Acceptance of Artificially Intelligent Digital Humans in Online Shops: A Modelling Approach

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ABSTRACT

The UTAUT2 model is used to investigate the factors that influence consumer acceptance of artificially intelligent digital humans in online stores. Digital humans can be defined as a digital avatar that can mimic a full range of human behaviors (Ward, Boom, and Majenburg 2022). Six simple linear regression analyses are conducted to identify the determinants of intention to use digital humans. In the final multiple regression model, which includes the influences of six independent latent variables and three control variables (gender, age, and experience) on behavioral intention, statistically significant influences are identified for two variables: performance expectancy and habit. The results show that there is a tendency to accept the use of digital humans in online stores. Performance expectancy emerges as the strongest positive predictor of behavioral intention. In addition, hedonic motivation shows a positive influence on behavioral intention in the simple regression analysis, while the multiple regression results show a minimal negative correlation. The results may provide important insights into the adoption of innovative digital human technologies.

KEYWORDS

Digital human, innovation, artificial intelligence, UTAUT2, online shopping

1. Introduction

Changes in the global economic and political landscape, combined with the ongoing COVID-19 pandemic, have created a need for rapid digital innovation in retail (Lim 2021, p. 103). Online retailers face the challenge of matching the product advice, brand loyalty, and communication of brick-and-mortar retail. To achieve this, online retailers must be able to create interactions with customers and provide a more natural and engaging customer experience (Denner 2021). It therefore makes sense for retailers

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to look at the applications of artificial intelligence (AI) and associated opportunities and challenges (Denner 2021). While a few years ago it was enough to provide a flawless customer experience, today companies know that their role is to enhance the human experience (Ward 2020). At the same time, the need of consumers for social interaction is increasing (Ward 2020).

Digital humans could be a solution for a more interactive, personalized, and modern shopping experience. A digital human can be defined as a digital avatar that can mimic a full range of human body language. Supported by AI, they can interpret the customer's input and return both the facts that consumers need and appropriate nonverbal responses (Ward, Boom, and Majenburg 2022). Digital humans combine the natural language processing abilities of chatbots with emotional intelligence. They use tones of voice, body language, and facial expressions to transmit empathy and kindness. A digital human can bridge the digital divide by offering the best of both worlds (AI Forum of New Zealand 2019; Futurside 2022), employing both conversational AI and machine learning (NTT DATA Business Solutions AG 2022).

A digital human can provide faster response times with less effort, freeing staff to address more complex tasks, and can provide personalized and consistent care at scale (UneeQ 2020). For customers, this means a significant improvement in the online experience, with personalized recommendations and interactions that feel empathetic, friendly, and trustworthy (Mills and Liu 2020, p. 3).

Digital humans are already being deployed in some industries, such as healthcare, financial services, retail, automotive, real estate, telecommunications, and technology (Futurside 2022). Since the ability to create digital humans is still in its infancy, there are many research gaps in the literature. In particular, there has been little research into consumer acceptance of digital humans. As a result, online retailers are hesitant to invest in the technology.

This study fills this research gap by determining which factors influence the acceptance of AI-supported digital humans. Six hypotheses are tested, based on the UTAUT2 model of Venkatesh and Bala.

The remainder of the paper is structured as follows. In the second section, the theoretical background of UTAUT2 is discussed and the hypotheses are outlined. In the third section, the research methodology is presented, with a detailed discussion of the rationale behind the data collection methods. In the fourth section, the results are presented and analyzed. The paper concludes with a discussion of the limitations of the study and possible future extensions.

2. Theoretical background and hypotheses

To uncover the factors influencing consumer acceptance of AI-powered digital humans, the research model and the hypotheses of this study were developed based on the UTAUT2 model (Venkatesh et al. 2003; Venkatesh, Thong, and Xu 2012). Five out of the seven original UTAUT2 constructs – behavioral intention, performance expectancy, effort expectancy, social influence, hedonic motivation, and habit – and one extended construct – trust – were adapted to the context of digital humans, as illustrated in Figure 1. The integration features of the UTAUT2 model make it well-suited to understanding the adoption and use of AI technologies. The extension of the model developed here, designed to explain the use of technologies in consumer markets, is appropriate for studying the adoption and use of specific applications of AI, like digital humans, in online purchasing situations.

Behavioral intention

Behavioral intention describes the extent to which an individual intends to use a particular technology (Fishbein and Ajzen 1975, p. 228). In acceptance research in the field of AI technologies (Gursoy et al. 2019, p. 169; Lu, Cai, and Gursoy 2019, p. 43), acceptance is operationalized as a hypothetical variable based on behavioral intention. According to Venkatesh et al. (2003, p. 427), forecasts of the actual use behavior of these systems can be derived based on consumers' behavioral intentions.

Performance expectancy

The performance expectancy reflects the expected individual utility of a new technology for the user (Venkatesh et al. 2003). The perceived benefits of a technology can motivate potential users to adopt it. Transferring the variable into the context of online shopping with the assistance of digital humans, performance expectancy (PE) means the degree to which a consumer expects to experience a performance advantage from using digital humans. This leads to the following hypotheses:

Hypothesis 1 − Performance expectancy (PE) positively influences the behavioral intention to use digital humans.

Effort expectancy

The effort expectancy of a technology is the extent to which users perceive it to be easy to learn and use. If users believe it is easy, they are more likely to use it (Venkatesh et al. 2003). In addition to performance expectancy, effort expectancy has also been shown to be a significant positive predictor of intention to use in previous acceptance studies of AI-based technologies (Schwendener 2018, p. 55). Therefore, the following hypothesis is proposed:

Hypothesis 2 − Effort expectancy (EE) positively influences behavioral intention to use digital humans.

Social influence

Users often rely on opinions and experiences from their social environment when evaluating new technologies (Venkatesh et al. 2003, pp. 451–453). For the purposes of this study, social influence is the extent to which consumers perceive that influential people can lead them to believe that they should use digital humans in online stores. Acceptance studies on AI technologies have confirmed a positive correlation between social influence and intention to use (Schwendener 2018, p. 55). This leads to the following hypothesis:

Hypothesis 3 − Social influence (SI) positively influences behavioral intention to use digital humans.

Hedonic motivation

Hedonic motivation is the fun or pleasure derived from using technology (Venkatesh, Thong, and Xu 2012). In the context of this study, hedonic motivation is defined as the extent to which a consumer perceives the use of digital humans during the customer journey as fun, entertaining, and enjoyable. This leads to the following hypothesis:

Hypothesis 4 − Hedonic motivation (HM) positively influences the behavioral intention to use digital humans.

Habit

Habit is the extent to which an individual believes that their behavior is a result of experience (Venkatesh, Thong, and Xu 2012). When looking beyond the initial acceptance of a technology, habit has proven to be an important factor in the willingness to use technology and integrate it into one's daily life (Kim, Malhotra, and Narasimhan 2005; Limayem, Hirt, and Cheung 2007; Venkatesh, Thong, and Xu 2012). This leads to the following hypothesis:

Hypothesis 5 − Habit (HT) positively influences behavioral intention to use digital humans.

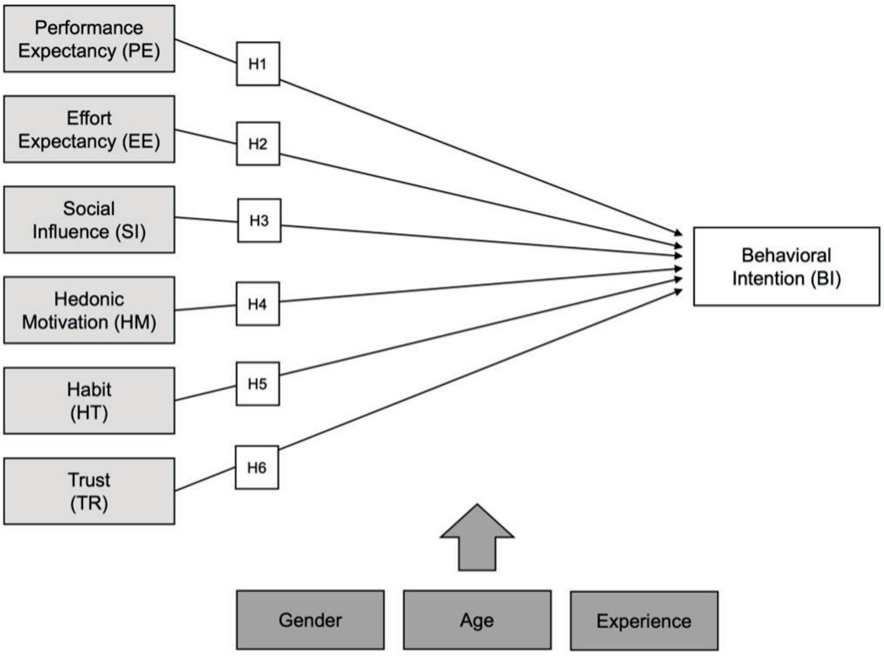

Figure 1: Research model.
Source: Own representation based on Venkatesh et al. (2003, p. 447) and Venkatesh, Thong and Xu (2012, p. 160).

Trust

Previous research has found that trust seems to affect potential users of AI technologies in addition to the UTAUT2 variables. Research by Mills and Liu (2020) draws on technology trust theory and explores the role of social presence, anthropomorphism, and privacy in determining people's trust and willingness to interact with digital humans. Ganesa, John, and Mane (2020) investigated the behavioral intention to use AI chatbots among telecom customers and extended the UTAUT2 model with the trust factor to quantify its effect on behavioral intention and user behavior, finding a positive relationship. This leads to the following hypothesis:

Hypothesis 6 − Trust (TR) positively influences the behavioral intention of using digital humans.

Control variables

In the original UTAUT2 model, in addition to the seven main determinants, moderating effects on **age**, **gender**, and **experience** were also taken into account. To avoid neglecting their influence in the present study, they were included as control variables. This procedure is in line with similar consumer research on technology acceptance. Since digital humans are a recent innovation, experience with chatbots is surveyed and included.

3. Research methodology

Venkatesh et al. (2003, p. 437) provided a quan-titative survey methodology for the evaluation of the UTAUT model, which can be adapted for the purposes of this study. In contrast to a qualitative survey, a quantitative survey allows a high degree of standardization, allowing for greater comparability of the results. In addition, quantitative surveys allow the research model to be tested directly and without major preparation (Homburg 2017, p. 267). Compared to other data collection methods, such as telephone or written questionnaires, the online survey offers two main advantages: respondents can be recruited quickly and easily, and a higher reach can be achieved through distribution on the internet. The latter advantage is often questioned, as it cannot be ensured that a specific target group will be reached. This problem of self-selection must therefore be considered when interpreting the results (Homburg 2017, pp. 269–70).

Data collection

Within the framework of an empirical cross-sectional study, an online survey was designed according to the chosen quantitative research approach and conducted in Germany from 30 June to 7 July 2022, employing convenience and snowball sampling. The online questionnaire was distributed via WhatsApp, email, and social media. The survey was conducted anonymously, and participants were requested to share the questionnaire with their social contacts.

Questionnaire rationale

Based on the literature review and the proposed research model, an online questionnaire was created, divided into four main sections:

1. Introduction and background information on AI-based digital humans

2. Experiences with chatbots and AI-based digital humans

3. Perceived acceptance of AI-based digital humans in online shops

4. Sociodemographic information of the survey participants

In the first section of the questionnaire, respondents received an explanation of AI-powered digital humans. In particular, a picture of Telekom's digital assistant Selena was shown, as well as a picture of the in-store digital assistant Kiri used at Vodafone stores in New Zealand, as shown in Figure 2. Participants were also provided with a link to a video showing a digital human in action at this point in the questionnaire.

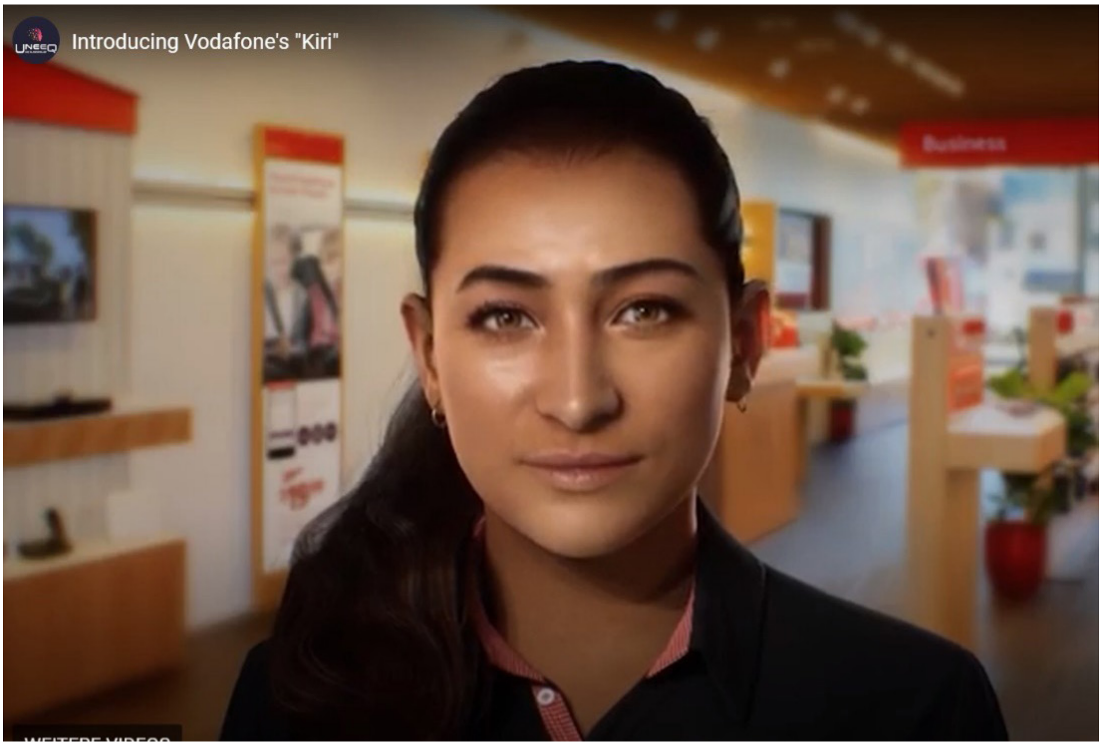

Figure 2: Screenshot from the video of the digital human "Kiri" used by Vodafone New Zealand.
Source: https://news.vodafone.co.nz/article/vodafone-reveals-identity-its-digital-assistant

In the second part of the questionnaire, participants were asked about their prior experience with chatbots. The use of digital humans is currently not a widespread practice, so experience with chatbots was used as a substitute. In two further questions, the respondents were asked about their level of knowledge of digital humans.

The third and main part of the questionnaire addressed the perceived acceptance of digital humans in online stores and its influencing factors. The modified UTAUT2 model was used to capture six theoretical constructs (behavioral intention, performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and trust) according to the definitions given in Section 2. Since these theoretical constructs are not directly observable variables, a reflective measurement model was applied. This involves the use of several directly measurable indicators to measure a theoretical construct (Kroeber-Riel and Weinberg 2003, p. 21). Discrete rating scales are usually employed to measure these indicators, and in particular, a Likert scale is often used to measure the attitudes of individuals (Homburg 2017, p. 314).

To operationalize the six constructs, a total of 22 indication- and application-specific items were adapted to the context of AI-based digital humans in online shops and were measured using a seven-point Likert scale ranging from "I strongly disagree" (1) to "I strongly agree" (7).

The final section of the survey collected sociodemographic information such as the age, gender, employment status, and educational status of participants. To ensure the validity of the questionnaire, it was tested in advance on test subjects to check the comprehensibility of the questions as well as the formal and technical correctness of the survey process.

Analysis strategy

The collected data were analyzed using the IBM software SPSS. Only complete data sets were considered in the analysis. The data include descriptive statistics on sociodemographic data, knowledge and experience values, and acceptance indicators of digital humans. The measurement instruments used were tested for internal consistency using reliability ratios and descriptive statistics of items. Linear and multiple regression analyses were used to test the relationships between the variables and the hypotheses derived from the proposed adapted UTAUT2 model. In the regression analysis, the model quality and the significance of regression coefficients were tested. A confidence level of 95% was used in all tests for statistical significance ($\alpha = 0.05$).

4. Analysis and results

In total, the online survey received 224 impressions, resulting in a final sample of 174 respondents with a dropout rate of 22.3 %. Table 1 shows the sociodemographic statistics of the sample with absolute and relative frequencies.

As shown in Table 1, the majority (56.9 %) of the 174 survey participants were female. The average age of the respondents was 30.2 years, with the majority (72.4 %) belonging to the young age group (15–29 years). The older age group (≥ 30 years) made up 27.6 % of the sample. The choice of age groups is based on the acceptance study by Monard et. al (2018, p. 16). The results show that the participants aged 20–30 had the most experience with chatbots and that the older age groups (> 30 years) were reluctant to use chatbots.

The division into the two age groups was intended to verify whether the reluctance of the older age group to use digital humans also applies at this early stage of the introduction of a technology. Regarding the level of education, the group with a university or university of applied sciences degree dominated (43.1 %). More than a third of the respondents (38.0 %) stated that they had graduated from a secondary school, whereas only 1.1 % did not have a degree. The remaining 17.8 % of the participants said that they had completed an apprenticeship. Table 2 summarizes the results and provides the absolute and relative frequencies regarding the level of knowledge.

Table 2: Previous experience and knowledge of digital humans.

Item	*Category*	*Frequency*	*%*
Experience with chatbots	Yes	114	65.5 %
	No	60	34.5 %
The term “digital human”	Yes	77	44.3 %
	No	97	55.7 %
Usage of digital humans	Yes	43	24.7 %

Source: Own research, 2022, n = 174.

More than half of the respondents (65.5%) have already used a chatbot. Regarding prior knowledge about digital humans, it was found that less than half (44.3%) of the respondents knew the term digital human before describing it, while 55.7% of the respondents did not recognize it. In addition, 43 of the 174 respondents (24.7%) confirmed that they had already spoken to a digital human, while most respondents had never used digital humans.

Looking at these results in conjunction with the sociodemographic data, it can be seen that 32 of the 43 respondents who had already interacted with a digital human belonged to the younger age group (15–29 years). Of these 43 respondents, 22 were female and 21 were male. These results initially suggest that there are age-specific differences in the sample regarding previous use of digital humans, but no gender-specific differences. Thus, it could be concluded that age plays a role in the adaptation decision of potential users of digital humans in online stores.

Before testing the proposed research model and the hypotheses based on it, the collected constructs were evaluated in terms of their suitability for further statistical analysis based on the reliability and descriptive statistics of the scales. A scale is considered sufficiently reliable when the Cronbach’s alpha reliability coefficient reaches a value of at least 0.70. For further validation, the minimum corrected item-total correlation (rIS) was recorded, which reflects the correlation of an item with the scale. This value is usually referred to as discriminatory power. According to Hair et al. (1998, p. 118), items should have a discriminatory power of at least 0.30 to be considered sufficiently reliable. The results of this analysis are shown in Table 3.

A preliminary test was conducted to assess the validity of the statistical procedures. The test for multicollinearity examined the correlations between the six latent variables. In the context of multiple regression, multicollinearity is an excessive correlation of two or more causal variables with each other. The correlation matrix is a suitable tool to test for the presence of multicollinearity. According to Field (2018, p. 402), correlation values above 0.8 between two independent variables are an indicator of multicollinearity. As shown in Table 4, all predictors correlated moderately to the behavioral intention, but none of the correlations between the predictors are above 0.8.

Table 3: Descriptive statistics and tests for reliability.

Construct	*Items*	*α_c / SB [a]*	*r_{IS}*	*M*	*SD*
Behavioral intention	3	0.92	0.82 – 0.86	3.69	1.71
Performance expectancy	4	0.91	0.75 – 0.83	4.33	1.55
Effort expectancy	4	0.91	0.78 – 0.85	4.94	1.39
Social influence	3	0.96	0.90 – 0.92	3.20	1.53
Hedonic motivation	3	0.92	0.79 – 0.86	4.25	1.59
Habit	3	0.93	0.82 – 0.90	4.25	1.63
Trust	2	0.67 [a]	0.50	4.10	1.72

* α_c = Cronbach's alpha; SB = Spearman–Brown coefficient; r_{IS}= minimum of corrected item-total correlation; M = mean; SD = standard deviation

Source: Own research, 2022, n = 174.

Table 4: Correlation matrix.

	BI	**PE**	**EE**	**SI**	**HM**	**HT**	**TR**
BI	1.00	0.779**	0.528**	0.570**	0.620**	0.818**	0.678**
PE		1.00	0.520**	0.516**	0.662**	0.760**	0.719**
EE			1.00	0.336**	0.467**	0.503**	0.501**
SI				1.00	0.439**	0.580**	0.478**
HM					1.00	0.701**	0.624**
HT						1.00	0.681**
TR							1.00

BI = behavioral intention, PE = performance expectancy, EE = effort expectancy, SI = social influence, HM = hedonic motivation, HT = habit, TR = trust; [** $p < 0.01$]

Source: Own research, 2022, n = 174.

Hypothesis testing

As illustrated in Table 5, in the simple regression analyses, all of the UTAUT2 variables **performance expectancy** (β = 0.78), **effort expectancy** (β = 0.53), **social influence** (β = 0.57), **hedonic motivation** (β = 0.62), and **habit** (β = 0.82), as well as the additional variable **trust** (β = 0.68) are significant determinants of the behavioral intention of AI-based digital humans (p ≤ 0.001). As indicated in the correlation matrix (Table 4), the linear regressions also reflect highly significant influences of the variables **performance expectancy** and **habit** on behavioral intention. Based on these results, all six hypotheses can be confirmed.

Table 5: Simple linear regressions.

Predictors [a]	R^2	*b*	*SE*	*β*	*p*
Performance expectancy	0.61	0.92	0.06	0.78	0.000***
Effort expectancy	0.28	0.67	0.08	0.53	0.000***
Social influence	0.33	0.61	0.07	0.57	0.000***
Hedonic motivation	0.38	0.66	0.06	0.62	0.000***
Habit	0.67	0.86	0.05	0.82	0.000***
Trust	0.46	0.76	0.06	0.68	0.000***

[a] criterion = behavioral intention; R^2 = coefficient of determination; b = unstandardized coefficients; SE = coefficients std. error; β = standardized coefficients; p = statistical significance [* p < 0.05 ** p ≤ 0.01 *** p < 0.001]

Source: Own research, 2022, n = 174.

Furthermore, due to the limited evidence base for the proposed relationship in the modified UTAUT2 model, a three-step hierarchical multiple regression was performed. Table 6 illustrates the three steps of the hierarchical multiple regression, indicating the model quality as well as the changes in the coefficient of determination (ΔR^2) and the degrees of freedom (ΔF) when including additional variables. Furthermore, the significance of the change (p) was calculated to determine whether the additional variance (ΔR^2) could contribute to a significant improvement in the model. Model 1 showed that the control variables of gender, age, and experience explained only 7.7 % of the variance in the behavioral intention of using AI-powered digital humans and thus did not contribute significantly to the variance explanation of the criterion behavioral intention ($\Delta F_{3,170}$ = 5.81; p = 0.001).

Adding the UTAUT2 predictors improved the variance explanation of behavioral intention in model 2 to 74.1 % ($\Delta F_{5,165}$ = 88.11; p = 0.000). Thus, the predictors of performance expectancy, effort expectancy, social intention, hedonic motivation, and habit explained 66.4 % of additional variance in the criterion relative to the control variables. Including the additional variable trust in model 3 resulted in a very slightly increased additional variance explanation of the behavioral intention of only 0.3 %.

Thus, the additional predictor trust could not significantly explain more variance of the criterion than the control variables and the UTAUT2 variables ($\Delta F_{1,1164}$ = 2.25; p = 0.135).

Table 6: Model quality of multiple linear regression.

Model	*Predictors* [a]	*adj.* R^2	ΔR^2	*ΔF (df1, df2)*	*p*
M1 [b]	Control variables	0.077		5.81 (3,170)	0.001***
M2 [c]	Control and UTAUT2 variables	0.741	0.660	88.11 (5,165)	0.000***
M3 [d]	Control, UTAUT2 and additional variables	0.743	0.003	2.25 (1,164)	0.135

[a] criterion = behavioral intention; [b] Step 1: predictors (gender, age, experience); [c] Step 2: predictors (performance expectancy, effort expectancy, social influence, hedonic motivation, habit); [d] Step 3: predictor (trust); adj. R^2 = adjusted corrected coefficient of determination; ΔR^2 = changes in the coefficient of determination; ΔF = changes in the degrees of freedom ; p = significance of the change [*** p = 0.001]

Source: Own research, 2022, n = 174.

Table 7: Multiple linear regression.

Predictors [a]	*b*	*SE*	*β*	*p*	*T*	*VIF*
Gender	0.51	0.13	0.02	0.687	0.94	1.07
Age [b]	0.01	0.01	0.08	0.049	0.83	1.20
Experience [c]	0.31	0.14	0.09	0.027*	0.85	1.17
PE	0.34	0.08	0.29	0.000***	0.32	3.12
EE	0.10	0.06	0.08	0.114	0.61	1.64
SI	0.08	0.05	0.08	0.133	0.61	1.65
HM	-0.02	0.06	-0.02	0.722	0.43	2.34
HT	0.49	0.07	0.47	0.000***	0.30	3.35
TR	0.10	0.07	0.09	0.135	0.40	2.50

[a] criterion = behavioral intention (b= -1,53); [b] reference category = female; [c] reference category = no experience; b = unstandardized coefficients; SE = coefficients std. error; β = standardized coefficients; p = significance [* $p < 0.05$ *** $p < 0.001$]; T = tolerance; VIF = variance inflation factor

Source: Own research, 2022, n = 174.

The final multiple regression model (model 3) thus explained a total of 74.3 % of the total variance of the criterion behavioral intention ($F_{9,499} = 56.52$; $p = 0.000$). Table 7 summarizes the results of the three-stage multiple regression analysis, reporting only the outcome measures from the last regression model (model 3) with the highest variance explanation ($R^2 = 74.3$ %).

In the hierarchical multiple regression, among the primary UTAUT2 predictors, performance expectancy (step 2, $\beta = 0.29$; $p = 0.000$) and habit (step 2, $\beta = 0.47$; $p = 0.000$) were also found to be significant independent determinants of behavioral intention. This implies that hypotheses 1 and 5 can be confirmed even when controlling for the other predictors. Contrary to hypotheses 2, 3, 4, and 6, the other predictors in the multiple regression model had no significant effect on behavioral intention ($p > 0.05$). That is, controlling for all other predictors included in the regression model, no significant relationship between the predictor's effort expectancy (step 2, $\beta = 0.08$; $p = 0.114$), social influence (step 2, $\beta = 0.08$; $p = 0.133$), hedonic motivation (step 2, $\beta = -0.02$; $p = 0.722$), or trust (step 3, $\beta = 0.09$; $p = 0.135$) and the criterion behavioral intention could be confirmed.

Regarding the control variables, significant results were found for the control variable experience (step 1, $b = 0.31$; $p = 0.027$). Accordingly, respondents with no experience with chatbots (reference category) seemed to have a higher behavioral intention than participants with experience. For the control variable age, a barely significant value (step 1, $b = 0.01$; $p = 0.049$) was observed. However, since this value is extremely close to the significance level $\alpha = 0.05$, the result could not be classified as statistically significant. Finally, the control variable gender did not have a significant influence on behavioral intention.

5. Discussion

The research question was motivated by the need to understand what factors influence the acceptance of AI-based digital humans in online stores. In this study, an extended UTAUT2 model was tested with respect to the acceptance of digital humans in online stores.

Overall, the acceptance of AI digital humans in the observed population was moderate (mean BI = 3.69). In six simple linear regression analyses, the UTAUT2 variables (performance expectancy, effort expectancy, social influence, hedonic motivation, habit) and the additional variable (trust) were found to be effective predictors of behavioral intention toward digital humans in online stores. Based on this, all hypotheses (1–6) could be confirmed, implying that the constructs are suitable for predicting the acceptance of digital humans.

The hierarchical multiple regression produced significantly different results. In the final multiple regression model (model 3), which accounted for the influences of the six independent latent variables as well as the three control variables (gender, age, and experience) on behavioral intention, statistically significant influences were found for the performance expectancy, habit, and experience variables. None of the other constructs (effort expectancy, social influence, hedonic motivation, and trust) had a statistically significant effect on behavioral intention.

In contrast to the results of the simple linear regressions, only hypotheses 1 and 5 were confirmed in the hierarchical multiple regression analysis. The results of this study show a statistically significant correlation between performance expectancy and behavioral intention. Performance expectancy ($\beta = 0.29$; $p = 0.000$) proved to be the strongest positive predictor of behavioral intention to accept digital humans, and the level of performance expectancy of the sample was moderate (mean PE = 4.33) on average. Although the participants did not think that digital humans could increase their productivity in online stores, they still showed general agreement with the use of digital humans in online stores. Based on the obtained results, hypothesis 1 is accepted.

Moreover, habit ($\beta = 0.47$; $p = 0.000$) was confirmed as a significant positive predictor of acceptance in addition to performance expectancy. These results are consistent with the findings of Ganesa, John and Mane (2020) regarding the acceptance of AI chatbots by telecommunications customers. Habit was also perceived to be in the medium range in this population (mean HT = 4.25), with endorsement of the use of digital humans in online stores receiving the highest level of agreement. According to the results, hypothesis 3 is accepted due to the significant and positive relationship between habit and behavioral intention.

In contrast, the relevance of the other three primary UTAUT2 factors of effort expectancy, social influence, and hedonic motivation appeared to be secondary when all variables were considered together. Overall, the participants largely believed that they possessed the skills (mean EE = 4.94) to use innovative technologies such as digital humans in online stores. Effort expectancy ($\beta = 0.08$; $p = 0.114$) showed a small positive beta coefficient, but the required significance threshold was not reached, so hypothesis 2 could not be confirmed.

The predictor of social influence was rather low in this population (mean SI = 3.20). This suggests that the customization decision of digital humans in online stores is not strongly influenced by the opinions and attitudes of people close to the participants. Furthermore, as with effort expectancy, there was a minimal positive beta coefficient for social influence ($\beta = 0.08$; $p = 0.133$). Due to this lack of significance, hypothesis 3 was also not confirmed.

The predictor of hedonic motivation was in the middle range (mean HM = 4.25). The population's opinion that digital humans in online stores can be fun and entertaining was the strongest. During the study, it was found that hedonic motivation showed a positive influence on behavioral intention in the simple linear regression, while the multiple linear regression showed a minimal negative correlation. However, hedonic motivation did not significantly influence the behavioral intention to use digital humans in online stores, so hypothesis 4 could not be confirmed. Furthermore, when considering all predictors at once, no direct significant influence of the additional variable trust ($\beta = 0.09$; $p = 0.135$) could be found. Trust was also in the medium range for this population ($M_{TR} = 4.10$). A differentiated picture emerged. Although the respondents were convinced that digital humans will offer the best deals, they did not trust in the technology behind AI-based digital humans.

The multiple regression included the control variables and yielded the following results. Within the sample, a higher acceptance of digital humans was found among participants without experience ($b = 0.42$; $p = 0.031$). Since this innovative technology is still sporadic in the European market, experience among participants with chatbots was used instead of experience with digital humans. Furthermore, although a significant value for age was found ($b=0.01$; $p = 0.049$), this value was too close to the significance level of $\alpha = 0.05$. For this reason, age was not considered statistically significant. Thus, no influence of age on digital human acceptance was found. In addition, no significant influence of gender was found as a predictor of acceptance. Therefore, future research should examine the moderation effects of these variables as suggested by Venkatesh et al. (2003, pp. 467–469), which would have required a larger sample than the 174 subjects in the present study.

Overall, for the proposed research model of the study, 74.3% of the variance in behavioral intention could be explained by variation in the independent variables, namely performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and trust. Since the majority of the hypotheses could not be confirmed within the fitted and modified UTAUT2 model, this is an indication that there are other important determinants that influence the adoption of digital humans in online stores but were not considered in the tested model.

6. Conclusion

The primary objective of this study was to investigate consumer acceptance of AI digital humans using the UTAUT2 model to identify the factors influencing acceptance. Since there are no findings to date on factors in the acceptance of digital humans, this study can be seen as having an exploratory character in addition to testing the hypotheses that have been formulated. As the results of the research show, there is a tendency to accept the use of digital humans in online stores. Performance expectancy and habit were found to be relevant and statistically significant determinants of the behavioral intention of digital humans in online shops.

The results of this study can provide important insights into consumer acceptance of innovative digital humans. Many brands are already preparing for conversational commerce, which will bring such fundamental change that retailers need to start familiarizing themselves with the innovative technologies involved.

Limitations

Although this study has made significant findings regarding consumer acceptance of digital humans, there are a few limitations to their generalizability. The study relies on a limited number of participants. Because of a lack in access to a sampling frame, this study had to rely on a non-probability sample. Due to the random sampling method used, the results cannot be generalized to the entire population, but they reflect the reality of emerging technology markets with a relatively high technology sensitivity within a younger population. It is to be expected that older age groups do not currently use digital humans in online stores to the same extent as younger age groups. A larger sample could provide better insights into the impact of the control variable age. In future research, the results of this study should be plausibilized by methods other than UTAUT2. This should primarily focus on uncovering further determinants that may influence the acceptance of digital humans in online stores. Future research could support an ordinal regression approach and compare the results to those linear models in this study. In addition, the use of digital humans is currently not widespread. Therefore, most participants had no personal experience with digital humans and had to rely on descriptions.

Conflicts of interest statement

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix I: Survey

Welcome,

Within the framework of my Master's thesis at the Neu-Ulm University of Applied Sciences, I am investigating the acceptance of digital humans in the sales processes of online shops.

With only about 8 minutes of your time, you can make a valuable contribution to my investigation and ensure valid results.

First, Digital Humans are described in general and illustrated with a short video. Subsequently, I ask you to answer the questions based on your personal opinion.

The survey is anonymous and your data will be treated confidentially.

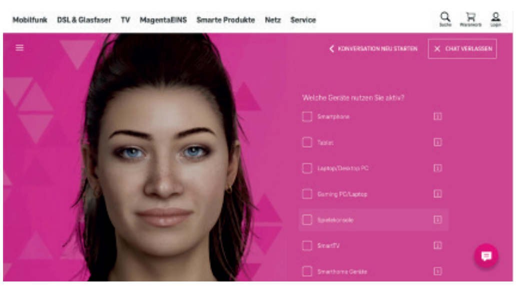
Thank you for your support!

Digital Humans are a combination of Artificial Intelligence (AI) and human conversation. They can be understood as a continuation of chatbots, with a human identity, appearance, and emotions. Behind Digital Humans is an AI platform that determines behavior, expressions, and language in real-time. This allows natural conversations to occur as they would in real life. Through verbal and non-verbal communication, they can realistically replicate natural human interaction on a large scale.

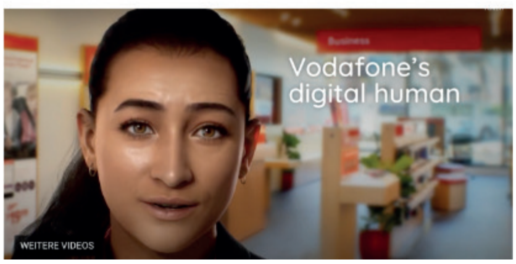
Today, they exist both in brick-and-mortar retail and online, where they can virtually advise a large number of customers 24/7 simultaneously. Digital Humans are already working for some of the biggest brands in the world such as Vodafone, Telekom, and BMW.

Examples from practice:

The digital assistant Selena helps you to find out in just a few steps what the necessary bandwidth is for your needs. This enables it to find the best individual internet tariff for you.



Digital assistant Kiki lives in Vodafone stores and helps customers manage their tariffs. She welcomes you with a smile and guides you through the entire transaction..



Click [here]() for more information and to see the Digital Human Sophie in action in a short video.

1. Have you ever used a chatbot on a website (e.g. an online shop)?

 Yes No

2. Did you know what Digital Humans were before you read the description?

 Yes No

3. Have you ever had a conversation with a digital human?

 Yes No

4. Which personal device do you prefer for interacting with Digital Humans?

 Laptop

 Smartphone

 Smartwatch

 Tablet

5. What is your attitude towards different forms of interaction with digital humans?

The ability to talk and communicate with a digital human is important to me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

The ability to type commands into a keyboard to interact with a digital human is important to me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

The ability to interact with a digital human through gestures is important to me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

6. Where would you most like to have a digital human in online shops to support you?

 More likely to welcome you in online shops

 More likely when searching for a specific product

 More likely when making recommendations

 More likely when advising on additional products

 More likely when advising on higher value products

 More likely when offering discounts

 More likely to list nearby stores

 More likely to track your delivery

 More likely in customer support

 More likely to handle returns

7. Please indicate how strongly you agree with the following statements:

BI1. I intend to use digital humans in online shops in the future.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

BI2. It is very likely that I will use digital humans in online shops, in my daily life.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

BI3. I plan to use digital humans in online shops frequently.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

8. Please indicate how strongly you agree with the following statements:

PE1. Digital humans in online shops are useful.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

PE2. Using digital humans in online shops increases my chances of achieving things that are important to me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

PE3. Using digital humans in online shops helps me accomplish things more quickly.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

PE4. Using digital humans increases my productivity.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

9. Please indicate how strongly you agree with the following statements:

EE1. Learning how to use digital humans in online shops is easy for me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

EE2. The use of digital humans in online shops is clear and understandable.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

EE3. I consider digital humans in online shops quite easy to me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

EE4. It is easy for me to become skillful at using digital humans in online shops.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

10. Please indicate how strongly you agree with the following statements:

SI1. People who are important to me think I should use digital humans in online shops.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

SI2. People who influence my behavior think that I should use digital humans in online shops.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

SI3. People whose opinions that I value prefer that I use digital humans in online shops.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

11. Please indicate how strongly you agree with the following statements:

HM1. I think using digital humans in online shops is fun.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

HM2. I think using digital humans in online shops is enjoyable.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

HM3. I think using digital humans in online shops is entertaining.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

12. Please indicate how strongly you agree with the following statements:

HT1. The use of digital humans in online shops could become a habit for me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

HT2. I am in favor to use digital humans in online shops.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

HT3. Using digital human in online shops could become natural to me.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

13. Please indicate how strongly you agree with the following statements:

TR1. I am convinced that digital humans in online shops are used to provide customers with the best offerings.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

TR2. I trust in digital humans.

Do not agree at all (1)	(2)	(3)	(4)	(5)	(6)	Completely agree (7)

14. What is your gender?

 Female Male Divers

Please enter your age.

What is your highest level of education?

 No degree

 Secondary level 1 school

 Secondary school degree

 University entrance qualification/ qualification for entrance to Universities of Applied Sciences

 Apprenticeship

 University/ University of Applied Sciences degree

Please select your current employment status.

 Currently not working

 Pupil

 Trainee

 Student

 Full-time employee

 Part-time employee

 Civil servant

 Self-employed, freelancer, farmer

 Pensioner

Appendix II: Table A1 Measurement instruments

Construction	*Definition*	*Measurement Instruments*
Behavioral intention (BI)	The degree to which an individual intends to use digital humans in online shops.	BI1. I intend to use digital humans in online shops in the future. BI2. It is very likely that I will use digital humans in online shops, in my daily life. BI3. I plan to use digital humans in online shops frequently.
Performance expectancy (PE)	The degree to which using digital humans in online shops will provide benefits to consumers in performing certain activities.	PE1. Digital humans in online shops are useful. PE2. Using digital humans in online shops increases my chances of achieving things that are important to me. PE3. Using digital humans in online shops helps me accomplish things more quickly. PE4. Using digital humans increases my productivity
Effort expectancy (EE)	The degree of ease/effort associated with consumers' use of digital humans in online shops.	EE1. Learning how to use digital humans in online shops is easy for me. EE2. The use of digital humans in online shops is clear and understandable. EE3. I consider digital humans in online shops quite easy to me. EE4. It is easy for me to become skillful at using digital humans in online shops.
Social influence (SI)	The degree to which an individual perceives that important others believe he or she should use digital humans in online shops.	SI1. People who are important to me think I should use digital humans in online shops. SI2. People who influence my behavior think that I should use digital humans in online shops. SI3. People whose opinions that I value prefer that I use digital humans in online shops.
Hedonic motivation (HM)	The pleasure or enjoyment derived from using digital humans in online shops.	HM1. I think using digital humans in online shops is fun. HM2. I think using digital humans in online shops is enjoyable. HM3. I think using digital humans in online shops is entertaining.
Habit (HT)	The extent to which people tend to perform behaviors automatically because of learning.	HT1. The use of digital humans in online shops could become a habit for me. HT2. I am in favor to use digital humans in online shops. HT3. Using digital human in online shops could become natural to me.
Trust (TR)	The degree to which people believe that digital humans in online shops works for their best interest.	TR1. I am convinced that digital humans in online shops are used to provide customers with the best offerings. TR2. I trust in digital humans.

Source: Adapted from Ha et al. (2019), Venkatesh et al. (2003) and Venkatesh, Thong & Xu (2012).