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Understanding the Adoption Dynamics of ChatGPT among Generation Z: Insights from a Modified UTAUT2 Model

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Abstract: This research delves into the factors influencing the adoption of ChatGPT, a sophisticated AI-based chatbot, among Generation Z members in Croatia. Employing an extended UTAUT2 model, the impact of various factors on the behavioral intention to use ChatGPT is explored. The study included 694 Generation Z participants, and data were collected through an online survey featuring self-reporting questions. The analysis utilized statistical software packages for performing both confirmatory and exploratory factor analyses, in addition to hierarchical linear regression. Key findings reveal that performance expectancy, social influence, hedonic motivation, habit, and personal innovativeness significantly influence the behavioral intention to use ChatGPT. However, effort expectancy, facilitating conditions, and price value do not exhibit a significant impact. Notably, the study excludes the use behavior factor due to multicollinearity issues with behavioral intention. While the research does not focus on moderating factors, it reports that the adapted UTAUT2 model explains 65% of the variance in the adoption of ChatGPT by Generation Z users.

Keywords: generative AI; ChatGPT; UTAUT2; generation Z; artificial intelligence adoption; behavioral intention; technology acceptance model; human-AI interaction

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1. Introduction

As a result of the development of Artificial Intelligence (AI)-based applications such as OpenAI's Chat Generative Pre-trained Transformer (ChatGPT), consumers' perceptions of the digital environment, work, and life have changed substantially. ChatGPT utilizes generative AI techniques to produce conversational responses from query prompts through Natural Language Processing (NLP) [1]. Chatbots conventionally employ NLP algorithms to interpret and respond to user inquiries by associating them with an array of potential answers available within the system. These systems have been enhanced by the incorporation of advanced Large Language Models (LLMs), which operate in tandem with deep learning techniques, to address challenges inherent to NLP. This integration facilitates the provision of immediate feedback to consumers [2].

ChatGPT, which was introduced on 30 November 2022, has rapidly emerged as a pre-eminent tool among generative AI technologies. This platform provides a diverse spectrum of applications, encompassing academic composition, programming, the identification of security flaws, assistance in social media management, and serving as a surrogate for traditional search engines [3]. This technology attracted 100 million users within two months, a rate of adoption that is notably rapid compared to other applications or technologies. For comparison, the social media platform Instagram required two and a half years to attain an equivalent number of users [4]. While the fundamental version of ChatGPT remains freely accessible, as of 14 March 2023, an enhanced iteration, designated as ChatGPT-4, was made available for a subscription fee of $20 per month. This advanced version is distinguished by its provision of prioritized access during periods of high demand, expedited response times, and the inclusion of novel features and enhancements [5–7].

Such a powerful tool can play an important role in numerous sectors, including education, healthcare, business and finance, law and legal services, creation of writing and art pieces, media, news and entertainment, sales and marketing, banking, academic work, and many others [8–13]. As Paul et al. [1] suggested, the UTAUT2 model is one of the theories that can be used to examine the factors influencing users' adoption and use of ChatGPT.

The topic holds significant implications for marketing professionals due to the changing landscape of consumer behavior and the potential benefits that AI can offer to the marketing field. AI-powered technologies can process vast amounts of data and deliver personalized responses to individual users. This allows marketers to gain deeper insights into customer preferences, behaviors, and sentiments. By leveraging these capabilities, marketers can refine their target audience segmentation, tailor content, and product offerings to align with specific needs and interests. Furthermore, with the rapid advancement of AI technologies, AI-driven tools can offer personalized and real-time interactions with consumers, enabling brands to enhance customer experiences, provide better customer support, and drive customer loyalty. Understanding the adoption factors can help marketers assess customer readiness to embrace AI solutions in their marketing efforts. Marketing professionals can use the research outcomes to make informed decisions about whether, and how, to invest in AI-powered chatbots for their marketing campaigns.

Generation Z represents a critical market segment for businesses, as they are a sizable consumer group with unique characteristics, preferences, and expectations. This research should help marketers gain insights into the factors influencing Generation Z's adoption of AI-powered chatbots such as ChatGPT. By understanding the factors that drive Generation Z's adoption of AI, marketers can leverage this knowledge to create more compelling marketing campaigns, deliver personalized content, and foster stronger customer relationships. Brands that successfully integrate AI into their marketing strategies may stand out from competitors and gain a competitive edge.

Generation Z, young people between the ages of 12 and 25, i.e., all those born between 1997 and 2009, currently receives the greatest attention by marketers. This is a generation with older parents and fewer siblings than previous generations [14,15]. It is a generation that has been shaken by the economic instability caused by the financial crisis at the end of the first decade of the 21st century and by the coronavirus pandemic [16]. They are called digital natives or the first digital natives because they were born at a time when the Internet and other digital technologies were already ubiquitous [14,17]. They are the first generation of the 21st century and they are always connected to the Internet, as they live in a hyperconnected world [14,15]. Generation Z brings positive changes, it is the generation that wants to change the world. They are interested in social issues, environmental protection, and sustainable development and expect the same from brands [14]. However, when it comes to brand marketing activities, members of the Generation Z expect these communications to be unique, personalized, and offer them additional experiences. They also expect companies to behave ethically, be honest, and be real [18]. According to BCW [19], Generation Z wants to be successful and recognized as successful. They find things that give them pleasure more important than other generations, they value social status, but also want to have an exciting lifestyle.

The paper investigates the factors affecting Generation Z's adoption of AI-based conversational tool in Croatia using an extended UTAUT2 framework. It begins with an introduction, followed by a comprehensive literature review, and the development of research hypotheses focusing on various constructs. The methodology section details the survey instrument, data collection, and analysis techniques, which precedes a discussion of the results. The paper concludes with a summary of findings, practical implications, and suggestions for future research, acknowledging the study's limitations.

2. Literature Review

Scientific research in the field of information systems has consistently explored models to elucidate user interactions with technology. Notable among these is the Technology Acceptance Model (TAM) proposed by Davis in 1989 [20], emphasizing perceived usefulness and ease of use as core components. Subsequent models were built on this foundation, with Goodhue and Thompson introducing the Theory of Task-Technology Fit in 1995 [21], considering technology's role in task completion. Venkatesh and Davis refined TAM [22], leading to TAM2 in 2000 [23] which offered detailed insights into system utility at various implementation stages. The Unified Theory of Acceptance and Use of Technology (UTAUT) further advanced the field in 2003, integrating performance expectancy, effort expectancy, social influence, and facilitating conditions as key behavioral predictors [24,25].

Continuing this progression, Venkatesh and Bala formulated TAM3 in 2008, merging TAM2 and determinants of ease of use into a comprehensive framework accounting for individual, system, and contextual influences. TAM3 is particularly relevant for managerial IT adoption strategies, highlighting experience as a significant moderating factor that evolves over time, impacting users' technological attitudes [25–27].

The UTAUT model was revised by Venkatesh and his co-authors in 2012 [28], after they incorporated three additional constructs that take into account user/customer aspects and renamed the model as UTAUT2. The original UTAUT model's performance expectancy, effort expectancy, and social influence constructs were adopted without modification, and a connection between facilitating conditions and behavioral intention was added. Some new constructs were added as well, such as Hedonic Motivation (HM), Price Value (PV), and Habit (HA) [28,29]. UTAUT2 was not designed to have an exclusive focus (e.g., new technology, location), but rather to serve as a comprehensive framework for analyzing technology adoption [30]. An extension of UTAUT2 based on literature was attained by Gansser and Reich [31], extending the factors of health, convenience, comfort, sustainability, safety, security, and personal innovativeness. They looked at how these factors influenced behavioral intention and use behavior for products containing AI in a real-world environment. In the initial version of the modified UTAUT2 model, the questions about the moderating factors were retained, but they will not be further examined in the context of this paper.

Both the UTAUT and the UTAUT2 models have been widely utilized to explore the adoption of AI-based systems across diverse domains, geographical locations, and industries, demonstrating their relevance and applicability in understanding individuals' behavioral intentions towards AI technologies. UTAUT and UTAUT2 have been applied to diverse contexts, such as the adoption of AI in marketing, consumer research, psychology, healthcare, education, and the hospitality industry [32–38]. Studies have leveraged UTAUT and UTAUT2 to investigate the adoption of AI-powered systems, including AI-based lead management systems, autonomous decision-making systems, voice-controlled AI, chatbots, and AI service robots [33,34,37–41]. Furthermore, UTAUT2 has been extended to incorporate pandemic threats and emotional behavioral intentions toward AI-adopting hotels during and after COVID-19 [35]. Additionally, UTAUT2 has been adapted to explore the adoption of AI wearables, accounting information systems, and cryptocurrency in emerging economies [42–44]. Furthermore, UTAUT and UTAUT2 have been employed to investigate the determinants of intention to use AI-based diagnosis support systems among prospective physicians and the use of AI in digital healthcare from patients' viewpoints [38,45,46].

This research stands out by specifically investigating the adoption of a generative AI conversational agent among Generation Z members in Croatia, using an extended UTAUT2 model. This focused approach not only aligns with the current technological landscape, but also minimizes potential measurement risks associated with broader sector analyses. By delving into unique regional insights and extending traditional acceptance models, this research provides a nuanced understanding of Generation Z's interaction with AI technology.

3. Hypotheses Development

Considering that the model has been modified and adapted from Venkatesh et al. [28] and Gansser & Reich [31], the hypotheses were modeled on other research papers dealing with the acceptance of new technologies based on the UTAUT2 model (Figure 1). The hypotheses in this paper are adapted from the modified model, and the study that was used as role model for generating the hypotheses is mainly Schmitz et al. [47], but with the influence of other studies such as Garcia de Blanes Sebastian et al. [48], Nikolopoulou et al. [49], and Strzelecki [50]. Table 1 provides an overview of all formulated hypotheses, with each hypothesis elaborated within a separate section of the manuscript.

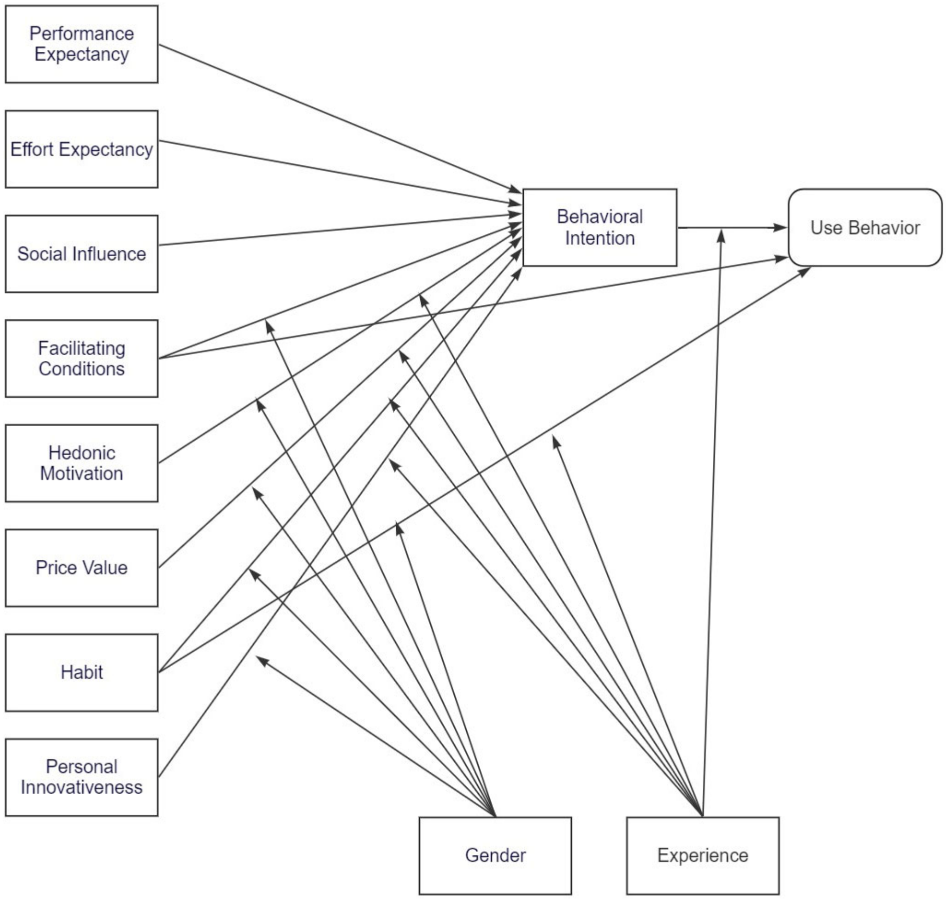

Figure 1. The initial version of the modified UTATU2 model. Source: based on Venkatesh et al. [28]; Gansser & Reich [31].

Table 1. Hypotheses summary.

H1	Performance expectancy has a positive, direct, and significant effect on behavioral intention
H2	Effort expectancy has a positive, direct, and significant effect on behavioral intention
H3	Social influence has a positive, direct, and significant effect on behavioral intention
H4	Facilitating conditions have a positive, direct, and significant effect on behavioral intention
H5	Hedonic motivation has a positive, direct, and significant effect on behavioral intention
H6	Price value has a positive, direct, and significant effect on behavioral intention
H7	Habit has a positive, direct, and significant effect on behavioral intention
H8	Personal innovativeness has a positive, direct, and significant effect on behavioral intention

3.1. Performance Expectancy

Venkatesh et al. [24] define performance expectancy as an individual's belief that technology will improve their job performance. Performance expectancy has been found to be the strongest predictor of behavioral intention to adopt technology, according to multiple studies [51–54]. The higher the consumers' expectations of the AI service, the more likely it is that consumers will use said service [55]. In the context of chatbots, and ChatGPT can be referred to as a chatbot, performance expectancy revolves around the perception of the consumer that the chatbot is useful. With the use of chatbots, users believe they are able to accomplish the necessary tasks more efficiently and thus increase their productivity [56]. Therefore, based on this, the following hypothesis is proposed:

H1. *Performance expectancy has a positive, direct, and significant effect on behavioral intention.*

3.2. Effort Expectancy

An individual's effort expectancy is a measure of how much effort they expect to put into the use of a particular technology [24]. In most cases, AI-based agents will appear implicitly to consumers, representing a barrier if they do not meet consumers' expectations or require too much effort, since they must allow for quick and efficient task completion [57,58]. If the user has a tendency to think that chatbots are simple to use and simply offer the necessary information, as a result they will be open to using chatbots in the future [56]. Additionally, it has been demonstrated in the past that confidence by an individual in their own technical abilities has a major impact, directly affecting the intention to use technology [59]. The following hypothesis is proposed to investigate the relationship:

H2. *Effort expectancy has a positive, direct, and significant effect on behavioral intention.*

3.3. Social Influence

In accordance with Venkatesh et al. [24], social influence is defined as the degree to which an individual believes other people will support the new technology. It has been reported that people related to the customer play an active role in contributing to the customer becoming more aware of and using technology [54,55,60]. Since AI technology is still in the early stages of societal acceptance and is being developed quickly in combination with a range of products, the opinion of other people continue to be important in establishing consumer trust in these goods [61]. The following hypothesis is proposed to investigate the relationship:

H3. *Social influence has a positive, direct, and significant effect on behavioral intention.*

3.4. Facilitating Conditions

Venkatesh et al. [24] defined facilitating conditions as the extent to which a person believes that a technological infrastructure is available to support them when using a new technology. The usefulness of technology will be realized under the assumption that facilitating conditions are actively in place within a given environment [62]. Crabbe et al. [63] and Hew et al. [64] supported findings showing that facilitating conditions, such as internet access, mobile devices, and available support, result in higher user perception of facilitating conditions, leading to high levels of behavioral intention. In UTAUT2, it is hypothesized that facilitating conditions have a direct effect on the behavioral intention to use new technology [28]. Therefore, the following hypothesis says:

H4. *Facilitating conditions have a positive, direct, and significant effect on behavioral intention.*

3.5. Hedonic Motivation

The concept of hedonic motivation, as defined by Venkatesh et al. [28], refers to the enjoyment and pleasure derived from the use of a specific technology, irrespective of its inherent benefits. This form of motivation is a crucial determinant of consumer acceptance and utilization of new technologies, as argued by Tamilmani et al. [65]. Hedonic motivation is particularly influential with respect to the adoption of technology across various domains, ranging from AI in leisure activities to virtual doctor appointments and mobile commerce [47,55,66]. Specifically, in the context of Generation Z's interaction with ChatGPT and other emerging AI technologies, hedonic motivation is a key factor, as demonstrated by Strzelecki's [50] findings. Consequently, the following hypothesis is proposed:

H5. *Hedonic motivation has a positive, direct, and significant effect on behavioral intention.*

3.6. Price Value

The concept of price value can be defined as the trade-off between the benefits perceived by the consumers and the cost of using the application or product [28]. It is commonly understood that individuals aim to maximize net benefits; thus, price value can be regarded as a measure of the net advantage gained from technology utilization. This principle implies that people will accept the cost of technology if its adoption yields significant benefits [48]. Cintron [67] further articulated that price value is a predictive factor of IT managers' behavioral intentions toward adopting AI for digital transformation. Similarly, Cabrera-Sanchez et al. [54] identified a correlation between price value and behavioral intention in the context of AI adoption. However, the relevance of price value is sometimes overlooked in studies where the technology in question is available at no cost, as exemplified by Strzelecki [50] who explored ChatGPT adoption among students. Despite this, based on the preceding discussion, the following hypothesis is proposed:

H6. *Price value has a positive, direct, and significant effect on behavioral intention.*

3.7. Habit

Limayem et al. [68] define the concept of habit in the context of technology use as the repetitive utilization of technology which stems from automated behaviors developed during the early stages of learning. Previous research has shown that prior use habits affect the intention to use a particular technology [49,68,69]. In the context of using ChatGPT among students or Generation Z members, Strzelecki [50] states that habit is positively associated with behavioral intention. Cintron [67] found that habit predicted IT managers' behavioral intentions to adopt AI, and multiple studies have found that habit has a significant influence on behavioral intention to use AI [48,54,55]. The following hypothesis is proposed to investigate the relationship:

H7. *Habit has a positive, direct, and significant effect on behavioral intention.*

3.8. Personal Innovativeness

The concept of personal innovativeness is based on research by Agarwal and Prasad [70]. They come to the conclusion that certain individuals adopt new technologies earlier than others. According to Gansser and Reich [31], that is crucial for AI-based goods and services. People must possess a certain amount of curiosity and be open to trying new things to consider utilizing new products or technologies. Xian [55] states that personal innovativeness can be integrated into the UTAUT2 model even as a moderating factor. Garcia de Blanes Sebastian et al. [48] suggest that personal innovativeness affects behavioral intentions, and it is most important in emerging technologies such as artificial intelligence. Strzelecki [50] found that personal innovativeness has a positive effect on the behavioral intention of students to use ChatGPT. Therefore, based on this, the following hypothesis is proposed:

H8. *Personal Innovativeness has a positive, direct, and significant effect on behavioral intention.*

4. Research Methods

4.1. Instrument

Gansser and Reich [31] made an extension of UTAUT2 and made some modifications. The basic model can serve as a comprehensive framework for analyzing technology adoption, while the extensions and modifications are intended to make the model more focused on the acceptance of products containing artificial intelligence. Some of the concepts from Gansser and Reich [31] were not used due to the fact that they do not have much sense in this study because ChatGPT is a piece of software, not a physical product. Still, the concept of personal innovativeness was retained due to its relevance in this context. The proposed model that is the focus of this paper is visible in Figure 2, and the research instrument is available in Appendix A (Table A1). The items were measured using a seven-point Likert scale ranging from 1 ("I do not agree at all") to 7 ("I completely agree"). The analysis of the data was performed through Confirmatory Factor Analysis (CFA) for multicollinearity diagnostics, Exploratory Factor Analysis (EFA) for factor validity and correlation matrix, hierarchical linear regression, and descriptive statistics using statistical software packages JASP and Jamovi [71–75].

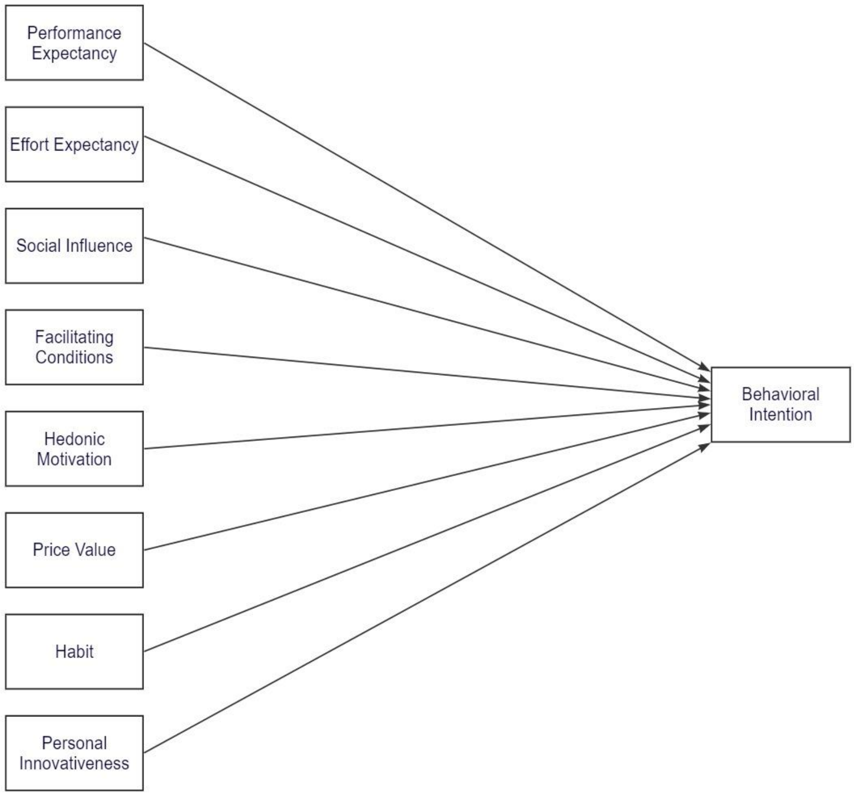

Figure 2. The final version of the modified UTAUT2. Source: adapted from Venkatesh et al. [28]; Gansser & Reich [31].

4.2. Data Collection

Data for this research were collected through an Alchemer online survey tool from 16 May to 27 May 2023. Employing the methods outlined in Gansser and Reich [31], a cohort of students received instructions on the specific number of respondents to engage with and the target demographic to focus on. Additionally, each student was allocated a distinct quota based on selected criteria such as age, student status, and location, ensuring comprehensive coverage within the specified target group. In addition, each student was tasked with meeting the predetermined quota of online respondents by creating a quota-based sample. Following the data collection process, the quality of the gathered data was assessed through various features offered by the software used for data collection. The survey reached 1159 respondents, i.e., members of Generation Z from Croatia. Respondents who answered that they had never used ChatGPT were disqualified after the first set of questions, i.e., 285 of them. Also, there were respondents who did not complete the questionnaire in its entirety, i.e., 180 of them. Therefore, this paper analyzes only the responses of the 694 respondents who fully completed the questionnaire (Table 2), indicating that 59.88% of Generation Z members have at least tried to use ChatGPT. The research focuses only on members of Generation Z, meaning that they were born between 1997 and 2010 (Kotler et al., 2021). The average age of the respondents was $\overline{x}$ = 22.69, st. dev. = 2.27.

Table 2. Sample characteristics.

N = 694		*n*	%
Gender	Female	391	56.3
	Male	303	43.7
Employment	Student	352	50.7
	Study and work	202	29.1
	Work	96	13.8
	Neither working or not working	13	1.9
	High school	31	4.5
ChatGPT experience	Just tried	313	45.1
	Using it more than month	250	36.0
	Using it more than three months	131	18.9

4.3. Results

The modified UTAUT2 model was developed in line with the research goals of this study. The initial model was based on the systematic analysis of previously tested and comparable UTAUT2 variants. The introduced modified UTAUT2 model was tested in JASP with Confirmatory Factor Analysis (CFA) which uncovered an issue with the model (the software reported that the covariance matrix of the latent variables was not a positive definite, preventing, as a consequence, the implementation of factor analysis). This is a general indication of issues with the correlation matrix that are the result of several possible causes. A further investigation revealed a multicollinearity problem in that there was a high probability of strong correlation among the used items. Theoretically, this suggests that some factors exhibited a large degree of similarity among the items and potential issues with content analysis. The next step in the investigation was the analysis of Use Behavior Factor (USE) and Behavioral Intention (BI), as the collected data signaled that this was the possible reason behind the issues with the model stability. Exploratory Factor Analysis (EFA) of these two factors (BI and USE) suggested that the items were grouped into one factor. After manually forcing the creation of two factors, EFA suggested that the items did not group as initially expected, but rather that the items were mixed (Table 3).

Table 3. EFA Factor loadings for BI and USE factors.

	Factor 1	**Factor 2**	**Uniqueness**
USE4	**0.925**		0.364
USE1	0.775		0.226
BI2	0.742		0.335
BI3	0.631		0.218
BI1		0.928	0.227
USE2		0.756	0.475
USE3		0.494	0.444

Note: Applied rotation method is promax.

In order to test the relationship between BI and USE factors, composite variables were created and tested for correlation. There was a strong positive correlation between the BI and USE factors (Pearson's r = 0.84, $p < 0.001$). Based on all the provided evidence, the conclusion was to eliminate the USE factor from the proposed model and from further investigation. One of the possible reasons for this situation is the potential similarity between the two factors (BI and USE) where intention and behavior are measured by self-assessment of the part of the respondents.

After elimination of the use behavior factor from the model, CFA suggested an acceptable factor structure with adequate model fit indices ($\chi^2 = 1339.26$, df = 398, $p < 0.001$; CFI = 0.935; TLI = 0.924; RMSEA = 0.058; SRMR = 0.063). In addition, Cronbach's alpha values for the described factors indicated acceptable validity while the correlation matrix suggested acceptable factor relationships based on composite variables (Table 4).

Table 4. Factor validity and correlation matrix *.

Factor	Cronbach's α	Mean	St. Dev	PE	EE	SI	FC	HM	PV	HT	PI	BI
PE	0.84	5.25	1.22	—								
EE	0.89	5.99	1.02	0.53	—							
SI	0.92	3.98	1.57	0.54	0.28	—						
FC	0.75	5.72	1.02	0.47	0.63	0.32	—					
HM	0.89	5.73	1.15	0.54	0.59	0.34	0.55	—				
PV	0.88	4.91	1.27	0.42	0.37	0.38	0.38	0.42	—			
HT	0.89	2.84	1.63	0.44	0.18	0.47	0.15	0.22	0.36	—		
PI	0.86	4.36	1.59	0.36	0.29	0.32	0.28	0.32	0.33	0.40	—	
BI	0.85	4.35	1.57	0.64	0.38	0.55	0.34	0.48	0.43	0.67	0.45	—

* All correlations are significant at $p < 0.001$.

Based on the provided evidence, the presented UTAUT2 model variation was accepted in this structure and, consequently, subjected to further stages of analysis. Based on the modified UTAUT2 model, eight hypotheses were formed, each one related to a specific predictor describing the effect on a dependent variable (behavioral intention). The mentioned hypotheses are listed in Table 1.

Hierarchical linear regression was used to examine the impact of variables at different levels of the hierarchy on the outcome (dependent) variable and to observe unique contributions of the variables in the hierarchical structure of the data. Based on the model summary (Table 5), it can be concluded that the model was able to explain 65% of the variance ($R^2 = 0.65$).

Table 5. Model Summary—BI.

Model	R	R^2	Adjusted R^2	RMSE	Durbin-Watson		
					Autocorrelation	Statistic	p
H_0	0.000	0.000	0.000	1.571	0.336	1.321	<0.001
H_1	0.806	0.650	0.646	0.935	−0.013	2.020	0.816

Table 6 provides information on model coefficients and data for hypotheses testing. There is enough evidence to support five out of the eight proposed hypotheses. This demonstrates significant, direct, and positive effects of performance expectancy, social influence, hedonic motivation, habit, and personal innovativeness on the behavioral intention to use ChatGPT. The remaining three hypotheses that argue that effort expectancy, facilitating conditions, and price value have significant, direct, and positive effect on behavioral intention were not supported and, thus, rejected (a summary is presented in Table 7).

Table 6. Coefficients.

Model		Unstandardized	Standard Error	Standardized	t	p	95% CI	
							Lower	Upper
H_0	(Intercept)	4.349	0.060		72.921	<0.001	4.232	4.466
H_1	(Intercept)	−0.846	0.236		−3.586	<0.001	−1.310	−0.383
	PE	0.341	0.042	0.265	8.121	<0.001	0.259	0.424
	EE	0.002	0.050	0.002	0.049	0.961	−0.096	0.101
	SI	0.117	0.029	0.116	4.050	<0.001	0.060	0.173
	FC	−0.022	0.048	−0.014	−0.452	0.652	−0.115	0.072
	HM	0.243	0.042	0.179	5.747	<0.001	0.160	0.326
	PV	0.020	0.034	0.016	0.582	0.561	−0.046	0.085
	HT	0.409	0.027	0.423	15.134	<0.001	0.356	0.462
	PI	0.091	0.026	0.093	3.558	<0.001	0.041	0.142

Note: PE: performance expectancy, EE: effort expectancy, SI: social influence, FC: facilitating conditions, HM: hedonic motivation, PV: price value, HT: habit, PI: personal innovativeness.

Table 7. Hypotheses testing.

Hypotheses		p-Value	Supported or Rejected
H1	Performance expectancy has a positive, direct, and significant effect on behavioral intention	<0.001	S
H2	Effort expectancy has a positive, direct, and significant effect on behavioral intention	0.961	R
H3	Social influence has a positive, direct, and significant effect on behavioral intention	<0.001	S
H4	Facilitating conditions have a positive, direct, and significant effect on the behavioral intention	0.652	R
H5	Hedonic motivation has a positive, direct, and significant effect on behavioral intention	<0.001	S
H6	Price value has a positive, direct, and significant effect on behavioral intention	0.561	R
H7	Habit has a positive, direct, and significant effect on behavioral intention	<0.001	S
H8	Personal innovativeness has a positive, direct, and significant effect on behavioral intention	<0.001	S

Note: S = supported, R = rejected.

5. Discussion

This study aims to conduct a deeper examination of the variables influencing Generation Z members' decisions to utilize ChatGPT as a generative AI language model, a chatbot that changes the way people use the Internet and fulfil their daily tasks. The modified UTAUT2 model proposed in this study contributes to its expanded applicability in the context of generative AI. Due to the fact that ChatGPT had been released less than six months before this study was conducted, it is understandable that the chosen topic is, at present, underexplored. The results of this study may be useful for managers, researchers, policy makers, and educators in universities and high schools.

The empirical findings reveal that four of UTAUT2′s original constructs—performance expectancy, social influence, habit, and hedonic motivation—have a significant, direct, and positive influence on behavioral intention, alongside the construct of personal innovativeness. These findings are consistent with those presented in Strzelecki [50], who similarly observed a significant effect of performance expectancy, social influence, hedonic motivation, habit, and personal innovativeness on the behavioral intention to use ChatGPT among a sample of students. However, Strzelecki [50] omitted the construct of price value due to ChatGPT being available for free, a decision that seems justified as the price value construct was found to be insignificant in this study.

Furthermore, Strzelecki [50] identified a significant effect of effort expectancy on behavioral intention and a significant effect of behavioral intention on use behavior, findings that are not supported by our research. Conversely, the study by Nikolopoulou et al. [49], conducted on Greek students (also Generation Z), reported no significant effect of effort expectancy, facilitating conditions, and price value on behavioral intention, but did observe significant effects in relation to performance expectancy, social influence, hedonic motivation, and habit.

Additionally, the effect of facilitating conditions on behavioral intention was found to be non-significant by multiple studies investigating the adoption of AI-based products or services [48,54,67], leading Gansser & Reich [31] to exclude this construct. It is important to note that Venkatesh et al. [24] suggest that facilitating conditions may be confounded with ease of use or effort expectancy.

In this study, this could potentially be the case, as the average value for the construct of effort expectancy was the highest among all constructs. As long as performance expectancy and effort expectancy constructs are present in the model, facilitating conditions may no longer significantly predict behavioral intention [24]. However, despite the inclusion of effort expectancy in the used model, the empirical findings presented in this paper did not identify such a construct as a significant predictor of behavioral intention.

This finding is consistent with studies examining the adoption of AI-based products and services [48,54–56,67]. The lack of significance of the effect of the effort expectancy construct on behavioral intention has also been observed in studies employing the UTAUT2 model to investigate the adoption of mobile apps [49,66,76], a phenomenon which can reasonably be compared to the adoption of ChatGPT.

Contrary to our hypothesis, effort expectancy was not a significant predictor of behavioral intention, contradicting previous findings [24,31,50]. Merhi et al. [76] suggested that this may be due to the increasing familiarity of the general population, especially young people, with the Internet and digital technologies. Despite ChatGPT having been available for only 6 months at the time of our research, effort expectancy had the highest average value, indicating the ease with which respondents were able to use the tool.

6. Conclusions and Implications

The results from this study show that the most important predictor of Generation Z members' behavioral intention to use ChatGPT is Habit (HT), followed by Performance Expectancy (PE) and Hedonic Motivation (HM). The same conclusion and predictor order was demonstrated by Nikolopoulou et al. [49] in their study, in which they investigated the use of mobile phones by applying a UTAUT2 model, also on a Generation Z population. Furthermore, the same study confirmed that Effort Expectancy (EE), Facilitating Conditions (FC) and Price Value (PV) did not have any statistically significant effect on behavioral intention, leading to the conclusion that the result is potentially related to the sample. These findings offer insights into the broader landscape of IT-based services and decision support systems. Habit, as a predictor, suggests a parallel with IT service adoption where continuous use is critical, and performance expectancy mirrors the user's anticipated improvement in task efficacy, a core aspect of decision support systems.

Strzelecki [50], in his study, also investigated acceptance of ChatGPT among Generation Z members, showing that habit was the strongest predictor, followed by performance expectancy and hedonic motivation. In agreement with previously stated assumptions, Imani and Anggono [77] also investigated Generation Z using UTAUT2 to test acceptance of QR in offline environment, with results showing that effort expectancy, facilitating conditions, and price value were not statistically significant predictors of behavioral intention. Habit was found to be the strongest predictor, followed by hedonic motivation and performance expectancy. It is interesting to emphasize that the construct of habit recorded the lowest average value ($\bar{x}$ = 2.84), followed by social influence ($\bar{x}$ = 3.98). All respondents in this study stated that they had used ChatGPT during the first 6 months of its existence, thus being early adopters by definition. Early adopters who have a well-educated background are unaffected by outside circumstances and more likely to utilize the AI-powered chatbot. Similarly to the study by Strzelecki [50], our results suggest that social pressure was weak, possibly owing to the fact that not enough time had been available for participants to build a habit of using ChatGPT since, at the time of our study, it was still a relatively new technology that had yet to reach wider acceptance.

In this study, the original model by Venkatesh et al. [28] was enhanced by personal innovativeness. This study shows that personal innovativeness had a significant effect on behavioral intention, aligning with previous studies [31,48,50]. The theoretical contribution of this paper is additionally reflected in the fact that personal innovativeness is confirmed as a significant predictor of behavioral intention. Consequently, the final modified model containing personal innovativeness explained 65% of the extracted variance. The insights into the role of personal innovativeness in the adoption of new technologies such as ChatGPT afforded by this study provide valuable parallels to IT service adoption, where innovativeness can be a differentiator in technology uptake. Similarly, the non-significance of Effort Expectancy (EE), Facilitating Conditions (FC), and Price Value (PV) may indicate that, as with other IT services, these factors are less impactful for technologies that users perceive as being inherently valuable or when costs are not prohibitive. However, because of the strong correlation between BI and USE factors (Pearson's r = 0.84, $p < 0.001$), the USE factor was dropped from the final version of the model. The self-perceptions of respondents may be biased on self-reporting scales, causing discrepancies in their actual behavior and their reported intentions [78]. In the case of self-reporting scales, respondents may not perceive a clear distinction between behavioral intention and use behavior, resulting in overlapping responses and further exacerbation of the multicollinearity problem.

Results presented in this paper demonstrate a statistically significant influence on the adoption of this cutting-edge technology and confirm some traditional relationships included in UTAUT2. The study identifies habit, performance expectancy, and hedonic motivation as the most important predictors for Generation Z's behavioral intention to use ChatGPT. Understanding these factors allows marketers to focus their efforts on elements that strongly influence the adoption of AI-powered chatbots in this demographic. The research reveals that all respondents in the study were early adopters of ChatGPT, indicating that Generation Z with a well-educated background is more likely to embrace AI-powered chatbots. This information is valuable for marketers targeting early adopters and highlights the importance of reaching out to tech-savvy and educated segments when introducing new AI technologies.

The findings are consistent with previous research conducted by Nikolopoulou [49], Strzelecki [50], Imani & Anggono [77], and others, further strengthening the reliability and generalizability of our conclusions. This alignment allows marketers to draw on existing knowledge and build upon established theories when crafting AI adoption strategies. The research enhances the original UTAUT2 model by including personal innovativeness and confirms its significance in predicting behavioral intention. This modification provides marketers with a more comprehensive and accurate framework for understanding AI adoption factors among Generation Z. It is noteworthy that the research findings contribute to a deeper understanding of ChatGPT integration into existing information systems, aligning with IT adoption frameworks which suggest that users' efficiency, effectiveness, and satisfaction are paramount. The identification of habit, performance expectancy, and hedonic motivation as pivotal factors is reflective of the broader IT systems adoption trends, emphasizing the importance of user engagement and perceived value.

This could be remarkable for companies in various sectors, but especially for companies that see ChatGPT as an opportunity, something that could be integrated into their work. It is anticipated that the outcomes of this study will contribute to the understanding of ChatGPT adoption and utilization, especially important for subjects working with Generation Z, including educators, policy makers, and companies, but also for marketers. By aligning marketing strategies with the identified adoption drivers, and by prioritizing the significant factors, marketers can optimize AI integration, improve customer experience, and gain a competitive advantage in the dynamic marketing landscape. These findings offer valuable knowledge to the marketing community, empowering marketers to make informed decisions and effectively harness the transformative potential of AI technologies. Marketers can leverage the insights from this study to identify potential opportunities in the market where AI-powered chatbots such as ChatGPT can be integrated to enhance customer experiences, streamline operations, and foster innovation in their respective industries. The findings have practical implications for companies across various sectors, especially those seeking to integrate ChatGPT into their operations. By understanding the key predictors and dynamics of AI adoption, companies can develop targeted strategies to effectively implement AI technologies and engage Generation Z consumers.

Finally, the practical implications of this study underscore the significance for companies looking to harness ChatGPT within their operations. By comparing the predictors of ChatGPT adoption with those of IT-based services, companies can craft strategies that not only target Generation Z, but also capitalize on the general tendencies observed in the adoption of innovative technologies. Thus, the findings herein not only fortify the UTAUT2 model with the integration of personal innovativeness, but also extend its applicability to the adoption of AI technologies within the dynamic sphere of information systems.

7. Limitations and Future Research

The methodology of UTAUT2 has certain inherent limitations. The model uses a self-reported scale to quantify intention to use, putting the validity and accuracy of the research findings in jeopardy. Many other technology acceptance models, such as the original UTAUT or TAM, have the same drawback as the UTAUT2 model [20,24,30]. Even after meeting our set of objectives, the present study still has limitations. Considering the fact that the original paper from Venkatesh et al. [28] did not provide items for the measurement of the use behavior, this paper used the items from Nikolopoulou et al. [49], and it seems that those items did not fit the context of the generative AI. Many other papers have not even included the USE factor into the UTAUT2 model [48,55,66,76,79–83], indicating that the UTAUT2 model is very adaptive, many constructs can be added to it, as well as subtracted from it. The factor of the use behavior was dropped due to multicollinearity problems between the BI and USE factors; therefore, a recommendation for future research in the context of generative AI and LLM is to use other modifications of the items in the construct of the USE factor, such as items used by Rahim et al. [37] or Strzelecki [50].

The results should be interpreted with caution because they only apply to Generation Z, and, specifically, to the Croatian population. In this study, moderating factors were not interpreted, although they could bring different dimensions to this paper, as the authors decided not to include them. As usage of LLMs, such as ChatGPT, is still a new area of research, future studies can improve the scale employed in this study. Due to the fact that this study used a modified and extended version of the UTAUT2 model, it could be interesting to see more studies on this topic, but they could be conducted on different generations, different countries, different generative AI tools and even with additional constructs and moderating factors. Lastly, in the first part of the questionnaire, 285 respondents stated that they had never used ChatGPT and they were thus disqualified. It is recommended for future research to ask these respondents what they know about ChatGPT and why they do not use it.

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Data Availability Statement: Data will be made available on request from the corresponding author.

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Appendix A

Table A1. Constructs and corresponding items.

	Performance Expectancy (PE)
PE1.	I find ChatGPT useful
PE2.	Using ChatGPT increases my chances of achieving things that are important to me
PE3.	Using ChatGPT helps me accomplish various activities more quickly
PE4.	Using ChatGPT increases my productivity
	Effort Expectancy (EE)
EE1.	Learning how to use ChatGPT is easy for me
EE2.	My interaction with ChatGPT is clear and understandable
EE3.	I find ChatGPT easy to use
EE4.	It is easy for me to become skillful at using ChatGPT
	Social Influence (SI)
SI1.	People who are important to me think that I should use ChatGPT
SI2.	People who influence my behaviour think that I should use ChatGPT
SI3.	People whose opinions I value prefer that I use ChatGPT

Table A1. *Cont.*

	Facilitating Conditions (FC)
FC1.	I have the resources necessary to use ChatGPT
FC2.	I have the knowledge necessary to use ChatGPT
FC3.	ChatGPT is compatible with other technology I use
FC4.	I can get help from others when I have difficulties using ChatGPT
	Hedonic Motivation (HM)
HM1.	Using ChatGPT is fun
HM2.	Using ChatGPT is enjoyable
HM3.	Using ChatGPT is very entertaining
	Price Value (PV)
PV1.	ChatGPT is reasonably priced
PV2.	ChatGPT is good value for money
PV3.	At the current price, ChatGPT provides a good value
	Habit (HT)
HT1.	The use of ChatGPT has become habit for me
HT2.	I am addicted to using ChatGPT
HT3.	I must use ChatGPT
HT4.	Using ChatGPT has become natural to me
	Behavioral Intention (BI)
BI1.	I intend to continue using ChatGPT in future
BI2.	I will always try to use ChatGPT in my dailylife
BI3.	I plan to continue to use ChatGPT frequently
	Use Behavior (USE)
USE1.	I regularly use ChatGPT in my studies
USE2.	ChatGPT usage is a pleasant experience
USE3.	I currently use ChatGPT as a supporting tool in my studies
USE4.	I spend a lot of time on ChatGPT
	Personal Innovativeness (PI)
PI1.	If I heard about new technology, I would look for ways to experiment with it.
PI2.	Among my peers, I am usually the first to try out new technologies
PI3.	I like to experiment with new technologies

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