Vacuum Cleaning as a Service

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Abstract. Smart technologies, such as autonomous robotic vacuum cleaners recently gained broader attention and change incumbent private work routines. In this research paper, we take the consumers' perspective and evaluate why consumers would intend or deter the use of vacuum cleaners. We investigate the positive influence of motivational drivers, such as trust, personal innovativeness, and hedonic values, as well as negative factors, such as perceived risk and perceived privacy violation. In this regard, we develop a research model that explains the consumers' intention to use an autonomous robotic vacuum cleaner. We use survey data (N = 223) and structural equation modeling for our analyses. Our results outline that trust and perceived risk, as well as other explicit motivational factors influence the consumers' intention to use robotic vacuum cleaners. Consequently, academic and practical implications are discussed.

Keywords: Robotic Vacuum Cleaner, Consumer, Intention to use.

1 Introduction

Autonomous robotic vacuum cleaners, commonly known as RVCs [1], are becoming extremely popular these days. These highly smart robots use artificial intelligence in order to replace the human operator for repetitive tasks respectively vacuum cleaning and can be understood as an example of a digital innovation [2]. Especially high-end models offer an appealing blend of cleaning power and smart home functionality. In this regard, researchers already investigate and test the actual performance of these devices in the laboratory to see whether they could navigate around obstacles, have adequate suction, move in an agile and efficient manner, and clean sufficiently [1, 3]. Although many of the current RVCs already do an impressive job on all those tasks, consumers are still skeptical regarding their intention to use RVCs in their private home.

In this study, we suggest a research model which examines the effect of trust, perceived risk, perceived convenience, hedonic value, personal innovativeness, perceived privacy violation, performance expectancy, social influence, and price value on the consumers' intention to use RVCs. In this regard, we draw on existing literature, such as Venkatesh et al. (2012), to identify potential drivers regarding the engagement in new technologies; thus we want to answer the following research question: *What are the main drivers of the consumers' intention to use RVC devices?*

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With our study, we contribute to the field of business informatics and information systems by complementing the adoption-theory in the context of smart technologies. In other words, by incorporating the aforementioned drivers in this study, we shed light on distinct antecedents of consumers' intentions towards intention to use RVCs as an example for smart services devices [5, 6].

The remainder of our study is structured as follows: In Section 2, we present the constructs under study and state our research hypotheses as well as the research model. In Section 3, we present our measurement model and perform structural equation modeling. Section 4, concludes our paper by outlining theoretical and practical implications of our findings.

2 Literature Review and Hypotheses Development

2.1 Autonomous Robotic Vacuum Cleaners

A large variety of different RVCs already exists. Whereas some of them are more advanced than others, they basically follow the same principle and often share an almost identical feature set. In this case "autonomous", does not simply mean that the robot has a battery, good computational power, and certain behavioral rules, but operates without any human instructions [7]. Generally, RVCs have a cleaning module and a separated fan as well as an internal hose that connects both modules. Further, the RVC has a microprocessor that performs navigation and control functions based on 'AI' or 'chaos mode'. (1) The AI mode usually represents an active evaluation of the cleaning surroundings. In those cases, the RVC generally uses its data sensors and cameras to scan the cleaning field and calculate the most efficient cleaning routes, whereas (2) chaos mode generally indicates that the RVC randomly decides which routes to take based on predefined algorithms. Since the technology is still at early stage, researchers and analysts argue that it is only a matter of time until RVCs will be the main cleaning force in our homes [8].

2.2 RVC Adoption Factors

Research in business informatics and information systems recognizes **trust** as a core predictor of technology usage and an important notion for understanding consumers' perceptions of new technologies [9]. Trust is a complex concept [10, 11] that has induced IS research from different perspectives in many disciplinary fields, such as sociology [12, 13], psychology [14], philosophy [15, 16], and economics [17]. Independent of the field, researchers state that trust is multi-faceted, context-sensitive, and has several peculiarities [18, 19]. However, there is no agreement on an explicit definition of trust in the setting of new technologies. Recently, scholars started rethinking how the advancement of IT has affected concepts like trust. Researchers agree that the need for trust surges with the growing dependency on further entities, such as new IT, due to greater transaction complexity and uncertainties [12, 20]. Before consumers can use those new technologies they have to overcome the perceptions of risk and uncertainty. In line with literature, we comprehend trust as the readiness to be exposed to the actions and consequences that new information technologies impose to their users. Therefore, we hypothesize: **H1a:** Increased degrees of trust in RVCs will increase the consumers' intention to use RVCs. **H1b:** Increased degrees of trust in RVCs will decrease the consumers' perceived risk of RVCs.

Sitkin and Pablo (1992) define **perceived risk** as follows: negative outcome expectations, negative outcome uncertainty, and negative outcome potential are incorporated into one broad risk concept. Our definition of perceived risk is further in line with other risk literature, especially with the definition by Nicolaou and McKnight (2006): the level to which one believes uncertainty is prevalent about whether desirable outcomes will occur. Thus, our research paper defines perceived risk as negative outcomes that might arise by using RVCs as a tool for automated cleaning – malfunctioning and poor cleaning performance. Perceived risk in general is an important barrier for potential consumers who consider using new IT [23, 24]. Prior research fortified us to explore the implications of trust and perceived risk on the consumers' intention to use RVCs [25]. In this regard, we hypothesize: **H2:** Increased degrees of perceived risk of RVCs will decrease the consumers' intention to use RVCs.

Technology adoption is influenced by **personal innovativeness**. This driver stems from the diffusion of innovations research and describes individuals who adopt an innovation at an early stage [26]. In 1998, Agarwal and Prasad were the first who specified and used this personality attribute to the domain of IT and defined it as the willingness to try and experiment with any new technology [27]. While the first RVCs were already commercially available in the early 2000s, many households still have not adopted this technology and use traditional vacuum cleaners [28]. IRobot estimates that around 20% of all households use RVCs – however, this number is steadily increasing [8]. We argue that people who are highly innovative towards IT are more likely to purchase and use RVCs. **H3:** Increased degrees of personal innovativeness in IT will increase the consumers' intention to use RVCs.

Hedonic value describes how enjoyable or entertaining a technology is [4]. Holbrook and Hirschman (1985) were among the first who differentiated between hedonic and utilitarian products. IS literature has adapted their definition and focuses further on this differentiation. Moreover, Venkatesh et al. (2012) incorporated hedonic motivation into the extension of the unified theory of acceptance and use of technology (UTAUT2). UTAUT2 was especially developed to explain use intentions and use behavior of consumers. As RVCs are IT-gadgets designed for the consumer market, we hypothesize: **H4:** Increased degrees of hedonic values in RVCs will increase the consumers' intention to use RVCs.

The driver **social influence** is defined as the extent to which a consumer perceives that important others believe he or she should be using RVCs [4]. In other words, the concept of social influence describes the pressure to behave in a way that is endorsed by a social group [30]. According to IS research social influence is an important antecedent for behavioral intention and use [4, 31]. Therefore, we hypothesize: **H5:** Increased degrees of social influence will increase the consumers' intention to use RVCs.

The cost of an IT device plays an important role in the decision process behind a purchase and future use [4]. Compared to normal vacuum cleaners RVCs are far more costly. The **price value** depends on the RVCs' features, such as smart AI modes, speed and suction power, or remote access via smartphone app. Consumers have to form a tradeoff between the benefits and the monetary cost [32]. Therefore, a high value relative to the price will increase the use intention. We hypothesize: **H6:** Increased degrees of price value will increase the consumers' intention to use RVCs.

Performance expectancy is a key driver of IT-adoption. Prior the initial purchase and use of IT, consumers have already formed a specific expectancy of the product and its expected performance [4, 33]. While performance expectancy was originally used in the work context, we apply it to the "job" or "service" of vacuum cleaning a house or flat. In other words, if people believe that the use of an autonomous vacuum robot will save time or increase the quality of their vacuum cleaning, they are more likely to purchase and use one. Therefore, we hypothesize: **H7:** Increased degrees of performance expectancy will increase the consumers' intention to use autonomous RVCs.

In the future, RVCs could replace most of the cleaning duties at homes as well as at workplaces. This could benefit elderly people, people suffering from allergies, and reduce the overall cleaning effort. Consequently, RVCs can help to simplify cleaning tasks. In this regard, we hypothesize for **perceived convenience**: **H8:** Increased degrees of perceived convenience will increase the consumers' intention to use autonomous RVCs.

Similar to trust, the **perceived privacy violation** is a common factor in the adoption of new and cloud-based IT. RVCs use several sensors and cameras to scan the environment, their cleaning path, and their general surroundings in order to optimize the cleaning procedure [34]. Most of the cleaners use cloud storage to store and process information and to make it available through smart services, such as smartphone apps or smart assistances like Google Home or Amazon Alexa. This imposes a potential privacy risk and consumers may be afraid that their personal data (e.g., the floor plan of the flat) might be available to the manufacturer of the cleaning device or even be shared publicly [35, 36]. Therefore, we hypothesize: **H9:** Increased degrees of perceived privacy violation in RVCs will decrease the consumers' intention to use RVCs.

Last, after the development of our hypotheses based on the conducted literature review, we outline our research model. Figure 1 gives an overview of all drivers, hypotheses, and relationships used in the given study.

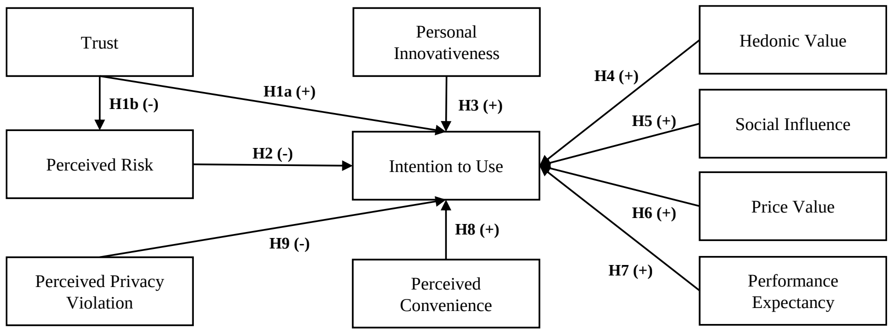

Figure 1. Research model

3 Methodology

3.1 Measurement Development and Data Collection

We designed an online survey to evaluate the potential consumers' intention to use RVCs. In order to assess the personal attitudes and beliefs of consumers, we decided to conduct a survey as a first research step and provides a good foundation for future research. For example, extended research could use methods like laboratory and field experiments to measure the behavioral traits [37]. The questionnaire used in the study contained 47 questions and covered ten constructs. Further, we included income, profession, marital status, age, education, and gender as controls [37], as all these variables could theoretically bias the consumers' intention towards the engagement of new technologies [38].

Table 1. Participants characteristics (N = 223)

	Count	*%*		*Count*	*%*
Age			**Marital status**		
16 to 20 years	14	6.28%	Single	119	53.36%
21 to 25 years	41	18.39%	Married	91	40.81%
26 to 30 years	47	21.08%	Separated	4	1.79%
31 to 35 years	37	16.59%	Divorced	9	4.04%
36 to 40 years	14	6.28%			
41 to 45 years	24	10.76%	**Profession**		
46 to 50 years	20	8.97%	Student	30	13.45%
51 to 55 years	12	5.38%	Employed for wages	94	42.15%
56 to 60 years	13	5.83%	Self-employed	58	26.01%
61 to 65 years	1	0.45%	Out of work	37	16.59%
			Retired	4	1.79%
Income in USD					
less than $20,000	50	22.4%	**Education**		
$20,000 - $29,999	28	12.6%	Less than high school	1	0.45%

$30,000 - $39,999	22	9.9%	High school graduate	82	36.77%
$40,000 - $49,999	45	20.2%	Associate degree	34	15.25%
$50,000 - $59,999	25	11.2%	Bachelor's degree	78	34.98%
$60,000 - $69,999	13	5.8%	Master's degree	23	10.31%
$70,000 - $79,999	16	7.2%	Doctorate degree	5	2.24%
$80,000 - $89,999	4	1.8%			
$90,000 - $99,999	7	3.1%	**Gender**		
above $100,000	13	5.8%	Male	78	34.98%
			Female	145	65.02%

In our survey, we employed a standardized 7-point Likert scale response format – going from strongly disagree (1) to strongly agree (7). Table 5 in the Appendix holds a summary of the items, including the constructs, the loadings, the corresponding item codes, and the references. Our study was conducted in late 2017 and we used clickworker a crowd sourcing platform similar to Amazon Mturk as a platform to target potential consumers of RVCs [39]. By the due date, 223 native English speakers from the US, UK, and Canada completed the survey – see Table 1.

3.2 Measurement Model

First, we evaluated the factor structure of the dataset (N = 223) to evaluate the reliability of the measurement model. In particular, we assessed the validity and reliability of ten constructs by following the recommendations made by Hair et al. (2014) and Straub et al. (2004) to judge for internal consistency. To this end, our tests showed satisfactory reliability for all our constructs, as the calculated Cronbach's Alpha, rho_A, and Composite Reliability score all above the threshold of 0.70 [42]. Table 2 shows the reliability indices for our ten constructs.

Table 2. Descriptive statistics and reliability index

Construct	*Cronbach's Alpha*	*rho_A*	*Composite Reliability*
Hedonic value	0.931	0.948	0.956
Intention to use	0.958	0.959	0.968
Perceived risk	0.918	0.944	0.934
Perceived privacy violation	0.981	0.985	0.985
Perceived convenience	0.936	0.944	0.951
Performance expectancy	0.955	0.960	0.971
Personal innovativeness	0.905	0.910	0.941
Price value	0.919	0.989	0.936
Social influence	0.976	0.977	0.984
Trust	0.931	0.933	0.946

Further, we valued construct validity by measuring convergent validity and discriminant validity [43]. Convergent validity can be understood as the degree to which the measures for an item perform as if they are measuring the principal theoretical construct because they share variance [44]. So, convergent validity can be considered satisfactory when the Average Variance Extracted (AVE) is higher than 0.50 for all constructs [42]. Finally, discriminant validity can be understood as the degree to which measures of different latent variables are exclusive [43]. To this end, discriminant validity can be considered acceptable when the square roots of the AVE values are higher than the correlations among the research constructs [42]. Moreover, the variance explained by every construct should be higher than the measurement error variance, which is the case.

Table 3. Convergent and discriminant validity coefficients

	AVE	*H*	*Int*	*PC*	*PPV*	*PR*	*PE*	*PI*	*PV*	*SI*	*T*
H	0.88	**0.94**									
Int	0.86	0.64	**0.93**								
PC	0.80	0.61	0.77	**0.89**							
PPV	0.93	-0.16	-0.18	-0.25	**0.96**						
PR	0.70	-0.21	-0.42	-0.45	0.54	**0.84**					
PE	0.92	0.52	0.75	0.74	-0.18	-0.35	**0.96**				
PI	0.84	0.36	0.43	0.33	0.00	-0.08	0.34	**0.92**			
PV	0.75	0.45	0.42	0.34	0.03	-0.07	0.42	0.32	**0.86**		
SI	0.95	0.45	0.55	0.41	0.04	-0.08	0.47	0.4	0.51	**0.98**	
T	0.74	0.47	0.65	0.61	-0.19	-0.41	0.53	0.41	0.43	0.4	**0.86**

Note: AVE = Average Variance Extracted. Diagonal elements of the last ten columns represent the square root of the AVE. Off diagonal elements are the correlations among latent constructs.
H = Hedonic values, Int = Intention to use, PC = Perceived convenience, PPV = Perceived privacy violation, PR = Perceived risk PE = Performance expectancy, PI = Personal innovativeness, PV = Price value, SI = Social influence, T = Trust

The results of our analyses indicate that there is strong evidence of construct validity in the collected dataset. Table 3 shows that discriminant validity seems not to be an issue in our data. Lastly, we evaluated a potential common method bias in SPSS. In particular, we used the Harman's single factor test to verify that no single component explains more than 50% of the total variance (the test scored with: 36.63%). Based on this analysis, we find that the common method bias is unlikely a potential concern in our data.

3.3 Structural Model Assessment

Our main goal of this study was to identify the drivers and the impediments of the consumers' intention to use RVCs. Hence, after we confirmed the adequate factor structure of our dataset, we conducted PLS-SEM to analyze both the measurement and structural relationships demonstrated in our research model [45, 46]. Our analyses show that the data collected through our survey adequately fits our research model. The selected items share only little residual variance and indicate unidimensionality of the SEM approach. Table 4 and Figure 2 show the results of the SEM approach. The explanatory power of our research model was evaluated by exploring the significance levels of the corresponding path coefficients. The results show support for seven out of ten hypotheses.

Table 4. Results of path coefficients

Hypothesis	*Path*	*Path Coefficient*	*Sample Mean*	*T Statistics*	*p-value*
H1a	T → Int	0.168	0.170	2.995	**0.003****
H1b	T → PR	-0.411	-0.418	5.493	**0.000*****
H2	PR → Int	-0.125	-0.124	2.477	**0.013***
H3	PI → Int	0.211	0.066	1.252	0.211
H4	H → Int	0.172	0.173	3.210	**0.001****
H5	SI → Int	0.160	0.159	3.511	**0.000*****
H6	PV → Int	-0.034	-0.034	0.760	0.447
H7	PE → Int	0.289	0.286	4.076	**0.000*****
H8	PC → Int	0.220	0.220	2.539	**0.011***
H9	PPV → Int	0.058	0.059	1.187	0.235

Note: * significant at a .05 level, ** significant at a .01 level, *** significant at a .001 level

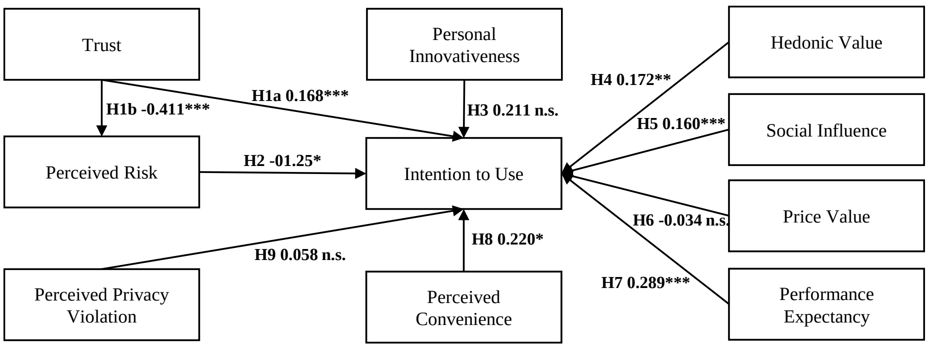

Figure 2. PLS analysis with standardized path coefficients

4 Discussion, Conclusion, and Implications

The objective of this study was to investigate the consumer motives behind the purchase and use of RVCs. To the best of our knowledge, our study is the first that focuses on the consumers' intention to use RVCs instead of (or as an addition to) a normal vacuum cleaner. Our research model is based on existing literature and our measurement instruments were adapted for the specific use case. We conducted a web-based survey with a total of 223 participants. Our PLS-SEM analysis shows that seven of our ten hypotheses were supported.

As hypothesized and in line with the literature, trust has a significant positive effect on the intention to use and a significant negative effect on perceived risk. Further, higher perceived risk leads to a decrease in the intention to use. Hedonic value, social influence, performance expectancy, and perceived convenience have a positive effect on the intention to use a RVC.

However, three of our hypotheses were not supported as determined by the PLS-SEM analysis. Perceived privacy violation had no significant effect on intention to use.

This might be due to two reasons: (1) people might not be aware of the fact that RVCs scan their surroundings and (2) people might perceive the upload to the manufacturer cloud not as a violation of their privacy. Further, personal innovativeness did not have a significant effect on the intention to use. A reason for this might be the fact that RVCs are a digital and enhanced version of normal vacuum cleaners and therefore, are not perceived as something completely new. People might perceive them more in terms of an upgrade instead of a new technology. The third construct that did not have a significant effect on intention to use was price value. One possible explanation might be that people do not know much about the actual price value of RVCs. Therefore, they are not able to distinguish between the features and the benefits.

The study at hand holds theoretical and practical contributions. First, we contribute to the theoretical topic of adoption. The developed research model helps to identify important drivers behind the use of RVCs. Second, RVC-companies can use that knowledge to further enhance their products and increase their market shares. However, there are several limitations. As we conducted an online survey, there is a lack of generalizability, further all our respondents came from western countries, consequently cultural differences could pose a potential issue. For further research, we recommend a focus on cultural differences and evaluate the hedonic value of RVCs through experiments or choice-based conjoint analyses.

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Appendix

Table 5. Overview of items after the content validity assessment

Construct	*Code*	*Item*	*Loading*	*Reference*
Perceived convenience	PC1	I feel that robotic vacuum cleaner are convenient.	0.913	Items adapted and modified from Mittendorf et al. (2017)
	PC2	Robotic vacuum cleaner involve little trouble or effort.	0.835	
	PC3	I believe robotic vacuum cleaner are convenient and suitable to use.	0.924	
	PC4	I feel that using robotic vacuum cleaner reduce effort.	0.888	
	PC5	I believe robotic vacuum cleaner are comfortable to use.	0.900	
Hedonic values	H1	Using robotic vacuum cleaner is fun.	0.952	Items adapted from Venkatesh et al. (2012)
	H2	Using robotic vacuum cleaner is enjoyable.	0.960	
	H3	Using robotic vacuum cleaner is very entertaining.	0.898	
Intention to use	Int1	I am very likely to use robotic vacuum cleaner in the future.	0.882	Items adapted and modified from Davis et al. (1989), Gefen et al. (2003), Pavlou (2001)
	Int2	I would use robotic vacuum cleaner in general.	0.937	
	Int3	I would not hesitate to use robotic vacuum cleaner in my home.	0.935	
	Int4	Given the chance, I would use robotic vacuum cleaner.	0.932	
	Int5	Given the opportunity, I intend to use robotic vacuum cleaner as a form of cleaning.	0.942	

Performance expectancy	PE1	Robotic vacuum cleaner would be useful in my daily life.	0.948	Items adapted from Venkatesh et al. (2012)
	PE2	Using robotic vacuum cleaner would help me to accomplish things more quickly.	0.960	
	PE3	Using robotic vacuum cleaner would increase my productivity.	0.965	
Personal innovativeness	PI1	If I heard about a new information technology, I would look for ways to experiment with it.	0.924	Items adapted from Agarwal and Prasad (1998)
	PI2	Among my peers, I am usually the first to try out new information technologies.	0.899	
	PI3	I like to experiment with new information technologies.	0.929	
Perceived privacy violation	PPV1	I have concerns that private data might be leaked when using robotic vacuum cleaner.	0.963	Items adapted from Pavlou and Gefen (2004), Zaleskiewicz (2001)
	PPV2	I have concerns that private data will be revealed to others when using robotic vacuum cleaner.	0.968	
	PPV3	I am afraid that private data will be stored without my knowledge when using robotic vacuum cleaner.	0.960	
	PPV4	I am afraid that private information will be stored insecurely when using robotic vacuum cleaner.	0.967	
	PPV5	I feel that my privacy could be violated when using robotic vacuum cleaner.	0.959	
Perceived risk	PR1	There is a considerable risk involved in using robotic vacuum cleaner.	0.790	Items adapted and modified from Pavlou and Gefen (2004), Zaleskiewicz (2001)
	PR2	There is a high potential for problems involved in using robotic vacuum cleaner.	0.848	
	PR3	A decision to use robotic vacuum cleaner as a cleaning device risky.	0.899	
	PR4	It is likely that a robotic vacuum cleaner, as a cleaning device, will fail to meet my expectations.	0.720	
	PR5	Using robotic vacuum cleaner is unsafe.	0.881	
	PR6	I think it is risky to use a robotic vacuum cleaner as a cleaning device.	0.884	
Price value	PV1	I think robotic vacuum cleaner are not costly.	0.815	Items adapted from Venkatesh, et al. (2012)
	PV2	I believe robotic vacuum cleaner are cheap.	0.765	
	PV3	Robotic vacuum cleaner are reasonably priced.	0.903	
	PV4	Robotic vacuum cleaner are a good value for the money.	0.909	
	PV5	At the current price, robotic vacuum cleaner provide a good value.	0.917	
Social influence	SI1	People who are important to me think that I should use robotic vacuum cleaner.	0.974	Items adapted from Venkatesh, et al. (2012)
	SI2	People who influence my behavior think that I should use robotic vacuum cleaner.	0.976	