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AI in Cosmetics. Determinants Influencing the Acceptance of Product Configurators.

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ABSTRACT

AI revolutionizes the cosmetics industry through innovative and digital personalization and advanced customer advice. AI-based product configurators enable individualization for customers and promote competitive advantages for companies. The acceptance of AI-based product configurators in the cosmetics industry has not been sufficiently researched. To fill this research gap, a quantitative study was conducted through a convenience sample of 116 female subjects. Ten hypotheses were used to investigate which determinants influence technology acceptance. This research showed that the age of the female customers has a significant influence on usage intention, perceived enjoyment and self-efficacy. The determinants subjective norm, personal image, and perceived ease of use significantly influence technology acceptance. The study provides added value for future adaptations of sales processes regarding digital ordering algorithms and product configurators along the customer journey.

Künstliche Intelligenz (KI) revolutioniert die Kosmetikindustrie durch innovative Personalisierung und erweiterte Kundenberatung. KI-basierte Produktkonfiguratoren ermöglichen Individualisierung für Kunden und fördern Wettbewerbsvorteile für Unternehmen. Die Akzeptanz von KI-basierten Produktkonfiguratoren in der Kosmetikindustrie ist noch nicht ausreichend erforscht. Um diese Forschungslücke zu schließen, wurde eine quantitative Studie mit einer Convenience-Stichprobe von 116 weiblichen Probanden durchgeführt. Anhand von zehn Hypothesen wurde untersucht, welche Determinanten die Technologieakzeptanz beeinflussen. Die Untersuchung zeigte, dass das Alter der Kundinnen einen signifikanten Einfluss auf die Nutzungsabsicht, den wahrgenommenen Genuss und die Selbstwirksamkeit hat. Die Determinanten subjektive Norm, persönliches Image und wahrgenommene Benutzerfreundlichkeit beeinflussen die Technologieakzeptanz signifikant. Die Studie liefert einen Mehrwert für zukünftige Anpassungen von Verkaufsprozessen hinsichtlich digitaler Bestellalgorithmen und Produktkonfiguratoren entlang der Customer Journey.

KEYWORDS

Artificial intelligence (AI), cosmetics industry, product configurators, technology acceptance, customer consultation

Künstliche Intelligenz (KI), Kosmetikindustrie, Produktkonfiguratoren, Technologieakzeptanz, Kundenberatung

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1. Introduction

The cosmetics industry continues to grow with the increasing introduction of new products. With global sales of $250 billion in 2018 (Hudson, Kim, and Moulton 2018), the cosmetics industry has grown steadily since then and is currently estimated to be worth around $472.8 billion, according to Consumer Markets Research (Beauty & Personal Care – Worldwide 2022). A large part of the success of the cosmetics industry can be attributed to brand names, the lifestyle the brand represents or the luxury it conveys. Individuality is suggested in the form of numerous line extensions of existing standard products. In order to meet the trend and the expectations of consumers for individual and personalized products, cosmetics companies are increasingly focusing not only on personalized recommendations but also on product variants tailored to the individual needs of each customer in a mass market (Gyan Research and Analytics 2018). The success of the entire customer experience, from wanting a solution through a product, to searching for it, to the ordering experience, to product usage, might significantly improve through the use of well-designed digital ordering algorithms and product configurators (Franke and Piller 2004). AI-based product configurators offer the cosmetics and beauty industry the opportunity for mass customization (Rainsberger 2021; Wabia 2020).

This paper investigates whether the technology acceptance study by Cengiz et al. (2020) can be transferred to the German cosmetics market for women within different age groups since no research results are available here (Davis, Bagozzi, and Warshaw 1989; Grosso, Forza, and Trentin 2017; Walczak, Kellogg, and Gregg 2010). Subsequently it is necessary to investigate which different factors influence the usage behavior of AI-based product configurators in the cosmetics industry and how these factors can be interpreted. Although cosmetic products can be consumed across genders, this study focuses on the female target group. The interest of the female target group in decorative cosmetics increased by 15% from 2013 to 2018. Female customers purchased 40% more decorative cosmetics than male customers during the period (GIK 2019). To analyze these aspects, two different female age groups representing the target groups (GIK 2019) of the cosmetics industry were interviewed with a convenience sample method about their usage behavior with AI-based product configurators as well as their perceived usefulness and sensed usability of such tools.

The paper is organized as follows. Section 2 reviews the theoretical background of AI and AI-based product configurators in relation to the cosmetics industry. Section 3 describes the research framework and hypotheses; Section 4 discusses the research design and technology acceptance model (TAM) 3 research methodology; Section 5 presents the results; Section 6 concludes with recommendations for the use of AI-based product configurators in a female target group and identifies opportunities for further research as well as the limitations of this work.

2. Theoretical Background

Artificial intelligence is an established part in the cosmetics industry and changes the way products are offered and the interaction with customers (Mangtani et al. 2020). The megatrend of individualization promotes the development of individualized products and services in the beauty industry (Rainsberger 2021)

Artificial intelligence

According to Rainsberger (Rainsberger 2021), AI is about processes in which machines learn how to learn. As a sub-field of computer science, AI is used to identify intelligent behavior and it imitates human intelligence (Hartmann 2018). A distinction is often made between soft and strong AI. Soft AI applications can analyze data to make predictions and support human-based tasks (Buxmann 2018). Strong AI has the ability to solve tasks intellectually on its own, as humans do. Strong AI does not yet exist (Paschen et al. 2020).

The development of AI applications will continue to increase. This is due to some key indicators: Computing capacity, high communication speed and expanded storage capacity, better algorithms and decreasing prices for them (J. Paschen, Wilson and Ferreira 2020). The combination of machine accuracy with human mental connections, emotions and creativity enables deep customer understanding along the entire customer journey, which can lead to competitive advantages in sales. (Rainsberger 2021)

Product configurators

Product configurators are an instrument of mass customization as they provide customers with the possibility to individually adapt products and at the same time, the company is benefiting from the scalability of the system (Davis, Bagozzi, and Warshaw 1989; Wabia 2020). Examples of product configurators range from the self-configuration of a car to a menu in a fast-food restaurant. Product configurators can be differentiated into five appearances according to their capabilities. Select-to-order (STO) configurators let customers choose from the standard range of a product. There is no dependency between the characteristics of the product and its availability, so that any products and variants such as colours can be combined here. This is the simplest form of product configuration (Henseler 2004; Lutz 2012). Pick-to-order (PTO) configurators are integrated in many online shops. The configuration options are additions and extensions to the already constructed product. Customers can add their individual preferences (Henseler 2004; Lutz 2012). For more extensive configurations, configure-to-order (CTO) configurators are used. Many combinations can be selected, leading to extensive product variations. To create a meaningful product, a relationship logic is required due to the dependency of the components. Individual options are added automatically to maintain functionality (Henseler 2004; Lutz 2012). This form of configurator is often used by both staff and customers for visualization. The CTO configurator is normally used as a configurator whose configured end product is only manufactured after the customer's preferences have been finalized. For customized products, specific parameters can be defined through the make-to-order (MTO) configurator. Manufacturing of the product begins as soon as the customer order is received (Henseler 2004; Lutz 2011). The visualizations of custom-made products in a configurator serve the purpose of individualization and should function in a customer-centric way. Finally, engineer-to-order (ETO) configurators promote the development of new products or product components. The configurations are done by experts and are used for the purpose of cost verification, handling, and functionality. In the following, product configurators are defined as pick-to-order configurators. The manifestations of product configurators can be empowered with soft AI.

AI-based product configurators learn continuously by searching for new solutions, based on data which they perceive and analyze changes in the environment and derive conclusions from that (Rainsberger 2021). One example of this is that customers can use configurators to influence the final product and, likewise, companies can use these customer requirements to directly modify products according to customer specifications (Lutz 2011). By systematizing the offer, the sales process is accelerated and relieved and costs can be reduced as a result (Kortmann, Klink, and Wüpping 2009). By combining different components within a product configurator, the product range can be expanded without changing or adapting internal processes (Kortmann, Klink, and Wüpping 2009).

By using AI-based product configurations, the customer receives products that exactly match their expectations and requirements (Helo 2006). As a result, customers get individualized products that fit them perfectly delivered to their homes without the need for face-to-face consultation. This is therefore beneficial to an increase in trust thus actively contributing to customer loyalty (Rainsberger 2021). Companies benefit from the AI-based collection and analysis of data in that they gain valuable insights into the moods, motives and behavior patterns of customers and can thus develop better-tailored products. Customers benefit from the shift from product-based offerings to customer experience-based models (Mangtani et al. 2020).

AI-based product configurators in the cosmetics industry

AI-based product configurators offer opportunities for the cosmetics industry in terms of higher shopping cart values, customer loyalty, and the intensification of customer relationships through customized digital advice (Hedin, Ohlsson, and McKenna 1998; Wabia 2020). Research on product configurators and mass customization has shown that consumers are willing to pay a significant premium to purchase some configured products, e.g., in the premium jewellery and fashion sectors, if they perceive the configuration process positively (Franke and Piller 2004; Grosso, Forza, and Trentin 2017; Wabia 2020). The main problem with this technique is that there are different preferences regarding technology acceptance, trust and willingness to pay for configured products depending on nationality, age or gender and the product (Wabia 2020). The research of Cengiz et al. (Cengiz and Bakırtaş 2020), Holden (Holden and Rada 2011) and Venkatesh and Bala (Venkatesh and Bala 2008) provides an indication that it is necessary to pick up the target group at its level of technical knowledge.

AI-based (PTO) product configurators are already used in the market and can be classified as an instrument of mass customization (Rogoll and Piller 2004). Artificial intelligence-based solutions within the cosmetics industry can be found in applications like quiz-based models, where customers can choose from different answer options, as well as chatbots and special DNA-based AI applications, for example, to receive individual skin and hair treatment recommendations (Rainsberger 2021).

One of the main uses of AI-based product configurators in the cosmetics industry are applications that analyze the condition and needs of the skin and can be characterized as PTO configurators or according to Helo (Helo 2006) as feature-based configuration. A practical example shown in this research is the skin analysis tool "Skin Advisor" by Olay of the Procter & Gamble group (“Olay Skin Advisor” 2022).

The process of Olay's skin analysis tool is as follows: The potential Olay customer takes a selfie after starting the analysis. The following text appears to bridge the waiting time:

"Thank you for your selfie! The following is analysed: Your 5 zones of skin ageing will be analysed." The customer then answers questions about their beauty routine in an online questionnaire and can choose answers from a series of multiple-choice questions. Exemplary questions included: "What concerns you most about your skin?"; "What is your main concern?" (related to the previous question); "What is your skin type?"; "What products do you use at least twice a week?". The image material is evaluated in the backend of the system with the answers and customer preferences and simultaneously matched with Olay's products. The frontend then outputs the skin age as a result, with corresponding product recommendations.
The recommendations can be customized according to preference. For each product, it is indicated which of the skin problems it is supposed to solve. The suggested products can be added directly to the shopping cart (Olay Skin Advisor 2022).

3. Research framework

As the current state of research shows, the question about the influence of AI-based product configurators on different female age groups in the German cosmetics industry could not be answered. To be able to determine differences in the usage behavior depending on age, the participants were divided into two age groups "0–49 years" and "older than 50 years".

As part of the investigation into the usage behavior of customers, the first hypothesis measured perceived enjoyment (ENJ) and usage intension (UI) within the age groups.

(H1a) Younger costumers perceive higher enjoyment in using AI-based product configurators than older costumers.

(H1b) Younger customers are more likely to use AI-based product configurators than older customers.

In the second hypothesis, computer self-efficacy (CSE) and computer anxiety (CANX) were measured. It was investigated whether there is a possible correlation between age and computer self-efficacy and computer anxiety.

(H2a) Older customers feel less computer self-efficacy using AI-based product configurators than younger customers.

(H2b) Older customers have higher concerns about using AI-based product configurators than younger customers.

Furthermore, the third hypothesis investigates whether there is a correlation between the acceptance of AI-based product configurators and subjective norm (SN) as well as objective usability (OU). The hypothesis proceeds from the proposition that such product configurators will be used more frequently if there is acceptance of them in the customer's social environment.

(H3) The more accepted AI-based product configurators are in the personal social environment, the higher the objective usability of the customer.

The fourth hypothesis relates perceived ease of use (PEOU) to perceived usefulness (PU) and predicts that perceived ease of use positively influences perceived usefulness.

(H4) The greater the perceived ease of use of the AI-based product configurator, the higher the perceived usefulness is rated.

The next hypothesis deals with the awareness of external control (PEC) and the traceability of the results (RES). It implies that younger customers are more likely to have the necessary skills and technical resources to use an AI-based product configurator, are more likely to get the required information and are aware of the limitations of such product configurators.

(H5a) Younger customers have a higher perception of external control of an AI-based product configurator than older customers.

(H5b) Younger customers comprehend the results of an AI-based product configurator better than older customers.

The personal image, which indicates the degree of self-identification with AI-based product configurators, is also associated with usage. The purpose of the sixth hypothesis is to find out whether one's image (IMG) influences purchasing relevance (REL).

(H6) The more the personal image matches the use of an AI-based product configurator, the more likely it is to become relevant for purchasing.

The last hypothesis focuses on the correlation between the output quality (OUT) of an AI-based product configurator and the enjoyment of using new technologies (ENJ). It relates output to the resulting use of new technologies.

(H7) The better the output quality of an AI-based product configurator, the more likely it is to enjoy the use of this technology.

To prove these hypotheses for innovative technologies such as AI-based product configurators, validated items from the TAM3 technology acceptance model (Venkatesh 2000) were used, as shown in Table 1 in the appendix. These were slightly adapted to the topic of customer usage behaviour towards AI-based product configurators. Voluntariness (VOL) according to Moore and Benbasat (Moore and Benbasat 1991) was not considered in this study, as it is assumed that the use of AI-based product configurator is voluntary (Venkatesh 2000). The research design allows the usage data to be collected separately from its determinants, such as perceived usefulness and perceived ease of use.

4. Research design

This survey was developed based on Curwin and Slater's ordinal rating scale (Curwin, Eadson, and Slater 2002) and following the TAM3 by Venkatesh and Bala (Venkatesh and Bala 2008). The methodology and evaluation are a replication of Cengiz et al. (Cengiz et al. 2020). It was created via an online survey tool. Participants in the survey were selected using a random sample within the female age groups "0–49 years" and "older than 50 years". To assess the participants' level of knowledge, two questions about knowledge and use were asked in advance. A total of 116 female respondents, which corresponds to a response rate of 73.89%, took part in the survey on the usage behavior of customers towards AI-based product configurators in the cosmetics industry.

In order to be able to make qualitative statements and to avoid selection bias, the participants from the convenience sample were matched with the basic population of the cosmetics industry and the age structure. The Appendix contains a detailed breakdown of the selected variables including the respective items with which they were measured. The questionnaire used Likert scales with a rating range of 1 (strongly disagree) to 7 (strongly agree).

In the context of this paper, the participants of the conducted survey were shown the function of an artificially intelligent product configurator with the help of the Skin Advisor of the cosmetics brand Olay (2021), which is described in chapter 2. In order to test the hypotheses, a t-test was performed for each case, using a 95% confidence level for all tests of statistical significance. The t-test is a statistical technique that assesses whether there is a significant difference between two groups, as in the between-subjects design of this study, by comparing their mean values for a particular variable specified by the corresponding hypothesis. A higher absolute t-value indicates a more significant difference between the mean values of the two groups. A sufficiently high absolute t-value can support the acceptance of the hypothesis with a certain level of confidence (Cengiz et al. 2020).

5. Findings

Of the 116 respondents, 73.3% are in the age group between 0 and 49 years and 26.7% are in the age group "older than 50". 41 participants in the 0–49 years' age group have already used an AI-based product configurator, while 27 participants in the over 50 age group have used a configurator. The first queries show that the younger age group has already used an AI-based product configurator more frequently than the over 50s.

t-tests were performed to test the hypotheses. The results were interpreted depending on the Levene's test. The results of the investigated 10 hypotheses are presented in numerical order.

(H1a) Younger costumers perceive higher enjoyment in using AI-based product configurators than the older costumers.

(H1b) Younger customers are more likely to use AI-based product configurators than older customers.

For ENJ, the age group under 49 has a mean of 4.6, and those over 50 have a mean of 3.5. For UI, the mean values within the age groups are identical to ENJ. The Levene's test for ENJ is significant, so there is no homogeneity of variance. Welch's t-test for unequal variances shows (Table 1) that there is a significant difference between age groups for ENJ ($t(45{,}49) = 4{,}01$, $p < 0.001$, CI 95% 0.56983–1.67988). The younger customers have a significantly perceived higher enjoyment in using AI-based product configurators than the older costumers. H1a is accepted.

The Levene's test for equal variance is not significant in UI and indicates homogeneity of variance. The results of the t-test show a significant difference between the age groups regarding UI ($t(114) = 3{,}80$, $p < 0.001$, CI 95% 0.49979–1.59148). This indicates that younger customers have a significantly higher usage intention than older customers. Therefore, H1b is accepted.

(H2a) Older customers feel less computer self-efficacy using AI-based product configurators than younger customers.

(H2b) Older customers have higher concerns about using AI-based product configurators than younger customers.

For CSE, the age group under 49 has a mean of 5.3, and those over 50 have a mean of 4.3. For CANX, the mean value of the younger age group is 3,3 and that of the older customers is 3,9. The Levene's test is not significant for CSE and CANX. Variance homogeneity can be assumed. The results of the t-test (Table 2) show that younger customers have significantly higher computer self-efficacy than the older customers ($t(114) = 4{,}354$, $p < 0.001$, CI 95% 0.54959–1.46730). Therefore, H2a is accepted. If the parameter of computer anxiety is considered, it can also be observed that the younger customers are significantly less afraid of using a computer than the older age group ($t(114) = -3.672$, $p < 0.001$, CI 95% -0.94005 to -0.28121). H2b is accepted.

Independent Sample Test

		Levene´s Test for Equality of Variances					*t-test for Equality of Means*		*95% Confidence Interval of Difference*	
		F	*Sig.*	*t*	*df*	*Sig. 2-tailed)*	*Mean Difference*	*Std. Error Difference*	*Lower*	*Upper*
Usage Intention (UI)	Equal variances assumed	2,192	0,141	3,785	114	<0,001	1,04564	0,27554	0,49979	1,59148
	Equal variances not assumed			3,549	47,413	0,001	1,04564	0,29461	0,45309	1,63819
Percieved Enjoyment (ENJ)	Equal variances assumed	4,734	0,032	4,479	114	<0,001	1,12486	0,25113	0,62736	1,62235
	Equal variances not assumed			4,081	45,482	<0,001	1,12486	0,27565	0,56983	1,67988

Table 1: Performed t-test for usage intention (UI) and perceived enjoyment (ENJ).

Independent Sample Test

		Levene´s Test for Equality of Variances					*t-test for Equality of Means*		*95% Confidence Interval of Difference*	
		F	*Sig.*	*t*	*df*	*Sig. 2-tailed)*	*Mean Difference*	*Std. Error Difference*	*Lower*	*Upper*
Self-Efficacy CSE))	Equal variances assumed	2,262	0,135	4,354	114	<0,001	1,00844	0,23163	0,54959	1,46730
	Equal variances not assumed			4,633	60,435	<0,001	1,00844	0,21768	0,57309	1,44380
Computer Anxiety (CANX)	Equal variances assumed	2,323	0,130	-3,672	114	<0,001	-0,61063	0,16629	-0,94005	-0,28121
	Equal variances not assumed			-3,319	44,924	<0,001	-0,61063	0,18401	-0,98125	-0,24000

Table 2: Performed t-test for computer self-efficacy (CSE) and computer anxiety (CANX).

(H3) The more accepted AI-based product configurators are in the personal social environment, the higher the objective usability of the customer.

If the two parameters subjective norm (SN) and objective usability (OU) are differentiated, it can be seen that OU is distributed relatively normally, with a slight shift to the right and one outlier. SN is distributed with a few outliers. Figure 1 shows the positive linear relationship of OU and SN with $R^2 = 0{,}252$.

To determine whether there is a significant correlation, a t-test was conducted. Two groups were formed of SN. The middle (value 4) was chosen as the boundary between the two groups. All values greater than or equal to 4 are on the right side of the Likert scale (4 = partially agree/ disagree to 7 = absolutely agree) and belong to group 1. All values less than 4 are on the left side of the Likert scale (3 = rather disagree to 1 = absolutely disagree) and belong to group 2. It is important to mention here that the two variables were examined for their difference and dependence independently of the age groups.
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Group 1, with measurements greater than or equal to 4, resulted in higher values (N = 82; Mean = 5.5; Std. Dev. = 0.89096) than Group 2, with measurements less than 4 of the second item SN (N = 34; Mean = 4.7; Std. Dev. = 1.02606). This difference could thus be proven to be significant (t (114) = 3.862; p < 0.001, CI 95% 0,3578–1,11085) and the formulated H3 can be accepted. It can now be concluded that the more an AI-based product configurator is accepted in the personal social environment, the higher the objective usability. Objective usability here means that the respondents tend to believe that AI-based product configurators will be used more in sales in the future, that there will be an increasing number of users of AI-based product configurators.

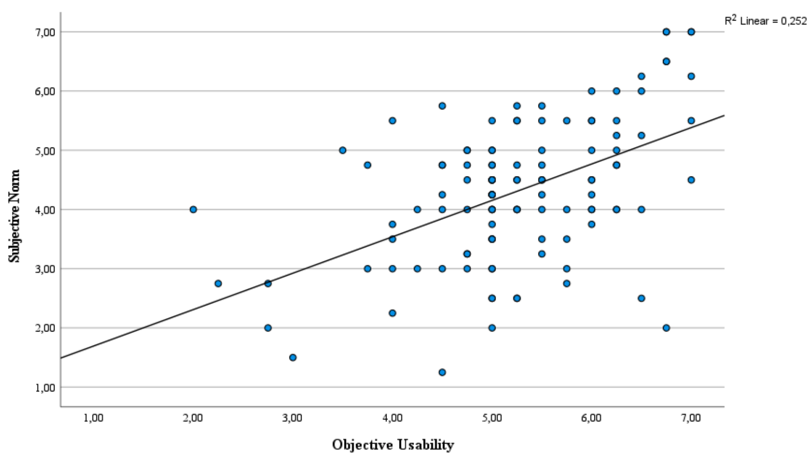

Figure 1: Scatter plot of the variables OU and SN.

(H4) The greater the perceived ease of use of the AI-based product configurator, the higher the perceived usefulness is rated.

To test and illustrate the correlation of perceived ease of use (PEOU) and perceived useful-ness (PU), a significant difference is to be demonstrated using the t-test. First, both variables are considered individually. PU shows a slightly right-skewed distribution. PEOU shows a right-sloping distribution. This indicates that the majority of participants consider an AI-based product configurator to be user-friendly and the opinion on the perceived usefulness of such a product configurator is more positive than negative. Figure 2 shows the positive linear relationship of PEOU and PU with $R^2 = 0{,}587$.

After establishing the null hypothesis, the two variables PEOU and PU were tested by means of a t-test. As described in hypothesis 3, the 7-point Likert scale was again divided into groups 1 and 2. In group 1 (PEOU), higher values (N = 99; Mean = 4.6894; Std. Dev. = 0.71615) were detected than in group 2 (N = 17; Mean = 3.0735; Std. Dev. = 0.68900). This difference was demonstrated to be significant (t (114) = 8.640; p < 0.001, CI 95% 1.245–1.986). It can therefore be concluded that there is a correlation between PEOU, and PU. It can be said that the higher the PEOU of an artificially intelligent product configurator, the better its PU is rated. Therefore, H4 can be accepted.

To test H5a and H5b, age groups were related to perceptions of external control (PEC) and the result traceability (RES) and analyzed with the help of a t-test (Table 3).

(H5a) Younger customers have a higher perception of external control of an AI-based product configurator than older customers.

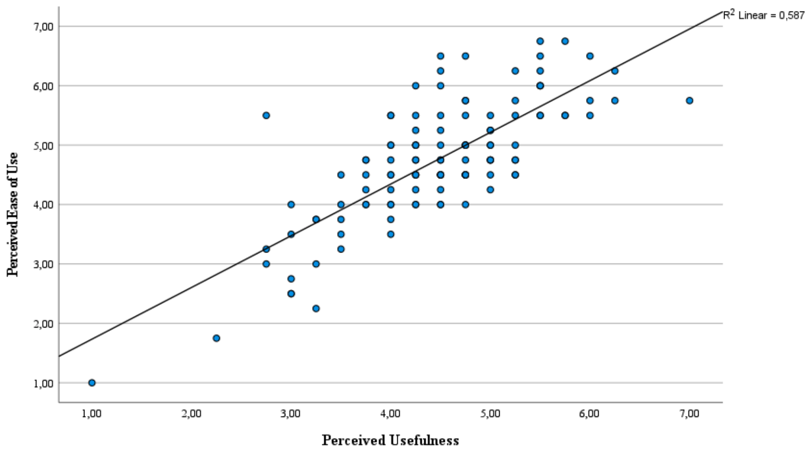

Figure 2: Scatter plot of the variables PEOU and PU.

Independent Sample Test										
		Levene´s Test for Equality of Variances					*t-test for Equality of Means*		*95% Confidence Interval of Difference*	
		F	*Sig.*	*t*	*df*	*Sig. 2-tailed)*	*Mean Difference*	*Std. Error Difference*	*Lower*	*Upper*
Perceptions of External Control (PEC)	Equal variances assumed	5,0334	0,027	4,231	114	<0,001	0,93482	0,22093	0,49716	1,37248
	Equal variances not assumed			3,704	42,878	<0,001	0,93482	0,25241	0,42575	1,44389
Result Traceability (RES)	Equal variances assumed	0,129	0,720	1,732	114	0,086	0,30672	0,17705	-0,04403	0,65746
	Equal variances not assumed			1,682	50,560	0,099	0,30672	0,182302	-0,05935	0,67278

Table 3: Performed t-test for perceptions of external control (PEC) and the result traceability (RES).

(H5b) Younger customers comprehend the results of an AI-based product configurator better than older customers.

After the null hypothesis was formed, the two variables PEC and RES were each tested for the significant difference in relation to the age groups.

Higher values for the perception of external control (N = 85; Mean = 5.5235; Std. Dev. = 0.95869) were observed in the younger group than in the group "older than 50" (N = 31; Mean = 4.5887; Std. Dev. = 1.28054). The Levene's test for PEC is significant, so there is no homogeneity of variance. Therefore, we use the Welch's t-test for unequal variances (Table 3). There is a significant difference between age groups for PEC (t (42,89) = 3,704; $p < 0.001$, CI 95% 0,42575–1,44389). The younger customers have a significantly perceived higher enjoyment in using AI-based product configurators than the older costumers. H5a is accepted.

No significant difference was found for RES with respect to age groups (t (114) = 1.732, p = 0.086, CI 95% -0.04403–0.65746). The results show that both young and old customers feel identical about the result traceability. Both groups tend to have difficulties telling others about the results of using an AI-based product configurator and thus to trace the results. Therefore, we reject H5b. Thus, it cannot be said that the result traceability of an AI-based product configurator in the cosmetics industry is dependent on age.

(H6) The more the personal image matches the use of an AI-based product configurator, the more likely it is to become relevant for purchasing.

To test this hypothesis, the variables image (IMG) and purchasing relevance (PR) were validated as to whether there is a significant correlation between the own image and the purchasing relevance. Both variables are normally distributed. Figure 2 shows the positive linear relationship of IMG and PR with $R^2 = 0{,}732$.

As for hypotheses 3a, 3b and 4, the results of the seven-point Likert scale were divided into two groups to conduct the t-test. The middle (value 4) was chosen as the cut-off point of the groups. All values of IMG greater than or equal to 4 belong to group 1. All values less than 4 belong to group 2.

In group 1, higher values (N = 59; Mean = 5.4407; Std. Dev. = 0.82511) were found than in group 2 (N = 57; Mean = 3.7222; Std. Dev. = 1.04669). This difference is proven to be significant (t (114) = 9.838, $p<0.001$, CI 95% 1,37246-2,06602).

From these results, the following conclusion can be drawn. Customers for whom the use of an AI-based product configurator corresponds to the perception of themselves, their values, and their personalities are more likely to think that AI-based product configurators are relevant, attractive, useful, and helpful for the purchase of products in the cosmetics industry. According to the results of the t-test, one's own image influences the customer's purchasing relevance when using an artificially intelligent product configurator in the cosmetics industry.

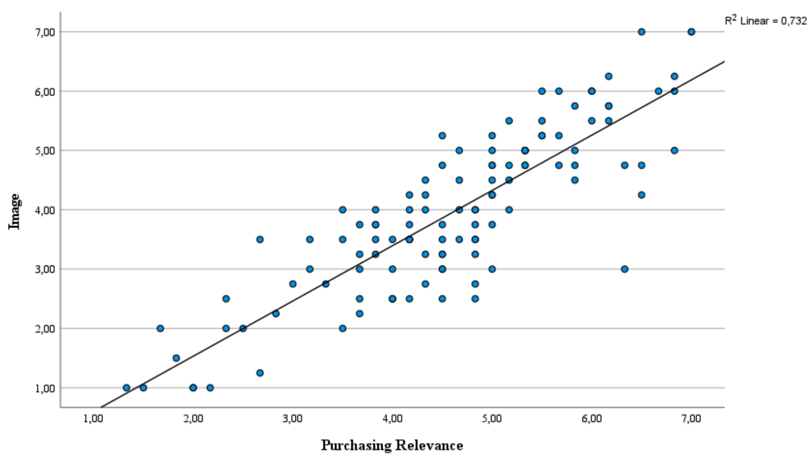

Figure 3: Scatter plot of the variables IMG and PR.

Therefore, hypothesis H6 is accepted.

(H7) The better the output quality of an AI-based product configurator, the more likely it is to enjoy the use of this technology.

The correlation between the variables output quality (OUT) and computer playfulness (CPLAY) is shown below. By looking at the variables individually, both variables are rather normally distributed. Figure 3 shows the relationship of OUT and CPLAY with $R^2 = 0{,}045$.

Again, two groups were formed based on the Likert scale. The two variables were examined for their difference and dependence independently of the age groups. In this case, group 1 with scores greater than or equal to 4 had similar scores (N = 79; mean = 4.2753; Std. Dev. = 0.75595) as group 2 with scores less than 4 (N = 37; mean = 4.0608; Std. Dev. = 0.70318). As was hypothesized after viewing the scatterplot and the low R^2, no significant relationship was found between output quality and enjoyment of computer play (t (114) = 1.456; p = 0.148, CI 95% -0,07741–0,50642). The analysis shows that the quality of the results of an AI-based product configurator does not influence and has no correlation to the customer's enjoyment of using such new technologies. As a result of the knowledge gained from the t-test, hypothesis H7 is rejected.

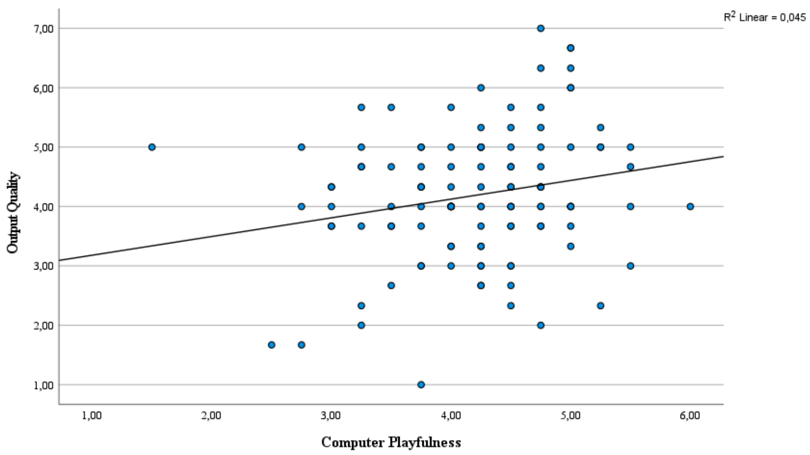

Figure 4: Scatter plot of the variables IMG and PR.

6. Discussion, limitations and conclusion

The technology acceptance and usage behavior of AI-based product configurators has not yet been investigated. This kind of applications is already in use in German cosmetics industry, as previous hurdles, e.g. storage capacity and costs are falling (Paschen, Wilson, and Ferreira 2020). Especially in the field of decorating cosmetics a large market potential can be seen (GIK 2019). However, when using product configurators, the focus should be on the users. Previous research work, e.g. by Venkatesh and Bala (Venkatesh and Bala 2008) has shown that the age of the target group is a decisive factor for acceptance of the benefits. This research shows the potential validity of some of the findings of Venkatesh and Bala (Venkatesh and Bala 2008) for the German cosmetics industry and the use of AI-based product configurators. Thus, of the ten hypotheses, eight were confirmed, and two were refuted.

In particular, the acceptance of hypotheses H1a and H1b showed that age is an important factor in terms of intention to use and perceived enjoyment. Consistent with this, hypothesis tests of H2a and H2b showed that older customers have lower self-efficacy regarding the use of computers and concurrent higher concerns about using AI-based product configurators. Other variables influencing the acceptance of product configurators that were found to be significant in the study were subjective norm and objective usability examined in H3a and H3b. Hypothesis H4 shows that the more user-friendly female participants perceive an AI-based product configurator to be, the more likely they are to perceive it as useful. In this context, the results of H5a and H5b regarding traceability and perceived external control seem plausible. Here, it was found that both age groups studied had problems comprehending the outcome of an AI-based product configurator. A significant result could also be demonstrated with respect to H6. It was shown that the customer's own image, the degree of self-identification with AI-based product configurators, influences the customer's purchase relevance when using an AI-based product configurator in the cosmetics industry. H7 investigated whether there is a relationship between the expected output quality of the configuration result and the enjoyment of using AI-based product configurators. No significant relationship could be demonstrated. In conclusion, the study shows that age has a significant effect on the acceptance of AI-based product configurators. The significant effect is supported by a positive subjective norm, perceived ease of use, and personal image.

Although the results of this work contribute to the current state of technology acceptance research by using a real-world use case of AI-based product configurators in the cosmetics industry (Olay Skin Configurators) to explore ten hypotheses, there are some limitations in this study that need to be considered. Since the respondents are all female, the outcomes could not be easily transferred in case of other target groups and industries. The sample participants were composed of different groups, but corresponded to the criteria, which in turn were known by the research-team. The division of age into two groups and the nature of the sample limit the interpretation of the results. By selecting the criteria, representativeness in terms of content can be assumed; a calculable mathematical-statistical representativeness or an objectively comprehensible selection procedure should be aimed for in further research. Furthermore, it would be interesting to see the results of a MANOVA test that might complement the results of dividing the data into age groups. In addition, the presented use case is a PTO configurator, so the validity in relation to other product configurators, e.g. ETO, is not guaranteed. It should be noted that, as in Venkatesh and Bala (Venkatesh and Bala 2008), only screenshots were shown to the respondents, leaving the impact of a real interaction with AI-based product configurators undetected.

Ideally, it would be interesting to see if the same results hold true in another industry or country. Future research should also address how the implications of this study can be mapped to in a corresponding customer journey and how this can influence sales revenue streams.

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