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Learners' Acceptance of ChatGPT in School

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Abstract

The rapid development of generative artificial intelligence (AI) systems such as ChatGPT (GPT-4) could transform teaching and learning. Yet, integrating these tools requires insight into what drives students to adopt them. Research on ChatGPT acceptance has so far focused on university settings, leaving school contexts underexplored. This study addresses the gap by surveying 506 upper secondary students in Baden-Württemberg, Germany, using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Performance expectancy, habit and hedonic motivation emerged as strong predictors of behavioral intention to use ChatGPT for school purposes. Adding personality traits and personal values such as conscientiousness or preference for challenge raised the model's explanatory power only marginally. The findings suggest that students' readiness to employ ChatGPT reflects the anticipated learning benefits and enjoyment rather than the avoidance of effort. The original UTAUT2 is therefore sufficient to explain students' acceptance of ChatGPT in school contexts. The results could inform educators and policy makers aiming to foster the reflective and effective use of generative AI in instruction.

Keywords: technology acceptance model; UTAUT2; artificial intelligence (AI); ChatGPT; school

1. Introduction

The digital transformation of schools is a multifaceted and far-reaching process that encompasses more than the adoption of new technologies. It also entails profound pedagogical, organizational, and cultural changes. This transformation is an ongoing and dynamic process that goes beyond technical infrastructure and requires the redesign of teaching methods, learning environments, and institutional structures. In this context, the integration of generative Artificial Intelligence (AI) such as ChatGPT (GPT-4) into daily school life has gained increasing relevance. On one hand, the use of such technologies offers potential for new instructional approaches, while on the other hand, it presents challenges for existing educational practices and demands a critical examination of its impact on learners, teachers, and institutional frameworks (Venkatesh et al., 2003).

Particularly with regard to the integration of generative AI such as ChatGPT in school-based and instructional contexts, the question of learners' acceptance has become a central research topic. Acceptance is a crucial factor for the sustainable and effective use of AI applications in educational settings. To fully realize the potential of technologies like ChatGPT, it is essential to understand the conditions under which learners are willing to adopt and integrate these technologies into their learning processes. Acceptance here is not only a matter related to students' attitudes towards the technology, but is also related to students' perception of its usefulness and the learning benefits it offers. Given ChatGPT's remarkable

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capabilities compared to other AI-based language models, its use has the potential to fundamentally revolutionize how learners acquire information and knowledge (Rudolph et al., 2023). However, these potentials must also be critically examined, particularly regarding the reliability of AI-generated content and the risks associated with inaccurate or incomplete information (Lund et al., 2023).

The acceptance of ChatGPT in school contexts has so far remained largely unexplored. This is remarkable given that the field of higher education has already produced numerous studies on the factors influencing acceptance and the usage patterns of ChatGPT and similar AI applications (Strzelecki, 2023a, 2023b; Foroughi et al., 2023). These studies show that factors such as *habit*, *performance expectancy*, and *hedonic motivation* are significant predictors of the effective use of ChatGPT (Strzelecki, 2023a, 2023b). While valuable, these findings primarily focus on the higher education sector and therefore provide limited answers to the specific challenges and opportunities associated with the use of generative AI in school contexts. In addition to individual attitudes, school-level conditions such as teacher support also play an important role. These conditions may be shaped by organizational structures, the availability of professional development opportunities, and a supportive technological infrastructure. In this context, it is necessary to understand how technological, institutional, and individual factors interact in order to effectively promote the acceptance of ChatGPT and similar AI systems in schools. In this regard, technology acceptance models are of particular relevance. These models provide valuable theoretical foundations for investigating the various factors that influence technology acceptance. They take into account both individual and contextual dimensions, allowing for a nuanced analysis of the relationships between *perception*, *motivation*, and *behavior*.

Building on this, the present study focuses on learners' perspectives and investigates their acceptance of ChatGPT in school contexts. The goal is to generate empirically grounded insights into the factors that influence students' willingness to engage with this specific form of generative AI in educational processes. By focusing on a specific technological application, this study contributes to empirical educational research by systematically examining the underexplored student perspective within the digital transformation of schools.

2. Theoretical and Empirical Background

2.1. Theoretical Foundations and Key Constructs of Technology Acceptance Models

Digital technologies are increasingly permeating all areas of life, from private lifestyles to the world of work, including education, health, and public administration. This development is accompanied by the need to better understand the conditions under which technological innovations are accepted by individuals and integrated into everyday behavior. In this context, the concept of technology acceptance has become a central object of research. It describes the willingness of individuals to adopt and actively use new technologies, which is a fundamental prerequisite for the sustainable implementation of technological innovations, including in the field of school education.

The theoretical foundation of technology acceptance research began with the *Theory of Reasoned Action* (TRA) developed by Ajzen and Fishbein (1975). This model is based on the assumption that human behavior is primarily determined by behavioral intention, which in turn results from personal attitudes toward the behavior and subjective norms. As an extension, the *Theory of Planned Behavior* (TPB) was developed by Ajzen (1991), adding the component of perceived behavioral control, which is understood as an individual's assessment of their ability and resources to perform a specific behavior. The *Theory of Planned Behavior* thus allows for the consideration of both inhibiting and facilitating factors. A technology-focused approach is provided by the *Technology Acceptance Model* (TAM), which was specifically developed by Davis (1989) for the context of digital information and communication systems. A schematic representation of this model is shown in Figure 1. The key determinants of acceptance in this model are *perceived usefulness* and *perceived ease of use*, both of which shape *attitude toward using* the technology and ultimately determine the *behavioral intention to use* a specific technology in the near future, reflecting the extent to which they have formed deliberate plans to perform or continue that behavior. *Behavioral intention to use* is also an immediate predictor of *actual usage* (Venkatesh et al., 2003; Ajzen, 1991).

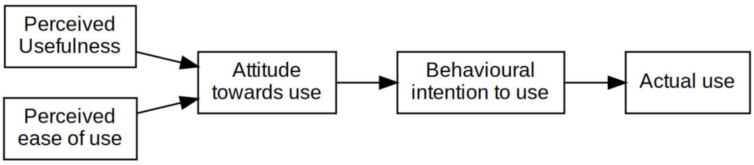

Figure 1. Technology Acceptance Model (TAM) (Davis, 1989).

TAM has gained wide distribution and application due to its conceptual clarity and empirical testability. At the same time, it has been criticized for neglecting social and contextual influences.

In response to this criticism, Venkatesh et al. (2003) developed the *Unified Theory of Acceptance and Use of Technology* (UTAUT). This model integrates various previous models and expands them by adding core influencing factors. It identifies four main dimensions: *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions*; these directly affect *behavioral intention to use* and *actual usage*. In addition, the model accounts for the moderating effects of age, gender, experience, and voluntariness of use.

Building on this, Venkatesh et al. (2012) introduced UTAUT2 as a refined extension specifically tailored to private and consumer-related contexts. In addition to the original four factors, *hedonic motivation*, *price value*, and *habit* were added as new influencing variables. The selection and combination of the respective constructs are based on a broad empirical foundation (Venkatesh et al., 2012). These extensions acknowledge that usage decisions in everyday life are not made solely on a rational basis, but also incorporate emotional, habitual, and experience-based aspects. UTAUT2 thus allows for a more differentiated analysis of individual acceptance processes and has proven particularly suitable for diverse application contexts such as the use of mobile applications, digital learning environments, or AI-supported systems. According to the UTAUT2 model, the independent variables facilitating conditions and habit are assumed to have a direct effect on actual *usage behavior*. These constructs are therefore not only relevant for influencing *behavioral intention* but are also theorized to directly shape users' *effective engagement* with the technology. Figure 2 shows a schematic representation of this model.

A comparison of the models reveals their different theoretical focuses. While the *Theory of Reasoned Action* and the *Theory of Planned Behavior* emphasize behavioral intentions and normative influences, TAM centers on cognitive evaluations of technological features. UTAUT, and especially UTAUT2, offer a more comprehensive approach to explaining technology acceptance by integrating additional factors.

Due to the particular relevance of UTAUT2 for empirical acceptance research, the most important factors of this model are explained in more detail below. A central influencing factor is *performance expectancy*, which refers to the subjective assessment of whether using a technology will lead to personal performance gains. It closely aligns with the concept of *perceived usefulness*, as described in the *Technology Acceptance Model* (TAM) (Davis, 1989), and has been shown to be the strongest predictor of *behavioral intention to use* a specific technology (Venkatesh et al., 2003). Its effect is moderated by gender and age: men and younger individuals tend to rate performance potential higher, as they respond more strongly to goal-directed, extrinsically motivated incentives (Venkatesh et al., 2012).

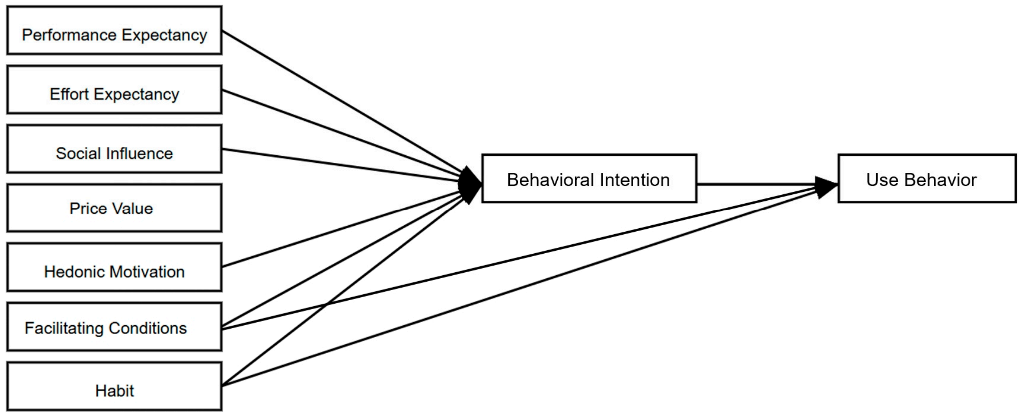

Figure 2. Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model proposed by Venkatesh et al. (2012); simplified representation without specification of moderator variables (age, gender, and experience).

Effort expectancy refers to the *perceived ease of using* a technology. The lower the expected cognitive and technical effort, the more likely a positive attitude toward use will develop. This effect is particularly pronounced among inexperienced or older users (Venkatesh et al., 2003), as they are more frequently confronted with uncertainties and usage barriers. Due to socialization differences, women also tend to show higher sensitivity to effort-related perceptions (Gefen & Straub, 1997).

Another relevant influencing factor is *social influence*, which refers to the perception that important people in one's social environment, such as colleagues, family members, or supervisors, support the use of a given technology. The perceived importance of these influences varies depending on gender, age, and experience (Venkatesh et al., 2003; Ajzen, 1991). For example, women and older individuals are more likely to incorporate social expectations into their decision making. As experience increases, the relevance of this social orientation typically decreases (Morris & Venkatesh, 2000).

Facilitating conditions encompass the subjectively perceived availability of resources, such as technical support, appropriate infrastructure, or help in case of problems. Unlike the previously mentioned constructs, facilitating conditions influence not only the intention but also directly affect the actual usage behavior (Venkatesh et al., 2003). Their impact becomes especially evident in situations where cognitive or technical barriers exist. Age and experience-related differences have a dual effect: while inexperienced or older users are particularly dependent on external support, experienced users can utilize available aids more efficiently and access them more purposefully (Venkatesh et al., 2012).

A newly introduced construct in UTAUT2 is *hedonic motivation*. It describes the joy or fun that individuals experience when using a technology. This construct gains particular importance in private, consumer-oriented usage contexts (Venkatesh et al., 2012). Studies show that especially young and male user groups respond strongly to hedonic incentives, while this effect tends to diminish with increasing experience, as utilitarian aspects come to the forefront (Brown & Venkatesh, 2005).

Price value is another factor explicitly included in UTAUT2. It describes the subjective assessment of whether the perceived benefits of a technology are in reasonable proportion to the associated costs. This construct is particularly significant in the private sector, where decisions about technology purchases are directly linked to cost–benefit evaluations (Venkatesh et al., 2012). Women and older individuals tend to display stronger price sensitivity, which affects the strength of this factor's impact (Chong, 2013).

Habit is a particularly dynamic and time-dependent construct. It refers to the degree to which the use of a technology has already become automated and routinized. As the duration and intensity of use increase, habit gains importance and can eventually replace *behavioral intention* as the strongest determinant of actual *usage behavior* (Venkatesh et al., 2012; Limayem et al., 2007). While *behavioral intention to use* is central shortly after the introduction of a technology, the relevance of *habit* increases significantly over time. Here too, individual characteristics play a role: older and more experienced individuals show a stronger tendency to develop usage patterns, while women often perceive changes in their environment more consciously and adapt their behavior accordingly (Kim & Malhotra, 2005).

In conclusion, it is important to emphasize that all the aforementioned constructs do not operate in isolation, but are influenced by moderating variables. UTAUT2 specifically considers gender, age, and experience as systematic moderators that affect the strength and direction of the relationships between constructs and *behavioral intention to use* or actual *usage behavior* (Venkatesh et al., 2012). This differentiation enables the context-specific application of the model and supports a nuanced analysis of heterogeneous user groups.

2.2. Extension of the UTAUT2 to Examine Students' Technology Acceptance

Although the UTAUT2 provides an established and differentiated framework for explaining technology acceptance, additional constructs are relevant in the context of the present study. This extension is based on the assumption that, beyond the classic UTAUT2 constructs, there are further factors that can significantly enhance our understanding of students' technology acceptance, particularly with regard to the use of ChatGPT. The selection of these additional constructs is based either on previous studies that have examined technology acceptance in educational contexts or on theoretical considerations that suggest their particular relevance for the present investigation. These extensions will be empirically tested in the context of this study.

A central additional construct is *personal innovativeness*. It is assumed that individuals' willingness and ability to try out new technologies and integrate them into their daily lives have a significant impact on the use of ChatGPT. This construct goes beyond a specific technology and instead describes a general openness to technological innovations (Agarwal & Prasad, 1998). Individuals with high personal innovativeness tend to adapt quickly to new technologies, whereas less innovative individuals tend to be more hesitant. The assumption that this construct influences ChatGPT acceptance is tested in this study, as the existing literature on ChatGPT use in educational settings already indicates the relevance of this factor (Strzelecki, 2023a, 2023b; Foroughi et al., 2023).

Another extended construct is *conscientiousness*, which is considered a potential predictor of technology acceptance in this study. Conscientiousness, one of the *Big Five personality traits* proposed by Costa and McCrae (1992), refers to an individual's level of self-discipline, sense of responsibility, and preference for order and structure. It is assumed that students with high conscientiousness are more likely to use technologies like ChatGPT in a careful and reflective manner, such as through targeted use for organizing knowledge or completing tasks. This assumption is also examined in the study to determine whether *conscientiousness* actually influences the way students use ChatGPT.

In addition, *challenge preference* is included as a relevant construct. It is assumed that students with a higher preference for difficult tasks are more inclined to engage more deeply with complex technologies such as ChatGPT. *Challenge preference* is part of the *Achievement Motivation Inventory* by Schuler and Prochaska (2000, 2001) and describes the tendency to seek or avoid challenging tasks. Students with high *challenge preference* may use ChatGPT more frequently as a tool for demanding tasks such as complex writing or research assignments. This assumption is also tested empirically to examine whether, and to what extent, the *preference for difficult* tasks influences students' engagement with and use of *ChatGPT*.

The extension of the UTAUT2 model by these constructs represents an assumption that will be empirically tested in the present study. The hypothesis is that these additional constructs not only modify the existing UTAUT2 factors but also significantly influence the acceptance and use of ChatGPT among students in an academic context. Through this extension, the study aims to gain a more differentiated understanding of which individual and psychological characteristics promote or hinder the use of ChatGPT.

3. Research Questions

The present study aims to gain further insights into the significance of relevant factors by empirically examining students' acceptance of ChatGPT usage based on established models of technology acceptance. The first two research questions focus on the actual *usage behavior* of students with regard to ChatGPT in the school context. Specifically, the study examines how frequently and for what purposes students primarily use ChatGPT. The associated research questions (RQ) are as follows:

RQ1: To what extent do students use ChatGPT in the school context?
RQ2: In which areas of application do students use ChatGPT in the school context?

Subsequently, the focus shifts to students' overall acceptance of ChatGPT usage. The *Unified Theory of Acceptance and Use of Technology 2* (UTAUT2) by Venkatesh et al. (2012) serves as the theoretical foundation for this part of the study. The corresponding research questions are as follows:

RQ3: Can UTAUT2 explain students' technology acceptance of ChatGPT usage in the school context?
RQ4: Which factors promote or hinder students' technology acceptance of ChatGPT usage in the school context?

In this study, the basic UTAUT2 model has been extended with additional independent variables (i.e., *personal innovativeness*, *conscientiousness*, *challenge preference*). The study investigates whether this extended model improves the explanatory power of the original UTAUT2. The associated research questions are as follows:

RQ5: Can the extended UTAUT2 improve the explanatory power of the original model regarding students' technology acceptance of ChatGPT usage in the school context?
RQ6: Which constructs in the extended UTAUT2 are related to students' technology acceptance of ChatGPT usage in the school context?

4. Method

A quantitative research design based on a standardised online questionnaire was chosen to examine students' acceptance of ChatGPT usage. The questionnaire consisted of 57 items.

Sociodemographic characteristics were assessed with three items capturing the learners' age, gender, and type of school attended. At the beginning of the survey, students were also asked about their *usage behavior* and *application areas* of ChatGPT in the school context. *Usage behavior* was measured with one item asking how often ChatGPT is used by students for school-related purposes. A seven-point Likert scale was used with the following options: 1 = *Never*, 2 = *Once a month*, 3 = *Several times a month*, 4 = *Once a week*, 5 = *Several times a week*, 6 = *Once a day*, *and* 7 = *Several times a day.*

The *application areas* of ChatGPT when used by students were assessed with two items. One item captured the purposes for which ChatGPT is used for school-related tasks. Respondents could select multiple options from the following: *homework*, *writing texts*, *information seeking*, *preparing a presentation*, *preparing for an exam*, and *during exams*. The second item assessed the school subjects in which ChatGPT is used by students.

In the further course of the questionnaire, the constructs of UTAUT2 according to Venkatesh et al. (2012) were assessed. *Performance expectancy, effort expectancy, facilitating conditions*, and *habit* were each measured using four items, while *social influence, hedonic motivation, price value*, and *behavioral intention to use* were each assessed with three items. All items were adapted from the original formulations by Venkatesh et al. (2003, 2012) to suit the technological context of ChatGPT use in schools (e.g., "*I believe that using ChatGPT for school is helpful.*").

Additionally, the questionnaire included measures for *personal innovativeness*, *conscientiousness*, and *challenge preference*, representing an extension of the UTAUT2 model in this study. *Personal innovativeness* was assessed using three items following Agarwal and Prasad (1998), *conscientiousness* was measured with four items based on the short version of the *Big Five Inventory* (BFI-K) by Rammstedt and John (2005), and *challenge preference* was assessed with three items adapted from the short version of the *Achievement Motivation Inventory* (LMI-K) by Schuler and Prochaska (2001).

The areas and constructs of the questionnaire are presented in Table 1. All items were rated using a five-point Likert scale with the following response options: 1 = *strongly disagree*, 2 = *rather disagree*, 3 = *neutral*, 4 = *rather agree*, and 5 = *strongly agree*.

Table 1. Instrument for measuring technology acceptance.

Construct	Source	Example Item	Number of Items	Scale
		UTAUT2		
Performance expectancy	Venkatesh et al. (2003)	*I believe that using ChatGPT for school is helpful.*	4	1–5
Effort expectancy	Venkatesh et al. (2003)	*Using ChatGPT is easy for me to learn.*	4	1–5
Social influence	Venkatesh et al. (2003)	*People who are important to me think that I should use ChatGPT.*	3	1–5
Facilitating conditions	Venkatesh et al. (2003)	*I have the necessary resources to use ChatGPT.*	4	1–5
Hedonic motivation	Venkatesh et al. (2012)	*Using ChatGPT is fun for me.*	3	1–5
Price value	Venkatesh et al. (2012)	*I think that ChatGPT offers good value for money.*	3	1–5
Habit	Venkatesh et al. (2012)	*Using ChatGPT has become a habit for me.*	4	1–5
Behavioral intention to use	Venkatesh et al. (2003)	*I intend to continue using ChatGPT for school.*	3	1–5
Usage behavior (Frequency)	Venkatesh et al. (2003)	*How often do you use ChatGPT for school?*	1	1–7

Table 1. *Cont.*

Construct	Source	Example Item	Number of Items	Scale
		Extension of UTAUT2		
Personal innovativeness	Agarwal and Prasad (1998)	*I enjoy experimenting with new technologies.*	4	1–5
Conscientiousness	Rammstedt and John (2005)	*I am lazy and tend to avoid effort.*	4	1–5
Challenge preference	Schuler and Prochaska (2001)	*I feel particularly motivated by difficult tasks.*	3	1–5

Within the scope of this study, the UTAUT2 model was operationalized almost entirely and without modifications. To ensure reliability, *Cronbach's alpha* (α) was calculated. Additionally, a confirmatory factor analysis was conducted. One item from the *facilitating conditions* scale was excluded, which increased the reliability from α = 0.733 to α = 0.808. As a result, all reliability coefficients for the examined constructs fall within a good to very good range. The reliability of the scales used in the study is presented in Table 2.

Table 2. Reliability of the scales utilized in the study.

	Number of Items	*Cronbachs α*
Performance expectancy	4	0.803
Effort expectancy	4	0.862
Social influence	4	0.906
Facilitating conditions	4	0.808
Hedonic motivation	3	0.858
Price value	3	0.900
Habit	4	0.857
Behavioral intention	3	0.915
Personal innovativeness	4	0.853
Conscientiousness	4	0.964
Challenge preference	3	0.821

4.1. Sample

Data were collected through a standardized online questionnaire targeting students of legal age in final-year classes at vocational schools and general upper secondary schools (Gymnasium) in Germany. The data collection took place between April and May 2024 with official approval from the relevant Ministry of Education.

A total of 568 responses were collected. However, 62 cases were excluded due to incomplete responses, resulting in a final sample of N = 506 upper secondary students from four different school types. Of the surveyed students, 52.6% were female and 44.7% were male. A total of 2.7% identified as non-binary. The age of the respondents ranged from 18 to 30 years, with an average age of 18.5 years. Regarding the type of school attended, 58.9% of the participants were enrolled in a vocational upper secondary school, 19.4% attended a vocational college, 11.3% were in vocational training and attended a vocational school, and 10.4% of the respondents attended a general upper secondary school. The composition of the sample is shown in Table 3.

Table 3. Socio-demographic characteristics of the sample.

Type of School	Students	Gender			Age	
	N (%)	Female	Male	Diverse	*M*	*SD*
Vocational Upper Second. School	298 (58.9%)	165	124	9	18.36	0.58
Vocational College	98 (19.4%)	48	48	2	18.35	0.50
Vocational School	57 (11.3%)	24	30	3	19.82	2.13
General Upper Second. School	53 (10.4%)	29	24	0	18.13	0.35
Total	506	266 (52.6%)	226 (44.7%)	14 (2.7%)	18.50	0.99

N = Number; M = Mean Value; SD = Standard Deviation.

While the sample is clearly defined in terms of school type, age, and gender, it is important to note that the data were collected exclusively in the federal state of Baden-Württemberg. This regional focus, combined with the predominance of students from vocational upper secondary schools, may limit the generalizability of the findings to other regions or school types. In addition, socioeconomic background was not assessed. These limitations should be taken into account when analyzing and interpreting the data.

4.2. Analysis of the Data

The statistical software SPSS (version 30) was used for the analysis of the collected data and the answering of the research questions. Prior to the analysis, the data were checked for completeness and plausibility. Descriptive analyses were carried out to examine the extent to which and in what areas ChatGPT is used by students in the school context. These analyses were based on the mean values of *behavioral intention to use* and actual *usage behavior*. In addition, the frequencies and distribution of students' responses regarding *usage behavior* and the *areas of application* of ChatGPT were considered. This provided insights into how extensively and in what ways students use ChatGPT for school-related purposes.

Subsequently, regression analyses were conducted based on the UTAUT2 model as well as the extended version of UTAUT2 developed in the context of this study. The coefficient of determination R^2 of the regression models was used to assess the explanatory power of UTAUT2 and its extension with regard to students' technology acceptance of ChatGPT in the school setting. Furthermore, the regression coefficients β of the independent variables allowed for further insights into which acceptance factors of UTAUT2 and which constructs of the extended model are predictive of students' *behavioral intention to use* and actual *usage behavior*, and thus of their overall technology acceptance of ChatGPT in the educational context.

In addition, the regression analyses aimed to examine whether and to what extent there are relationships between the constructs of the extended UTAUT2 model, namely *personal innovativeness*, *conscientiousness*, and *preference for challenge*, and students' technology acceptance of ChatGPT in school.

The regression analyses conducted aimed to examine the direct and indirect effects of key independent variables derived from the underlying theoretical models. However, the potential moderating effects of moderator variables (e.g., *age*, *gender*) were not included in the analyses.

5. Results

5.1. Use of ChatGPT by Students

Table 4 presents the descriptive analysis of students' use of ChatGPT. In this context, the mean values and standard deviations of *behavioral intention* to use and actual *usage behavior* were examined.

Table 4. Descriptive analysis: students' use of ChatGPT in school contexts.

	N	*M*	*SD*
Behavioral intention to use	475	3.25	1.16
Usage behavior	506	3.33	1.73

N = Number; M = Mean Value; SD = Standard Deviation.

The students indicated a generally positive attitude toward the use of ChatGPT in the school context. The mean value for *behavioral intention* was 3.25, with a standard deviation of 1.16, which places it slightly above the midpoint of the five-point Likert scale (3.00). These values are based on responses from 457 students in the sample. The mean value for actual *usage behavior* was 3.33, with a standard deviation of 1.73, also exceeding the scale midpoint.

Table 5 presents the students' responses regarding the frequency of their ChatGPT use in the school context. The data include both the absolute frequency and the relative percentage in relation to the overall sample.

Table 5. Student ChatGPT usage frequency in school contexts.

	N	%
Never	71	14.0
Once a month	131	25.9
Several times a month	101	20.0
Once a week	46	9.1
Several times a week	108	21.3
Once a day	16	3.2
Several times a day	33	6.5
Total	506	100.0

N = Number; % = Percentage share.

Regarding the frequency of ChatGPT use by students in the school context, the results show that 14% of respondents stated that they never use ChatGPT for school purposes. Roughly one quarter turn to it about once per month, one fifth engage with it several times per month, and a comparable share do so several times per week. Fewer than ten percent use it daily, suggesting that occasional to moderate usage is typical in the school context.

The descriptive analysis of ChatGPT use focuses on the purposes for which students apply the tool and the subjects in which it is most frequently used. Table 6 presents students' responses regarding the purposes for which they use ChatGPT for school. The data include both absolute frequencies and their proportional share in relation to the sample.

Table 6. Students' purposes for using ChatGPT in school contexts.

	N	%
Information seeking	325	64.2
Writing texts	264	52.2
Homework	247	48.8
Preparing presentations	215	42.5
Preparing for exams	114	22.5
Translations	112	22.1
During exams	16	3.2

N = Number; % = Percentage share.

Regarding the purposes for which students use ChatGPT, the tool is primarily employed for *information seeking*, *writing texts*, and *completing homework*. It is also frequently used in *preparation for presentations*, with 42.5% of respondents indicating such use. In contrast, ChatGPT is used less often for studying for *exams*, and its use *during actual exam situations* is negligible, with only 3.2% of students reporting this.

Table 7 presents students' responses about the school subjects in which they use ChatGPT. The data include both absolute frequencies and their proportional share in relation to the sample.

Regarding the subjects in which students use ChatGPT, it appears that ChatGPT is particularly relevant in language and social science subjects. Students use ChatGPT especially in subjects such as *History* and *Social Studies* (53.2%), *German* (52.0%), and *English* or *other languages* (50.2%). In *Economics* and *Natural Sciences*, the use of ChatGPT is less common. About 39.3% of students reported using ChatGPT in *Economics*. In subjects like *Biology*, *Chemistry*, and *Physics*, 38.7% of students use ChatGPT. In *Mathematics* or *Computer Science*, usage is noticeably lower, with only 13.8% of students indicating that they use ChatGPT in these subjects.

Table 7. Areas of application (subject) of ChatGPT use by students in school contexts.

	N	%
History/Social studies	269	53.2
German	263	52.0
English/other languages	254	50.2
Economics	199	39.3
Biology/Chemistry/Physics	196	38.7
Mathematics	70	13.8
Computer science	70	13.8

N = Number; % = Percentage share.

5.2. Regression Analysis to Examine Students' Acceptance of ChatGPT

In this study, various linear regression models were developed based on the UTAUT2 model by Venkatesh et al. (2012) and its extension. The results allow for the depiction of relationships within the UTAUT2 and its extension, as applied in this study. Using the model fit measure R^2, statements can be made about the explanatory power of the UTAUT2 and its extension regarding students' technology acceptance of ChatGPT in the school context. Based on the regression coefficients (β), insights can be gained into which acceptance factors from UTAUT2 or constructs from its extension predict students' acceptance of ChatGPT in the school context. Furthermore, the analysis shows to what extent there are interaction effects between the extension constructs (*personal innovativeness*, *conscientiousness*, and *preference for challenge*) and students' acceptance of ChatGPT.

Initially, two regression models were created based on the original UTAUT2. The first regression model is presented in Table 8. It aims to explain the *behavioral intention* to use ChatGPT in the school context, which serves as the dependent variable. The independent variables integrated into the model are constructs from the UTAUT2 that are known to influence *behavioral intention to use* and *actual usage behavior*.

The model shows a very high explanatory power, with an R^2 of 0.645, and is significant (p = 0.001). *Performance expectancy*, *hedonic motivation*, and *habit* have a significant influence on *behavioral intention* to use (p = 0.001) and thus represent the predictors of *behavioral intention to use*. *Performance expectancy* has the strongest effect, with a β of 0.388, followed by *habit* (β = 0.319) and *hedonic motivation* (β = 0.179). *Performance expectancy* and habit show medium to large effect sizes, while the effect of *hedonic motivation* is weak to moderate. *Effort expectancy*, *social influence*, *facilitating conditions*, and *price value*, however, do not significantly affect *behavioral intention to use* ChatGPT in school contexts.

Table 8. Linear regression model: UTAUT2 (Dependent variable: Behavioral intention to use).

	B	SE	β	T	p
Performance expectancy	*0.504*	*0.054*	*0.388*	*9.403*	*0.001*
Effort expectancy	0.067	0.059	0.045	1.140	0.255
Social influence	0.031	0.034	0.029	0.890	0.374
Facilitating conditions	0.033	0.050	0.024	0.660	0.510
Hedonic motivation	*0.216*	*0.048*	*0.179*	*4.495*	*0.001*
Price value	0.046	0.035	0.042	1.313	0.190
Habit	*0.379*	*0.039*	*0.319*	*9.765*	*0.001*

Note: The constructs identified as significant ($p \leq 0.01$) are shown in italics.

The second regression model is presented in Table 9. It aims to explain learners' *behavior to use* ChatGPT in the school context. *Usage behavior* is the dependent variable in this regression model. The independent variables included are those constructs from the original UTAUT2 that have a direct effect on the actual *usage behavior* of a specific technology.

Table 9. Linear regression model: UTAUT2 (Dependent variable: Usage behavior).

	B	SE	β	T	p
Behavioral intention to use	*0.575*	*0.068*	*0.390*	*8.403*	*0.001*
Facilitating conditions	*0.238*	*0.075*	*0.118*	*3.173*	*0.002*
Habit	*0.511*	*0.077*	*0.290*	*6.622*	*0.001*

R^2 = 0.431 (N = 484; F(2.93) = 121,005; p = 0.001). Note: The constructs identified as significant ($p \leq 0.01$) are shown in italics.

The model has a high explanatory power, with an R^2 of 0.431, and is significant (p = 0.001). *Behavioral intention* to use (p = 0.001), *facilitating conditions* (p = 0.002), and *habit* (p = 0.001) have a significant influence on *usage behavior*. Thus, all independent variables in the model have a significant impact and serve as predictors of *usage behavior*. *Behavioral intention to use* has the strongest effect (β = 0.390), followed by *habit* (β = 0.290) with a medium effect size, and *facilitating conditions* (β = 0.118) with a weak effect.

5.3. Extension of the UTAUT2 Model

Regarding the extension of the UTAUT2 in this study, two additional regression models were developed. These models include additional constructs that are not part of the original UTAUT2. The extended regression models are supposed to provide further insights into how these extensions might contribute to increasing the explanatory power concerning learners' acceptance of ChatGPT in the school context. At the same time, they are supposed to offer insights into the influence of the constructs considered here on learners' technology acceptance.

The third regression model is presented in Table 10. It aims to explain learners' *behavioral intention to use* ChatGPT in the school context. *Behavioral intention to use* is the dependent variable in this regression model. The independent variables integrated into the model are those from the original UTAUT2 that influence *behavioral intention to use*. Additionally, *personal innovativeness*, *conscientiousness*, and *challenge preference* were included as independent variables representing the extension of the UTAUT2 in this study.

The model has a very high explanatory power, with an R^2 of 0.647, and is significant (p = 0.001). Compared to the first regression model (see Table 8), which includes only constructs from the original UTAUT2, the explanatory power can hardly be increased. The explanatory power of the first regression model was an R^2 of 0.645. Thus, the increase in R^2 is 0.002. *Performance expectancy, hedonic motivation*, and *habit* have a significant effect on *behavioral intention to use* (p = 0.001) and therefore serve as predictors of this construct. *Performance expectancy* exhibits the strongest effect (β = 0.379), followed by *habit* (β = 0.316) with a medium effect size, and *hedonic motivation* (β = 0.167) with a weak effect. Again, the constructs from the UTAUT2 extension (*personal innovativeness*, *conscientiousness*, and *challenge preference*) have no significant influence on *behavioral intention to use*.

Table 10. Linear regression model: UTAUT2 (Dependent variable: Usage behavior).

	B	SE	β	T	p
Performance expectancy	*0.493*	*0.054*	*0.379*	*9.058*	*0.001*
Effort expectancy	0.066	0.059	0.045	1.123	0.262
Social influence	0.035	0.035	0.033	1.000	0.318
Facilitating conditions	0.020	0.052	0.014	0.387	0.699
Hedonic motivation	*0.203*	*0.050*	*0.167*	*4.048*	*0.001*
Price value	0.043	0.036	0.039	1.215	0.225
Habit	*0.374*	*0.040*	*0.316*	*9.449*	*0.001*
Personal innovativeness	0.059	0.046	0.046	1.291	0.197
Conscientiousness	−0.036	0.038	−0.030	−0.954	0.341
Challenge preference	0.022	0.046	0.016	0.481	0.631

R^2 = 0.647 (N = 467); F(df) = 83.696; p = 0.001. Note: The constructs identified as significant ($p \leq 0.01$) are shown in italics.

The fourth regression model is presented in Table 11. It aims to explain the *usage behavior* of learners regarding the use of ChatGPT in the school context. *Usage behavior* is the dependent variable of this regression model. As independent variables, the constructs that influence *usage behavior* in the original UTAUT2 were integrated into the regression model. Additionally, *personal innovativeness*, *conscientiousness*, and *challenge preference* were included as independent variables representing the extension of the UTAUT2 within this study.

Table 11. Linear regression model: Extension of UTAUT2 (Dependent variable: Usage behavior).

	B	SE	β	T	p
Behavioral intention to use	*0.566*	*0.072*	*0.383*	*7.900*	*0.001*
Facilitating conditions	*0.207*	*0.080*	*0.102*	*2.575*	*0.010*
Habit	*0.503*	*0.078*	*0.286*	*6.409*	*0.001*
Personal innovativeness	0.054	0.080	0.029	0.678	0.498
Conscientiousness	0.118	0.069	0.066	1.708	0.088
Challenge preference	−0.023	0.085	−0.011	−0.276	0.783

R^2 = 0.436 (n = 475; F(df) = 60.347; p = 0.001). Note: The constructs identified as significant ($p \leq 0.01$) are shown in italics.

The model shows a high explanatory power, with an R^2 of 0.436, and is significant (p = 0.001). Compared to the second regression model (see Table 9), which includes only constructs from the original UTAUT2, the explanatory power can hardly be increased. The explanatory power of the second regression model was an R^2 of 0.431. Thus, the increase in R^2 is 0.005. *Behavioral intention to use* (p = 0.001), *facilitating conditions* (p = 0.010), and *habit* (p = 0.001) have a significant influence on *usage behavior*. *Behavioral intention to use* ChatGPT has the strongest effect, with a β of 0.383, followed by *habit* (β = 0.286) and *facilitating conditions* (β = 0.102). *Behavioral intention to use* and *habit* show medium to high effect sizes, as in the second regression model. The effect of *facilitating conditions* is again a weak effect size. The additional constructs from the UTAUT2 extension (*personal innovativeness*, *conscientiousness*, and *preference for challenge*) again do not have a significant influence on *usage behavior*.

6. Discussion

The present study examined the use and acceptance of ChatGPT among students in upper secondary education. The findings reveal how often students use ChatGPT, for what purposes, in which subjects it is most common, and which psychological and contextual factors shape acceptance and use. The study also tests whether the established UTAUT2 model and its proposed extensions account for students' acceptance of ChatGPT. The discussion is organized around six guiding research questions.

In relation to *research question 1 (RQ1)*, which addressed the extent to which students use ChatGPT in the school context, the descriptive analyses revealed that a significant majority of students already use the tool. A total of 86% of the respondents reported using ChatGPT for school-related tasks, while only 14% indicated that they had never done so. This shows that ChatGPT has already become a widely established tool among upper secondary students. These results are consistent with findings from Strzelecki (2023b), who reported similar usage patterns among university students. Although the present study focused on a younger population, the usage rates suggest that ChatGPT is already deeply integrated into the academic routines of students. Given this reality, an outright ban on ChatGPT in schools appears both unrealistic and educationally counterproductive. Rather, schools are called upon to adapt both instruction and assessment practices. Traditional assignments, such as purely text-based writing tasks, are becoming less effective in assessing student performance, as AI tools can easily generate coherent and formally correct responses. Accordingly, a pedagogical shift is needed, moving away from reproduction-focused assessments and toward formats that emphasize *critical thinking*, reflection, and evaluation. In line with the demands articulated by Foroughi et al. (2023), it seems increasingly relevant to design learning tasks in which students engage with ChatGPT outputs, such as by evaluating their quality, identifying errors, or revising AI-generated texts as part of classwork or exams.

With regard to *research question 2 (RQ2)*, which examined the purposes and subject areas in which ChatGPT is used by students, the findings show that the tool is primarily used for *research* (64.2%), *writing texts* (52.2%), and *homework* (48.8%). Less frequent purposes include preparing presentations (42.5%) and studying for exams (22.5%). Very few students (3.2%) reported using ChatGPT during actual examinations. This usage pattern reflects the perceived utility of ChatGPT in open-ended or text-based learning tasks, while more formal or controlled assessment settings appear less influenced by its presence. In terms of subjects, the tool is used most frequently in *History* or *Social Studies* (53.2%), *German* (52.0%), and *English* or *other foreign languages* (50.2%). Its use is less common in *Economics* (39.3%) and *Natural Sciences*, such as *Biology, Chemistry or Physics* (38.7%). The lowest usage rates were found in *Mathematics* and *Computer Science* (both 13.8%). These results highlight the role of ChatGPT as a predominantly language- and content-processing tool. In practice, this suggests that AI integration is already progressing unevenly across subjects. Teachers in language and social science subjects can draw on existing student practices and design lessons that incorporate ChatGPT use meaningfully, for instance by analyzing text versions created with and without AI assistance. For STEM subjects, however, there is a need for new instructional approaches that clarify how ChatGPT and similar tools can support analytical or conceptual thinking in those domains.

Turning to *research question 3 (RQ3)*, which asked whether the UTAUT2 model can explain students' technology acceptance of ChatGPT in the school context, the regression analyses showed that the model offers strong explanatory power. Specifically, the regression model based on the original UTAUT2 yielded an R^2 = 0.645 for *behavioral intention to use* and an R^2 = 0.431 for *actual usage behavior*. These results confirm that the UTAUT2 model is highly suitable for analyzing technology acceptance in secondary education. The values are comparable to those reported by Strzelecki (2023b), although his models, based on structural equation modeling, achieved slightly higher R^2 values. This confirms the general robustness of the model even when applied to younger learners.

Regarding *research question 4 (RQ4)*, which examined the specific factors that promote or hinder students' acceptance of ChatGPT, the findings show that *performance expectancy*

(β = 0.388), *habit* (β = 0.319), and *hedonic motivation* (β = 0.179) significantly predicted students' *behavioral intention to use*. These results are in line with those of Foroughi et al. (2023), who also identified these constructs as central predictors of technology acceptance. The particularly strong effect of performance expectancy suggests that students are most likely to adopt ChatGPT when they believe it will enhance their academic performance. This implies that instruction should focus on showing students how ChatGPT can be used strategically and effectively. Integrating AI literacy into the curriculum, such as by explaining how language models work or where their limitations lie, can help foster informed use. The significance of *habit* as a predictor highlights the role of routine and familiarity. Many students already use ChatGPT as part of their regular study habits, which reinforces the need to raise awareness about the limitations of AI-generated content. Errors in training data, misinformation, and overconfidence in AI outputs must be explicitly addressed in instruction. Prior studies, such as Lund et al. (2023) and Ahmed et al. (2023), have emphasized these risks, which should be explored through targeted classroom activities. The influence of *hedonic motivation* suggests that students are also more inclined to use ChatGPT when the experience is enjoyable. This finding supports pedagogical designs that make learning with AI engaging and motivating.

In addressing *research question 5 (RQ5)*, which examined whether the extended UTAUT2 model improves the explanatory power of the original model, the results show only a marginal increase in R^2, from 0.645 to 0.647 for *behavioral intention*, and from 0.431 to 0.436 for *actual usage behavior*. Thus, adding the constructs *personal innovativeness*, *conscientiousness*, and *challenge preference* did not meaningfully improve the model. This suggests that these personality-related traits play only a limited role in students' acceptance of ChatGPT in school settings.

This interpretation is confirmed by the findings related to *research question 6 (RQ6)*, which investigated which of the additional constructs in the extended model are related to students' technology acceptance. The analysis showed that none of the three added constructs had a significant effect on either *behavioral intention* or *actual usage behavior*. From an educational perspective, this is a highly relevant finding. It indicates that AI-based tools like ChatGPT are not only used by particularly curious, innovative, or challenge-seeking students. Rather, their use is widespread across personality types. As a result, didactic strategies should be designed to support all learners, regardless of individual disposition. Instruction should offer all students the opportunity to explore the benefits and risks of AI systems and develop competencies for their responsible use. Differentiated instructional approaches and reflective activities can help ensure that every learner is able to navigate the digital learning environment safely and effectively.

While the findings of this study are robust and largely consistent with prior research, several limitations must be considered. First, the study was based on a convenience sample of 506 students and thus cannot claim to be representative. The sample size is comparable to those in Strzelecki's studies (534 and 503 participants) and exceeds that of Foroughi et al. (2023) (406 participants), yet the generalizability of the findings remains limited. In addition, data collection was conducted exclusively in one German federal state, which further restricts the transferability of the results to other regional or institutional contexts. Furthermore, all data were collected via self-report questionnaires, which may be biased by social desirability effects. In terms of methodology, it is important to note that the study used multiple regression analysis rather than structural equation modeling. This limits its ability to capture complex mediating and moderating relationships between constructs. While Strzelecki (2023a, 2023b) and Foroughi et al. (2023) applied structural models to assess causal pathways more holistically, the present study offers a partial yet focused investigation of key acceptance factors. To deepen the understanding of the mechanisms underlying students' acceptance and use of AI tools, future studies should apply more advanced multivariate methods, particularly structural equation modeling. This would enable a more precise analysis of mediated effects and interdependencies within the UTAUT2 framework.

In addition to methodological refinement, upcoming research should also consider relevant contextual conditions. These include access to digital infrastructure, institutional expectations, curricular frameworks, and available support structures. Such factors may significantly influence how students adopt and use generative AI technologies in everyday school settings and should therefore be more systematically integrated into future explanatory models.

Despite these limitations, the findings clearly demonstrate that ChatGPT is already widely used and accepted by upper secondary students and that this use is shaped primarily by practical benefits, habit, and the enjoyment of using the tool. For educational institutions, these results highlight the urgent need to rethink how learning is organized, how digital tools are integrated, and how AI-related competencies are fostered. Instructional formats and assessment methods must be adapted to reflect the realities of AI-enhanced learning. Schools are thus challenged to actively shape digital transformation processes and to prepare students for a future in which artificial intelligence will be an integral part of their learning and working environments.

To translate these insights into practice, it is essential that educators and school leaders take an active role in supporting students' responsible and informed engagement with AI tools. Teachers can incorporate activities that require students to critically analyze, compare, and revise AI-generated texts, helping them recognize both the potential and limitations of such tools. At the same time, school leaders can support this process by promoting AI-related professional development and fostering a culture of reflective technology use across the school. These efforts can strengthen students' digital literacy and ensure that AI is integrated into classroom settings in pedagogically meaningful ways.

At the same time, contextual conditions such as teacher support, school policy frameworks, and access to digital infrastructure may also influence students' use of AI tools in classroom settings. These factors could shape how frequently and in what ways students engage with ChatGPT, and they may moderate or mediate the relationship between individual acceptance and actual usage. Considering such school level variables can help to better understand differences in AI integration across educational contexts.

Building on the findings of this study, it would also be valuable to explore instructional formats that align with students' current use patterns and motivational factors. For example, future research could examine how structured learning activities involving the critical evaluation or revision of AI-generated content affect learning outcomes and student engagement. This may help develop pedagogical approaches that foster both critical thinking and the competent use of generative AI for school purposes.

7. Conclusions

The present study examined how upper secondary students perceive the use of ChatGPT in the school context and to what extent they are willing to integrate this AI-based tool into their everyday learning. The goal was to gain a differentiated understanding of students' *technology acceptance* and to systematically capture their attitudes toward ChatGPT using a theoretically grounded model. The study thereby contributes to current discourse on how digital technologies can be meaningfully integrated into school-based learning processes.

The findings indicate that ChatGPT is already used routinely by a majority of learners, particularly for tasks such as *homework*, *information seeking*, and *text production*. This use takes place largely independent of formal instructional integration, pointing to the coexistence of informal, *technology-supported learning* alongside traditional classroom structures. This development underscores the need for schools to reflect and respond to students' evolving learning practices.

The analysis of influencing factors was based on the *UTAUT2* model. The results show that students' *behavioral intention to use* ChatGPT is significantly predicted by *performance expectancy*, *habit*, and *hedonic motivation*. These findings confirm that students tend to use ChatGPT when they perceive it as useful for academic achievement, when its use is already established in daily routines, and when interacting with the tool is experienced as enjoyable. The model demonstrated high explanatory power.

In contrast, the additional constructs included in the extended model (*personal innovativeness*, *conscientiousness*, *challenge preference*) were not significant and increased the explanatory power only marginally. This suggests that stable personality traits and value orientations are not primary determinants of ChatGPT usage in the school context. Students' willingness to use ChatGPT appears to be shaped predominantly by practical, experience-based factors rather than by individual dispositions.

These findings point to concrete implications for school development. Since acceptance is linked to perceived usefulness and motivational factors, pedagogical strategies should focus on enabling students to use ChatGPT purposefully and reflectively. Instructional formats should include exercises that promote the critical examination of AI-generated content and foster awareness of the limitations of such tools. The integration of *AI literacy* into curricula could support these aims.

At the same time, several limitations of the study must be acknowledged. The data are based on a convenience sample and rely entirely on self-reports, which may be subject to social desirability bias. Moreover, data collection was limited to a single federal state in Germany, which restricts the generalizability of the findings to other regional contexts. The statistical analyses were conducted using multiple regression. While this method is suitable for estimating direct effects, it does not allow for the modeling of indirect or moderating relationships. In addition to methodological refinement, future research should also examine how school specific conditions, such as access to digital infrastructure, institutional norms, curricular constraints, or support structures, influence the acceptance and use of AI tools in educational settings.

In summary, the study shows that students already use ChatGPT in diverse and autonomous ways. Their acceptance is not driven by avoidance tendencies but by perceived learning benefits, motivation, and habitual integration into everyday learning. Schools are therefore called upon to develop teaching concepts that respond to these realities and promote the competent, goal-oriented, and reflective use of AI-based technologies.

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