based SEM approach because under conditions of non-normality, moderate effect sizes, and smaller samples, the PLS approach appears preferable [22][34]. The data points of survey-collected data usually do not follow a multivariate normal distribution, which is an important precondition of the covariance-based approach but not for PLS [11]. In addition to that, we asked for the respondents' opinion regarding several different scenarios. Therefore, the observations in our study are not fully independent from each other, which is another assumption for the covariance-based approach. In contrast, independence of observations is not an assumption of PLS [11].

We employed the PLS implementation of Smart-PLS version 2.0M3 [36] with a 5000 sample bootstrapping technique for model assessment. All statistical tests were assessed with two-tailed t-tests. In a first step, we assessed the measurement model to ensure that good construct measures are represented in a valid structural model. Table 1 shows the results of our factor analysis. All item loadings are well above the threshold of 0.707, indicating that over half of the variance is captured by the latent construct [11][22]. No problematic cross-loadings could be observed. Further, Cronbach's α and composite reliability values as measures for internal consistency are well above the recommended value of 0.7 for each construct [33]. Convergent validity [12], which refers to the degree to which the items measuring the same construct agree, is examined by considering the average variance extracted (AVE). Table 1 shows that it is well above the recommended threshold of 0.5 for all constructs [19].

Discriminant validity, which refers to the degree to which measures of distinct concepts differ, was examined by comparing the correlations between the measurement items of distinct constructs with the squared root of the AVE by each construct. The squared root of the AVE for each construct was higher than its correlations with other constructs indicating satisfactory discriminant validity (Fornell-Larcker criterion [19]).

6.2 Structural Model

With sufficient evidence from reliability and validity measures, the next step was to test the hypothesized paths and the explanatory power of the model. The explanatory power is examined by inspecting the R^2 values (i.e., the explained variance) of the dependent variables. Chin finds that R^2 values of 0.67, 0.33, and 0.19 in PLS path models should be regarded as substantial, moderate, and weak, respectively [11]. Because PLS does not assume a particular distribution, re-sampling techniques such as bootstrapping have to be used to determine statistical significance of the path coefficients. The corresponding t-values indicate whether the hypothesis that the respective parameter estimates equal zero must be rejected.

For the basic model without moderators, Figure 2 shows that we obtained R^2 values of 0.69 for *Behavioral Intention* and 0.52 for *Performance Expectancy*. Moreover, the t-tests conducted on the relationships reveal that all relationships are significant, and the absolute path weights show that they are sufficiently substantial. Therefore we accept hypotheses H1, H2, H3, H4, H5. Consequently, the relations between independent and dependent variables as proposed by our modified UTAUT model can be confirmed.

For an examination of moderation effects, we need to distinguish between categorical variables such as *Gender* and latent variables such as *Personal Relevance*, which we measured on a Likert scale. As proposed in [27] and applied in [34], [45], we adopted multiple t-tests to examine the moderation effects of *Gender* and *Age*. The PLS t-test uses the standard errors obtained from bootstrapping to test for group equality of path coefficients. The following statistic, which is asymptotically t-distributed with $m+n-2$ degrees of freedom, is calculated [27]:

$$ t = \frac{Path_{Sample\ 1} - Path_{Sample\ 2}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} * S.E._{Sample\ 1}^2 + \frac{(n-1)^2}{(m+n-2)} * S.E._{Sample\ 2}^2} \right] * \left[\sqrt{\frac{1}{m} + \frac{1}{n}} \right]} $$

In this formula, *m* and *n* denote the sample sizes of the two groups, $Path_{Sample1}$ and $Path_{Sample2}$ are the path coefficients for the path that is being compared, and $S.E._{Sample1}^2$ and $S.E._{Sample2}^2$ are the variances in each group for the paths that are compared. Our finding from this analysis is that only *Gender* has a moderating effect on the SI-BI relationship with p<0.01 (see Table 2). All other effects cannot be regarded as significant. Consequently, we accept hypothesis 6c, while we reject hypotheses 6a, 6b, 7a, 7b, and 7c.

To test *Importance*, *Personal Relevance*, and *Personal Innovativeness* for their moderating effects, we employed the product-indicator approach [10], which was specifically designed for continuous variables. With the
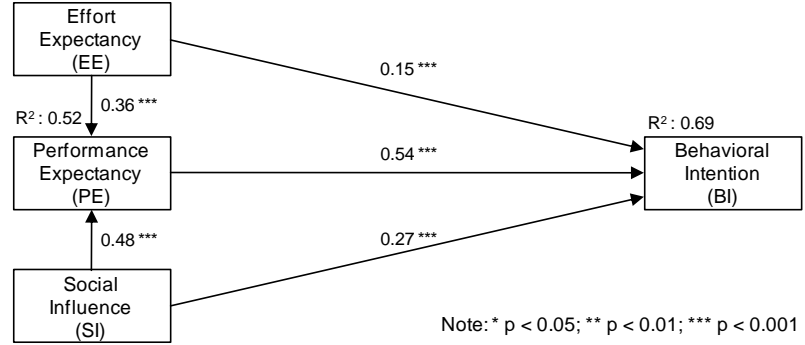

Note: * p < 0.05; ** p < 0.01; *** p < 0.001

Figure 2: Results for the strutural model

product-indicator approach, a new interaction construct is created by using the products of the indicators of the moderating construct and the predictor construct. An F-value based on the effect size is calculated to decide via an F-test whether there is a significant moderator effect [3][9][25]. The F-value is calculated according to the following formula:

$$ F = \frac{(R_2^2 - R_1^2)/(k_2 - k_1)}{(1 - R_2^2)/(N - k_2 - 1)} $$

R_1 and R_2 are the explained variances before and after introducing the interaction term; k_1 and k_2 represent the number of predictors before and after introducing the interaction term; *N* is the sample size. *F* then follows an F-distribution with $df_1=(k_2-k_1)$ and $df_2=(N-k_2-1)$ degrees of freedom. An F-test reveals whether the explained variances are significantly different for the two models. Following the results presented in Table 3, we can conclude that only *Importance* has a significant moderating effect with regard to the explained variance, although this effect turns out rather week if we compare the explained variances with and without the interaction term. Further, Table 3 shows that the moderating effect of *Importance* is significant only for two of the three tested relationships for p<0.05, namely the PE-BI and the SI-BI relationship. The effect on the EE-BI is not sufficiently significant. Consequently, hypotheses H8a, H8b can be accepted, whereas hypotheses 8c, 9a, 9b, 9c, 10a, 10b, and 10c are rejected.

Table 2: Moderating effects of categorial variables

Moderator		R^2		Path Coefficients		
		BI	PE	EE → BI	PE → BI	SI → BI
None		0.689	0.517	0.15 ***	0.54 ***	0.27 ***
Gender	Female	0.687	0.556	0.14 ***	0.51 ***	0.32 ***
	Male	0.693	0.480	0.16 ***	0.57 ***	0.21 ***
	T-Test	-	-	ns	ns	**
Age	≤ 40 y.	0.686	0.450	0.14 ***	0.54 ***	0.29 ***
	> 40 y.	0.700	0.647	0.17 ***	0.54 ***	0.22 ***
	T-Test	-	-	ns	ns	ns
Note: * p < 0.05; ** p < 0.01; *** p < 0.001						

7. Discussion

7.1 Theoretical Implications

The objective of this study was (i) to test the applicability of the proposed modification of the UTAUT research model, which was adapted to the smart kitchen domain, and (ii) to analyze which variables exert a moderating role on the predictor relationship of *Effort Expectancy*, *Performance Expectancy*, and *Social Influence* on *Behavioral Intention*. For this purpose, we developed a modified version of the UTAUT model, extending it by *Gender*, *Age*, *Importance*, *Personal Relevance*, and *Personal Innovativeness in IT* as moderator variables. Furthermore, we added indirect effects from *Effort Expectancy* and *Social Influence* as proposed and affirmed in prior works.

Empirical analysis using PLS confirmed the applicability of the modified UTAUT model in a smart kitchen environment. *Performance Expectancy* has shown to have the strongest direct effect on *Behavioral Intention*. *Effort Expectancy* and *Social Influence* act as significant predictors, too, but at a weaker level. Moreover, our analysis has shown that *Gender* poses a significant moderator of the relationship between *Social Influence* and *Behavioral Intention*. For women, *Social Influence* seems to work as a stronger predictor than for men, which can be interpreted such that it is relatively more important to women that friends and family would appreciate adopting the proposed technology. In contrast to the original UTAUT model, our data do not support the assumption that *Gender* would exert a significant influence on the other relationships in our study. The same holds true for *Age*, which could not be confirmed to be a significant moderator. Regarding the moderators that were added to the original model, only *Importance* showed a significant effect on the relationships of *Performance Expectancy* and *Social Influence* on *Behavioral Intention*. With increasing *Importance*, *Performance Expectancy* has a relatively stronger effect on *Behavioral Intention*, whereas the effect size of *Social Influence* decreases. *Personal Relevance* and *Personal Innovativeness in IT* could not be affirmed as moderators.

All considered, the basic structural model could be confirmed, whereas only few moderating effects could be found. Whereas *Gender* could be approved as a moderator in many studies, *Importance* seems to have a significant, albeit so far underestimated moderating role. Against the background of our results, we encourage to further investigate *Importance* as a measure of intrinsic motivation to accept a novel technology in the private domain.

7.2 Practical Implications

Besides the aforementioned theoretical implications, our study also allows for drawing conclusions relevant to practice, particularly in the home appliance domain. Descriptive results indicate that the proposed smart kitchen environment was perceived positively across several population groups. In particular, there were no major differences between older vs. younger persons, innovative vs. non-innovative persons, persons with and without technology-related educational backgrounds. We are in favor of interpreting these results such that smart kitchen environments, and perhaps smart home environments in general, have the potential to leave their narrow market niches and become broadly adopted by the home appliance industry. Consequently, it may be the right time for managers in charge at the respective companies to develop innovative product portfolios that make use of the *Smart Product* concepts as described in this paper.

At the same time, more research effort should be focused on the question why home automation, although commercially available for more than a decade, does not gain more attraction. Reasons may be found in missing standards and consequently a lack of interoperability between different vendors, consumers that fear lock-in, long investment cycles for home appliances, or merely a price premium that is regarded to be inappropriate in relation to the additional value. Our study has shown that consumers basically have a positive attitude towards such technologies, so reasons for non-adoption decisions require further investigation.

Not least, we can learn from this empirical investigation that consumers regard functional capabilities of a smart kitchen environment as key to their adoption decision, whereas potential adopters are less concerned about usability issues. With regard to *Social Influence*, we have seen that it is quite important for consumers that friends and family appreciate the smart kitchen environment. As a consequence for market introduction, marketing measures should not only focus on technological capabilities. In addition, an image campaign seems to be appropriate such that potential adopters get the feeling that they improve their social image by using a smart kitchen environment at home.

8. Summary and Outlook

In this study, we investigated user acceptance towards a smart kitchen environment. Smart environments emerge from the interplay of individual smart products, a novel class of product/service bundles enabled by digital technologies that show complex behavior through context-awareness, communication among each other, processing power, and a paradigm shift away from PC-like interfaces towards tangible human-computer interaction. As such, smart environments can be regarded as a

Table 3: Moderating effects of continuous variable

Moderator		R^2 (BI)	EE $\rightarrow$ BI	PE $\rightarrow$ BI	SI $\rightarrow$ BI
			Path Coefficients		
None		0.6887	0.15 ***	0.54 ***	0.27 ***
IMP	Direct Effect	0.6977	0.15 ***	0.52 ***	0.25 ***
	Interaction	-	0.03	0.08 *	-0.07 *
	F-Test	4.7923 *	-	-	-
PRE	Direct Effect	0.6934	0.14 ***	0.54 ***	0.27 ***
	Interaction	-	0.02	0.05	0.00
	F-Test	2.47	-	-	-
PIIT	Direct Effect	0.6915	0.14 ***	0.54 ***	0.27 ***
	Interaction	-	-0.02	0.00	0.06
	F-Test	1.46	-	-	-
Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$					

concrete implementation of the ubiquitous computing paradigm for a specific domain. Our study has shown that potential adopters appreciate such novel approaches. In contrast to our initial expectation, usability was regarded as a minor issue whereas performance and social aspects turned out to be more important. We contributed to technology acceptance research by proposing an adapted version of the UTAUT model, and by demonstrating its practicability as an analytical tool in the smart home environment domain. Furthermore, we tested several constructs for their moderating effect and concluded that *Gender* and *Importance* play a significant role.

Even though every effort has been made to ensure the validity of our findings, the present study comes with limitations that point to opportunities for further research. First of all, while the size of our sample is sufficient for testing the constructed structural model, larger samples would be helpful to investigate simultaneously the differences in adoption behavior between geographic regions and additional demographic factors such as income, family status, etc. Second, although having achieved sufficient explanatory power, our results nevertheless leave room for additional factors not included in our research model that might influence adoption behavior. We therefore propose to discuss and empirically test the relevance of other constructs beyond the scope of the present study. Third, our investigation has been based on scenario descriptions, which limits the transferability to a commercial offering. As a consequence, the scenarios should next be implemented and tested in an experimental setting to increase the validity of our results.

9. References

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