The role of habit in promoting generative AI adoption among social science students and researchers

Aivars Spilbergs,
BA School of Business and Finance, University of Latvia,
K.Valdemara 161, Riga, LV-1013
Latvia
ORCID ID_0000-0003-2537-8053

Received: April 9, 2025. Revised: July 11, 2025. Accepted: August 16, 2025. Published: April 17, 2026.

Abstract—The rapid expansion of generative AI (GenAI) in higher education raises important questions about what drives its sustained and responsible use. This study applies an extended UTAUT2 framework to examine GenAI adoption among social science students and researchers. Using PLS-SEM on responses from 569 participants across Baltic Sea region universities, the study evaluates how performance expectancy, effort expectancy, social norms, study value, facilitating conditions, hedonic motivation, and habit shape self-reported GenAI use in classroom tasks, homework, self-study, and thesis work. Habit emerges as the strongest predictor for both groups (students = 0.420; staff = 0.712), explaining substantial variance (R^2 = 0.479 and 0.558). Students exhibit modest positive effects from performance expectancy, effort expectancy, social norms, and study value. In contrast, study value is the sole additional predictor identified for staff. These findings underscore the importance of scaffolded GenAI activities that foster responsible habits, as well as institutional strategies that prioritize demonstrable academic value.

Keywords—adoption determinants, effect size, generative AI, habit, predictive power, social sciences students and researchers, PLS-SEM, UTAUT2.

I. INTRODUCTION

The rapid proliferation of generative artificial intelligence (GenAI) tools, including large language models, has created both opportunities and challenges across academic disciplines, notably within the social sciences [1]. Although these tools enhance productivity and analytical capabilities, their integration into higher education has sparked debate over academic integrity and potential effects on critical thinking skills [2]. The effective integration of GenAI in academic contexts depends on understanding the factors that influence adoption among students and researchers. This requires examining behavioral patterns such as habit formation, which can significantly affect sustained technology use. Key determinants, including performance expectancy, effort expectancy, social influence, and hedonic motivation, have been identified as influencing students' behavioral intentions to use generative AI, with habit serving a crucial role in linking intention to actual use behavior [3]. Collectively, these studies reveal a complex interplay between psychological and contextual factors that shape the adoption of advanced AI technologies in academic practice. However, a notable gap remains in understanding how challenges unique to academic environments, particularly intercultural differences and data-specific divergences, vary across academic segments and influence habit formation in AI adoption [4], [5]. In contrast to STEM disciplines, where concerns about data accuracy and reproducibility are paramount, the social sciences encounter distinct integrity challenges, including authorship, originality, interpretive validity, and the contextual nature of qualitative data. These differences highlight the need to examine GenAI adoption within the social sciences, as the associated risks and necessary safeguards for responsible use differ substantially from those in quantitatively oriented fields [6], [7].

The objective of this research is to bridge this gap by exploring the specific role of habit in the adoption of GenAI among social science students and researchers, acknowledging the distinct data specifics and academic integrity considerations inherent to these disciplines.

This study examines how habit formation affects sustained engagement with GenAI tools, accounting for the distinctive frameworks and disciplinary norms of the social sciences. It also aims to identify variables that influence the implementation of AI models in research activities and to analyze the impact of perceived social norms and academic integrity on their adoption within this academic context. By investigating these factors, the research seeks to provide insights for developing strategies that enhance learning outcomes and promote equitable access to the benefits of AI, while maintaining academic integrity in the social sciences. This investigation is essential for informing guidelines and pedagogical approaches that support responsible and effective integration of AI tools into social science curricula and research methodologies. This endeavor will draw on established models of technology acceptance, such as the Unified Theory of Acceptance and Use of Technology 2, to construct a comprehensive framework for analyzing GenAI adoption in this specialized academic domain.

II. Literature review

A. Social information specifics and GenAI application

The integration of GenAI within academic frameworks, particularly in the social sciences, introduces a complex interplay between technological advancements and ethical considerations, [8]. The ethical concerns and biases associated with GenAI use are not merely abstract challenges but have direct implications for the constructs examined in the empirical model. For instance, concerns about bias and authenticity may reduce performance expectancy, as users question whether GenAI outputs can reliably enhance their academic work, [9]. Similarly, the need for additional verification to ensure originality and avoid plagiarism may increase perceived effort expectancy, as students and staff must invest time in checking AI-generated content, [10]. Integrity norms also shape social influence, since peer and institutional expectations often emphasize responsible use and adherence to ethical standards, [11]. Moreover, perceptions of study value are influenced by whether GenAI is viewed as enhancing learning outcomes without compromising authenticity, [8]. Finally, the development of habit may depend on whether repeated use incorporates integrity practices such as citation and verification, thereby embedding ethical routines into daily workflows.

This necessitates a thorough investigation into how these biases manifest in GenAI outputs and, crucially, how social scientists perceive and react to such biases when considering the adoption of these tools for their research endeavors, [10].

The verifiability of AI-generated content's authenticity, coupled with unresolved issues concerning data privacy and intellectual property rights, further compounds the ethical concerns surrounding the adoption of GenAI, [12]. These challenges, encompassing content interpretation and plagiarism, significantly impede the widespread integration of GenAI within higher education settings, [13]. These concerns extend to the potential for AI tools to influence academic integrity, with studies indicating that social influence, educational self-efficacy, and perceived ethics significantly predict researchers' utilization of AI models. Moreover, academic roles, gender, and prior experience with generative AI tools have been shown to influence ethical awareness regarding their use. This highlights the importance of adopting discipline-specific ethical frameworks, since concerns in STEM fields often differ markedly from those in the humanities, particularly regarding data accuracy, originality, and authorship [11].
The evolving landscape of AI applications presents persistent challenges for higher education institutions in enforcing integrity policies and establishing clear guidelines for responsible AI use. These challenges emphasize the urgent need for a structured approach to AI integration that addresses ethical considerations, promotes AI literacy, and maintains equilibrium between technological progress and human oversight [14]. Consequently, developing institutionally grounded ethical guidelines for generative AI in social science research is essential. Such guidelines should move beyond general principles to address the specific challenges of individual disciplines and contexts, [15].

B. Determinants of GenAI adoption in social science studies

Prior research indicates that the willingness to use GenAI, such as ChatGPT, largely centers on its perceived benefits, limitations, ethical considerations, and user perceptions, often analyzed through principal component analysis, [3]. The Technology Acceptance Model and its extensions provide a comprehensive framework for analyzing the adoption of ChatGPT in higher education [16], [17]. Critical determinants such as perceived ease of use, perceived usefulness, attitude, feedback quality, trust, and personal innovativeness have been shown to significantly influence technology adoption. In contrast, factors including hedonic motivation, perceived enjoyment, price value, and technology readiness have not been conclusively established, underscoring the complexity and variability inherent in technology adoption processes.
The original Unified Theory of Acceptance and Use of Technology (UTAUT) model is designed to explain technology acceptance within organizational contexts. This model integrates eight prominent technology acceptance frameworks into a single structure, identifying four primary determinants of intention and usage: performance expectancy (PE), effort expectancy (EF), social influence (SI), and facilitating conditions (FC), [18]. The extended version of the UTAUT model, UTAUT2, incorporates constructs such as hedonic motivation, price value, and habit, which significantly influence user intention and behavior, [19]. The UTAUT model serves as a valuable instrument for managers seeking to evaluate the potential success of novel technology introductions and to discern the factors influencing acceptance, thereby enabling them to proactively create interventions tailored to user groups who may exhibit reluctance toward adopting and utilizing new systems to provide a robust understanding of the determinants of sustained technology use among academic staff, [20].

Given that GenAI tools like ChatGPT have recently emerged, the UTAUT2 framework is particularly well-suited for examining their adoption during these initial stages, explaining a substantial portion of the variance in behavioral intention and actual use, [21]. Several studies have employed the UTAUT model to investigate the acceptance of various technologies, adjusting the model to align with the specific technology under examination, such as generative AI tools, [22], [23], [24].

Within the realm of higher education, the UTAUT2 model is investigated to identify the factors influencing students' or teachers' intentions to utilize diverse technological tools, including e-learning systems, mobile applications, immersive virtual and augmented reality, and learning management systems, [25], [26], [27]. This model posits that performance expectancy, effort expectancy, social norms, facilitating conditions, hedonic motivation, price value, and habit directly influence an individual's intention to use a technology, and subsequently, their actual use of that technology.

Performance expectancy (PE), defined as the extent to which individuals consider that using a particular technology will enhance their job performance, is a critical factor in technology adoption, [18]. Effort expectancy (EF), on the other hand, refers to the level of ease concerned with using a technology, [28]. Social norms (SN) reflect the extent to which an individual perceives that important others believe they should use a particular technology, [28]. Facilitating conditions (FC) relate to the extent to which an individual perceives that an organizational and technical infrastructure persists to support the use of the system, [18]. Habit **(**HA) refers to the extent to which an individual perceives using GenAI tools as an automatic part of their routine activities, [28]. Study value (SV**)** refers to the perceived benefits and enhancements that GenAI tools bring to the educational experience of higher education students, [8]. Hedonic motivation (HM), defined as the enjoyment derived from using a technology, plays a significant role in determining technology acceptance and usage, [29]. By integrating these diverse factors, the study aims to deliver a holistic perspective on the complex interplay of psychological, ethical, and technological dimensions that influence the integration of GenAI within the social science academy.

Based on the literature review, the following hypotheses were formulated:

H1: Performance expectancy positively influences GenAI adoption by social science students and researchers

H2: Effort expectancy has a favorable influence on the adoption of GenAI by social science students and researchers.

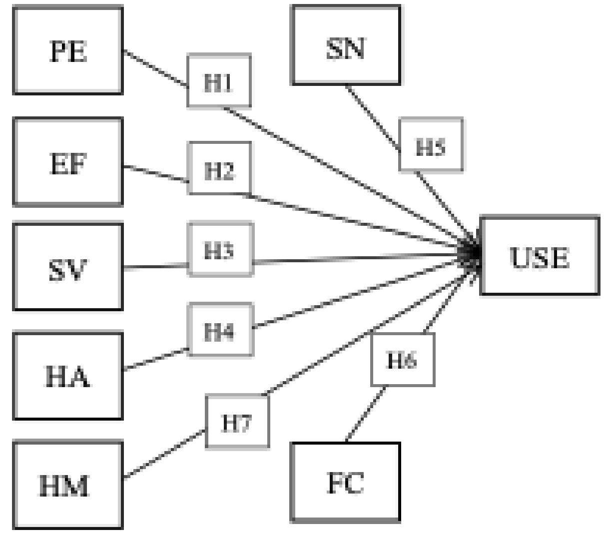
H3: Study value positively influences GenAI adoption by social science students and researchers.

H4: Habit has a positive influence on the adoption of GenAI among social science students and researchers.

H5: Social norms positively influence GenAI adoption by social science students and researchers

H6: Facilitating conditions positively influence GenAI adoption by social science students and researchers

H7: Hedonic motivation positively influences GenAI adoption by social science students and researchers.



Source: created by the authors

Fig. 1. Conceptual model for testing factors affecting social science students' and researchers' adoption of GenAI

III. Data and Methods

To assess the conceptual model shown in Fig. 1, a measurement scale was developed following an extensive review of the academic literature to specify the key factors influencing the adoption of GenAI. Independent variables were assessed using a 10-point Likert scale, with response options from *"strongly disagree"* to *"strongly agree."* USE was measured on a 5-point Likert scale, ranging from *"never"* to "daily."

The survey questionnaire was piloted with a small sample from the target population in Autumn 2024. This preliminary phase ensured item clarity and enabled an estimate of completion time. Minor revisions were made to several questions based on participant feedback. Respondents provided demographic information, including age, study level, and region (see Table 1). The survey link was distributed through multiple channels, including networks within higher education institutions in the Baltic region. Data collection occurred between January 2 and March 31, 2025, resulting in 580 responses. After excluding 11 incomplete questionnaires, the final dataset was prepared for analysis.

The sample under investigation comprised 441 participants: 297 bachelor's students, 100 master's students, 44 doctoral students, and 128 academic staff members. Within the student subgroup, 43.3% were under 23 years of age, followed by 32.7% in the 23–27 age range. Among academic staff, 41.4% were aged 43–52, while 34.4% were 53 or older. Overall, the convenience sample broadly reflected the demographic distribution of social science students and faculty in Baltic higher education institutions in terms of age, gender, and educational level.

Table 1. Descriptive statistics of the demographics of survey respondents

Variable	Item	Students		Academic staff	
		n	*n* (%)	*n*	*n* (%)
Age	< 23	191	43.3	1	0.8
	23 – 27	144	32.7	3	2.3
	28 – 32	52	11.8	4	3.1
	33 – 37	23	5.2	10	7.8
	38 – 42	13	2.9	13	10.2
	43 – 47	12	2.7	33	25.8
	48- 52	1	0.2	20	15.6
	53 – 57	5	1.1	25	19.5
	58 +	0	0.0	19	14.8
Gender	Female	270	61.2	69	53.9
	Male	171	38.8	59	46.1
Study level	Secondary	224	50.8	-	-
	Bachelor	167	37,9	-	-
	Master	50	11.3	57	44.5
	Doctoral	44	10,0	71	55.5
Region	Latvia	261	59.2	63	49.2
	Denmark	35	7.9	27	21.1
	Lithuania	56	12.7	4	3.1
	Estonia	33	7.5	4	3.1
	Other	56	12.7	30	23.4

Source: created by the authors

The conceptual model was assessed through a two-stage analytical approach utilizing partial least squares–structural equation modelling (PLS-SEM), based on the characteristics of the collected data and supported by evidence of its effectiveness in comparable studies, [8], [21], [29], [30].

IV. Results

A. Measurement model evaluation – factor loadings, reliability, and validity analysis

The quality of the constructs, PE, EF, SN, SV, HA, HM, FC, and USE (see Table 2), was examined through the evaluation of the measurement model. This evaluation involved assessing indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), as well as validity measures, including convergent and discriminant validity.

Table 2. Measurement model variables

Construct	Items
PE	PE1: GenAI is useful for my studies/research
	PE2: GenAI enhances the quality of my studies/research
	PE3: GenAI allows me to accomplish study/research activities more quickly
	PE4: GenAI increases my study/research productivity
EF	EE1: Learning how to use GenAI is easy for me
	EE2: My interaction with GenAI is clear and understandable
	EE3: GenAI is easy to use
SN	SI1: My fellow students/colleagues who influence my behavior recommend that I use GenAI
	SI2: My lecturers, who are important to me, recommend that I use GenAI
	SI3: Employers whose views I value recommend that I use GenAI
	SI4: Public opinion leaders, who are important to me, recommend that I use GenAI
SV	SV1: Application of GenAI in the study process is worth more than the time and effort given to it
	SV2: GenAI allows me quickly and easily share my knowledge with others
	SV3: GenAI allows me to decide on the pace of my own study
	SV4: GenAI allows me to increase my knowledge and to control my success
HA	HA1: The use of GenAI has become a habit for me
	HA2: I am addicted to using GenAI to accomplish my study/research tasks
	HA3: I intend to continue using GenAI in the future
FC	FC1: I have resources necessary to use GenAI
	FC2: I have knowledge necessary to use GenAI
	FC3: GenAI is compatible with other technologies I use
	FC4: I can get help from others when I have difficulty using GAI
HM	HM1: I enjoy using GenAI for my studies/research
	HM2: Using GenAI for my studies/research is very entertaining
	HM3: Using GenAI for my studies/research is very entertaining
USE	US1: I am using GenAI to write my thesis (undergraduate/master's/PhD)
	US2: I am using GenAI while in classes at the university
	US3: I use GenAI for doing homework/preparing projects/and writing papers
	US4: I use GenAI for self-study, gaining knowledge and skills on an interesting topic related to my studies/research

Source: created by the authors

DOI: 10.46300/9109.2026.20.8 Volume 20, 2026

Factor loadings specify the degree to which each item is related to its corresponding construct. In this study, all items demonstrated loadings above the recommended threshold of 0.708, [31], and were statistically significant at the $\alpha < 0.01$ level. The detailed factor loadings are reported in Table 3 and Table 4.

Table 3. Measurement model factor cross-loadings in the students' subgroup

Items	PE	EF	SN	SV	HA	FC	HM	USE
PE1	0.836	0.449	0.278	0.429	0.544	0.366	0.636	0.409
PE2	0.917	0.401	0.291	0.555	0.606	0.368	0.646	0.468
PE3	0.898	0.424	0.309	0.529	0.606	0.338	0.659	0.474
PE4	0.872	0.416	0.390	0.668	0.589	0.378	0.618	0.531
EF1	0.373	0.880	0.102	0.214	0.316	0.426	0.452	0.270
EF2	0.422	0.889	0.161	0.299	0.392	0.461	0.450	0.297
EF3	0.470	0.913	0.274	0.454	0.456	0.468	0.535	0.418
SN1	0.386	0.284	0.717	0.266	0.411	0.321	0.347	0.336
SN2	0.260	0.169	0.839	0.367	0.392	0.310	0.261	0.409
SN3	0.243	0.133	0.838	0.297	0.303	0.255	0.206	0.336
SN4	0.263	0.065	0.751	0.281	0.265	0.246	0.245	0.240
SV1	0.568	0.308	0.276	0.804	0.542	0.392	0.589	0.383
SV2	0.459	0.264	0.353	0.837	0.539	0.380	0.458	0.414
SV3	0.501	0.342	0.348	0.897	0.615	0.443	0.559	0.494
SV4	0.584	0.357	0.328	0.830	0.534	0.399	0.577	0.512
HA1	0.550	0.425	0.395	0.482	0.875	0.403	0.680	0.533
HA2	0.433	0.230	0.336	0.550	0.803	0.335	0.505	0.527
HA3	0.679	0.454	0.382	0.625	0.834	0.467	0.686	0.580
FC1	0.397	0.528	0.212	0.264	0.347	0.648	0.443	0.236
FC2	0.273	0.465	0.157	0.231	0.248	0.706	0.302	0.227
FC3	0.320	0.245	0.339	0.441	0.415	0.815	0.341	0.322
FC4	0.253	0.342	0.329	0.469	0.395	0.782	0.352	0.314
HM1	0.739	0.531	0.330	0.525	0.678	0.470	0.883	0.497
HM2	0.504	0.396	0.189	0.421	0.469	0.379	0.763	0.312
HM3	0.516	0.397	0.282	0.626	0.656	0.328	0.810	0.470
US1	0.349	0.164	0.369	0.329	0.442	0.172	0.303	0.705
US2	0.441	0.333	0.385	0.365	0.480	0.324	0.400	0.803
US3	0.439	0.344	0.280	0.383	0.532	0.274	0.482	0.808
US4	0.453	0.336	0.332	0.592	0.587	0.390	0.482	0.824

Source: created by the authors.

Table 4. Measurement model factor cross-loadings in the academic staff subgroup' subgroup

Items	PE	EF	SN	SV	HA	FC	HM	USE
PE1	0.854	0.284	0.196	0.433	0.433	0.262	0.549	0.279
PE2	0.902	0.368	0.273	0.581	0.515	0.193	0.561	0.345
PE3	0.936	0.363	0.214	0.614	0.636	0.328	0.665	0.436
PE4	0.912	0.498	0.245	0.697	0.645	0.379	0.662	0.447
EF1	0.365	0.927	0.282	0.365	0.294	0.535	0.352	0.131
EF2	0.477	0.952	0.349	0.478	0.425	0.560	0.414	0.173
EF3	0.385	0.969	0.347	0.452	0.387	0.638	0.402	0.230
SN1	0.252	0.374	0.876	0.461	0.329	0.251	0.351	0.240
SN2	0.251	0.335	0.850	0.500	0.373	0.326	0.397	0.227
SN3	0.223	0.327	0.871	0.416	0.231	0.193	0.291	0.180
SN4	0.132	0.109	0.807	0.342	0.265	0.246	0.245	0.240
SV1	0.669	0.273	0.337	0.776	0.619	0.391	0.626	0.447
SV2	0.308	0.322	0.455	0.753	0.406	0.352	0.437	0.325
SV3	0.520	0.525	0.483	0.891	0.545	0.470	0.613	0.493
SV4	0.643	0.399	0.441	0.907	0.679	0.442	0.713	0.554
HA1	0.548	0.454	0.361	0.570	0.914	0.491	0.774	0.664
HA2	0.437	0.317	0.338	0.642	0.832	0.430	0.600	0.614
HA3	0.621	0.202	0.258	0.517	0.766	0.328	0.649	0.548
FC1	0.199	0.489	0.287	0.350	0.337	0.838	0.470	0.188
FC2	0.327	0.529	0.013	0.231	0.320	0.741	0.393	0.209
FC3	0.354	0.600	0.182	0.397	0.359	0.667	0.390	0.196
FC4	0.182	0.356	0.391	0.494	0.470	0.810	0.501	0.330
HM1	0.694	0.389	0.256	0.498	0.668	0.505	0.821	0.459
HM2	0.325	0.113	0.255	0.497	0.546	0.390	0.752	0.387
HM3	0.619	0.456	0.480	0.755	0.741	0.517	0.876	0.572
US1	0.434	0.252	0.285	0.518	0.615	0.259	0.513	0.850
US2	0.233	0.057	0.125	0.299	0.535	0.238	0.385	0.808
US3	0.408	0.084	0.187	0.490	0.617	0.236	0.500	0.882
US4	0.368	0.253	0.268	0.557	0.686	0.341	0.578	0.854

Source: created by the authors.

The two most widely applied measures of reliability are Cronbach's alpha and composite reliability (rho_C). Cronbach's alpha represents the lower bound, while composite reliability (rho_C) reflects the upper bound of internal consistency. Positioned between these two, the reliability coefficient (rhoA) provides a balanced and accurate representation of a construct's internal consistency reliability.

Table 5. Reliability ratios in the students and academic staff subgroups

Subgroup	Con-struct	*alpha*	rho_C	*AVE*	rho_A
Students	PE	0.904	0.933	0.777	0.911
	EF	0.878	0.923	0.799	0.929
	SN	0.798	0.867	0.621	0.816
	SV	0.864	0.907	0.710	0.875
	HA	0.787	0.876	0.702	0.789
	FC	0.726	0.828	0.548	0.745
	HM	0.760	0.860	0.673	0.787
	USE	0.793	0.866	0.618	0.803
Academics	PE	0.924	0.945	0.813	0.951
	EF	0.947	0.965	0.902	0.989
	SN	0.874	0.913	0.725	0.883
	SV	0.854	0.901	0.697	0.883
	HA	0.788	0.877	0.705	0.800
	FC	0.770	0.850	0.588	0.813
	HM	0.754	0.858	0.669	0.785
	USE	0.871	0.911	0.720	0.878

Source: created by the authors.

Convergent validity depicts the degree to which a construct explains the variance of its indicators. It is assessed using the average variance extracted (*AVE*), which is calculated as the mean of the squared indicator loadings. An *AVE* of at least 0.50 indicates sufficient communality, [31]. Table 5 demonstrates that all constructs exceed the specified threshold, thereby confirming strong convergent validity.

Discriminant validity evaluates whether constructs are empirically distinct. According to the Fornell–Larcker criterion, discriminant validity is established when the square root of each construct's average variance extracted (AVE) exceeds its correlations with other constructs, [31]. The results, included in Table 6, provide clear evidence of discriminant validity.

Table 6. *FL* ratios in the students and academic staff subgroups

Sub-group	Con-struct	PE	EF	SN	SV	HA	FC	HM	USE
Students	PE	0.881							
	EF	0.478	0.894						
	SN	0.364	0.215	0.788					
	SV	0.627	0.381	0.389	0.843				
	HA	0.666	0.445	0.444	0.662	0.838			
	FC	0.412	0.507	0.363	0.480	0.482	0.741		
	HM	0.725	0.542	0.336	0.648	0.747	0.479	0.820	
	USE	0.538	0.380	0.431	0.542	0.654	0.377	0.536	0.786
Academics	PE	0.902							
	EF	0.430	0.950						
	SN	0.257	0.348	0.851					
	SV	0.660	0.461	0.509	0.835				
	HA	0.633	0.395	0.383	0.687	0.839			
	FC	0.331	0.616	0.304	0.499	0.501	0.767		
	HM	0.683	0.413	0.420	0.710	0.806	0.580	0.818	
	USE	0.430	0.196	0.259	0.558	0.727	0.319	0.588	0.849

Source: created by the authors.

B. Structural model evaluation

Evaluation of the structural model involved testing for multicollinearity, examining R^2, the adjusted R^2, and path coefficients. Variance inflation factor (*vif*) values of 5 or higher indicate potential collinearity, [31]. In this study, *vif* values ranged from 1.322 to 3.781 (see Table 7), well below the threshold, confirming the absence of multicollinearity among the constructs.

The *R-squared* (R^2) quantifies the variance explained by each independent variable for the endogenous variable, serving as a gauge of the model's explanatory power. More significant predictor variables result in higher R^2 values.

Table 7. *vif* ratios in the students and academic staff subgroups

Sub-group	PE	EF	SN	SV	HA	FC	HM
Students	2.462	1.634	1.322	2.178	2.852	1.639	3.213
Academics	2.471	1.914	1.454	2.908	3.089	2.228	3.781

Source: created by the authors.

The observed R^2 value for GenAI use was 0.479, and the adjusted R^2 was 0.471 in the student subgroup, and 0.558 and 0.532 in the academic staff subgroup, respectively, indicating moderate predictive power. Among the independent variables, habit shows the highest influence (0.420 in the student subgroup and 0.712 in the academic staff subgroup) on the use of GenAI. In the student subgroup, the second most influential factor was social norms (0.152), followed by the study value (0.133), see Table 8.

Table 8. Bootstrapped paths statistics for the students' subgroup

Paths	Orig. Est.	Boot. Mean	Boot. SD	*t*-stat	2.5% CI	97.5% CI	H tests
PE → USE	0.109	0.108	0.053	2.057	0.004	0.214	H1 Yes
EF → USE	0.083	0.086	0.041	2.024	0.002	0.164	H2 Yes
SN → USE	0.152	0.153	0.047	3.220	0.058	0.242	H3 Yes
SV → USE	0.133	0.133	0.059	2.264	0.016	0.246	H4 Yes
HA → USE	0.420	0.419	0.063	6.633	0.292	0.541	H5 Yes
FC → USE	-0.016	-0.014	0.050	-0.327	-0.113	0.082	H6 No
HM → USE	-0.031	-0.031	0.071	-0.429	-0.170	0.110	H8 No

Source: created by the authors.

PE, EF, SN, SV, and HA estimates are statistically significant at a 95% confidence level in the students' subgroup, thus supporting hypotheses H1, H2, H3, H4, and H5. Regarding FC and HM, the survey results do not provide sufficient evidence to support hypotheses H6 and H7 in the student subgroup at a 95% confidence level.

In the academic staff subgroup, the second most influential factor was study value (0.229), as shown in Table 9. SV and HA estimates are statistically significant at a 95% confidence level in the academic staff subgroup, thus supporting hypotheses H4 and H5. Regarding PE, EF, SN, FC, and HM, the survey results do not provide sufficient evidence to support hypotheses H1, H2, H3, H6, and H7 in the academic staff subgroup at a 95% confidence level.

Table 9. Bootstrapped paths statistics for the academic staff subgroup

Paths	Orig. Est.	Boot. Mean	Boot. SD	*t*-stat	2.5% CI	97.5% CI	H tests
PE → USE	-0.107	-0.102	0.125	-0.859	-0.358	0.140	H1 No
EF → USE	-0.102	-0.096	0.085	-1.201	-0.262	0.074	H2 No
SN → USE	-0.059	-0.047	0.085	-0.698	-0.209	0.126	H3 No
SV → USE	0.229	0.234	0.114	2.001	0.003	0.454	H4 Yes
HA → USE	0.712	0.700	0.121	5.885	0.447	0.922	H5 Yes
FC → USE	-0.043	-0.029	0.113	-0.377	-0.250	0.197	H6 No
HM → USE	0.013	0.007	0.146	0.087	-0.287	0.287	H7 No

Source: created by the authors.

To assess the practical significance of the independent variables' impact on GenAI use, this study uses an effect size indicator, the *f*-squared ratio. As shown in Table 10, in the student subgroup, habit (HA) is the strongest predictor, with an effect size approaching a medium, suggesting that established usage patterns significantly drive adoption among students. Social norms (SN) and study value (SV) exert a slight but noticeable influence. Other predictors, e.g., PE, EF, FC, and HM, show negligible effects.

Table 10. Effect size statistics for the students and academic staff subgroups

Con-struct	Stu-dents	Effect size	Aca-demics	Effect size
PE	0.008	Negligible	0.011	Negligible
EF	0.008	Negligible	0.010	Negligible
SN	0.030	Small	0.006	Negligible
SV	0.017	Negligible/Small	0.043	Small
HA	0.117	Medium	0.356	Large
FC	0.000	Negligible	0.002	Negligible
HM	0.001	Negligible	0.000	Negligible

Source: created by the authors.

In the academic staff subgroup, habit (HA) stands out with a large effect size (0.356), highlighting that entrenched behavioural routines are the dominant factor influencing GenAI adoption among academic staff. Study value (SV) reveals a small effect, suggesting that academics adopt GenAI to some extent when they perceive it as valuable for teaching or research. PE, EF, FC, and HM remain negligible.

C. Predictive power of created models

To evaluate the predictive validity of the estimated model, this study uses the 'predict_pls' function in the R package. The predictive validity was assessed by comparing root mean square error (*RMSE*) and mean absolute error (*MAE*) values for SEM-PLS and linear models (LM) across four GenAI use behaviors. For both students and academic staff, SEM-PLS consistently demonstrated superior out-of-sample (OOS) predictive accuracy, particularly for homework (US3) and self-study (US4) scenarios (see Table 11). Among students, predictive validity was on average 3.57 times higher for SEM-PLS compared to LM, as measured by *RMSE*, and 3.61 times higher, as measured by *MAE*. The strongest predictive validity was observed in the student subgroup for classroom use (US2) and homework use (US3). Among academic staff, predictive validity was on average 4.49 times higher for SEM-PLS compared to LM, as measured by *RMSE*, and 2.19 times higher, as measured by *MAE*. The strongest predictive validity in the academic staff subgroup was highest for self-study (US4) and homework (US3). Thesis writing (US1) and classroom (US2) use showed moderate predictive accuracy across both groups.

DOI: 10.46300/9109.2026.20.8 Volume 20, 2026

Table 11. PLS predict statistics for the students' subgroup

Sub-group	Varia-ble	Mea-sure	PLS in-sample	PLS OOS	LM in-sample	LM OOS
Students	US1	*RMSE*	0.971	0.997	0.901	0.997
		MAE	0.765	0.783	0.729	0.795
	US2	*RMSE*	0.771	0.798	0.751	0.834
		MAE	0.594	0.611	0.577	0.627
	US3	*RMSE*	0.680	0.700	0.662	0.726
		MAE	0.529	0.541	0.513	0.557
	US4	*RMSE*	0.758	0.778	0.698	0.772
		MAE	0.563	0.576	0.528	0.576
Acade-mics	US1	*RMSE*	0.909	0.990	0.792	1.056
		MAE	0.696	0.764	0.615	0.823
	US2	*RMSE*	0.806	0.869	0.682	0.984
		MAE	0.601	0.657	0.511	0.737
	US3	*RMSE*	0.660	0.725	0.566	0.814
		MAE	0.499	0.545	0.434	0.600
	US4	*RMSE*	0.617	0.672	0.528	0.728
		MAE	0.465	0.508	0.408	0.548

Source: created by the authors.

V. Discussion

This study's central finding, that habit is the dominant driver of continuous GenAI use for both social science students and academic staff, converges with and extends recent UTAUT2-based investigations that foreground habit as a key continuance mechanism in educational contexts, [19], [32]. The enormous effect size of habit among academic staff warrants a more nuanced interpretation. While habit is conceptualized in UTAUT2 as automaticity in technology use, in the case of faculty, it may also reflect broader aspects of routine professional practice, such as established workflows, disciplinary conventions, or identity-related commitments to teaching and research. Prior critiques of the habit construct in UTAUT2 research have noted that it may capture both automaticity and routinization depending on context, [33], [34].

Faculty routines are deeply embedded in long-standing scholarly and pedagogical workflows; when GenAI demonstrably reduces friction or adds clear productivity gains to these routines, it can rapidly become entrenched. This aligns with other studies, [20], which account for continuous usage among academic staff, and with qualitative reports suggesting that staff adoption often follows concrete demonstrations of research or teaching effectiveness rather than abstract assurances of usefulness. It also aligns with recent longitudinal and mixed-methods work, cautioning that habit formation can be double-edged: it fosters efficiency; however, it may also normalize uncritical acceptance of outputs unless paired with verification practices and ethics training, [35].

It is also important to acknowledge that the COVID-19 pandemic sped up the use of digital tools in higher education through remote learning and online collaboration. This prior exposure to technology likely shaped both students' and staff members' readiness to integrate GenAI, reinforcing the role of habit formation in sustaining its use, [36], [37].

Subgroup divergence, where students exhibit several small but significant predictors (performance expectancy, effort expectancy, social norms, and study value), while academics rely mainly on habit and perceived study value, mirrors patterns reported by other recent higher-education studies on the use of GenAI. Previous studies, [19], [21], also report stronger roles for social influence and perceived usefulness among students and early-career learners. At the same time, faculty adoption often depends on concrete perceived value and workflow fit rather than novelty or peer pressure. Other authors, [20], [38], likewise suggest that for staff, longitudinal satisfaction and actual workflow integration (value) trump ease or hedonic appeal as drivers of ongoing GenAI use, which aligns with our finding that study value and habit explain most of the variance for academics.

A key finding of this study is the non-significance of facilitating conditions and hedonic motivation when habit and study value are considered. While meta-analytic evidence often identifies these constructs as meaningful predictors of technology adoption in higher education, [39], other studies have shown that their effects can be masked when stronger predictors such as habit and perceived value dominate, [40]. In our context, infrastructure support and enjoyment appear secondary to routinized use and perceived academic benefits. This underscores the primacy of behavioral repetition and utility over contextual or affective factors, suggesting that institutions may achieve greater impact by embedding repeated, value-driven GenAI tasks rather than investing disproportionately in technical facilitation or gamified features.

The weak or non-significant role of facilitating conditions (FC) and hedonic motivation (HM) in our models is consistent with a growing body of evidence that infrastructure alone does not guarantee sustained, responsible AI use. Previous studies, [41], [42], emphasise that technical provisioning must be paired with pedagogical integration and assessment redesign for meaningful uptake; otherwise, tools remain available but underutilised or misused. Our results suggest that FC matters only insofar as it enables repeated, low-friction practice that can transform trial into habit; this nuance aligns with practical integration frameworks in the literature.

Our results, which indicate that social norms and study value are meaningful predictors among students, build on and nuance prior findings about peer influence and pedagogical beliefs. Studies, [43], [44], document strong social influence effects in student intentions to use ChatGPT and similar GenAI tools; we extend these findings by showing that social norms operate not only at the intention stage but also contribute to observed use when combined with habit formation and perceived study benefits. Other authors, [45], emphasize the role of pedagogical beliefs in shaping acceptance. Our findings suggest that when instructors design tasks that highlight the value of study, student perceptions of legitimacy and peer norms become more influential, helping to integrate GenAI into routine study practices.

The pattern of non-significant hedonic motivation is notable, given earlier work that flagged enjoyment as a driver of adoption of interactive technologies. Several GenAI studies identify HM as relevant in early exploratory use, particularly among discretionary or recreational users, [46]. Our data, which target study-related use behaviors (homework, self-study, thesis work, and classroom tasks), indicate that enjoyment alone does not sustain academic use; instead, pedagogical utility and routinization are key factors. This finding aligns with education-centric reviews that stress the primacy of task alignment and assessment design over novelty or amusement in shaping durable educational technology adoption.

Ethical and epistemic concerns appear implicitly linked to our findings through the mediating role of habit. If routine use is not accompanied by explicit verification and integrity practices, it may increase throughput but reduce critical scrutiny. Several recent pieces issue warnings about bias amplification, trust erosion, and the risk of "automation bias" when AI outputs are accepted without critical examination. Researchers, [10], [15], advocate for institutionally grounded ethical frameworks that prioritize the governance of routinized AI use. Our data suggest that embedding ethics and verification into the very tasks that create habits is essential to prevent the normalization of problematic practices.

The predictive validity analysis further strengthens the explanatory power of the extended UTAUT2 model. The finding that the model achieved “3.57 times higher” predictive validity compared with linear benchmarks can be interpreted in practical terms as a substantial improvement in forecasting actual GenAI use behaviors. Out-of-sample prediction techniques such as PLSpredict are designed precisely to assess this kind of predictive accuracy, [47], [48]. In practical terms, the inclusion of habit and study value allows the model to predict with more than triple the accuracy whether students and staff will engage in GenAI-supported homework or self-study. This means the model is not only statistically robust but also practically valuable for anticipating real-world adoption patterns. This outcome complements a review, [48], which notes the importance of predictive, rather than purely explanatory, models in nascent GenAI adoption research.

Finally, the balance of our findings with broader calls for pedagogy suggests that, first, AI integration is straightforward, [49]. Authors advocating for scaffolded, values-driven integration of GenAI into curricula, [13], [41], [42], recommend shifting from bans or ad-hoc use to structured tasks, verification training, and assessment reform - exactly the levers our results point to if the goal is to channel habit formation into responsible practice.

Overall, the study synthesises and extends contemporary empirical and conceptual work: it confirms habit’s centrality identified in UTAUT2 extensions while clarifying role-specific differences (students vs academics), showing how social norms and perceived study value interplay with habit for students, and exposing that FC and HM are insufficient levers by themselves to produce sustained, integrity-aware GenAI use. These alignments and contrasts contribute nuance to a rapidly evolving literature that increasingly emphasizes curricular design, verification literacy, and governance as the practical complements needed to turn GenAI use into constructive academic practice.

VI. CONCLUSION

This study demonstrates that habit is the single most potent predictor of continuous GenAI use among social science students and academic staff. Among students, habit functions in conjunction with performance expectancy, effort expectancy, social norms, and perceived study value. In contrast, for academics, habit and perceived study value are the primary determinants. These findings indicate that promoting sustained and responsible adoption of GenAI requires moving beyond isolated training sessions or technical solutions. Instead, curricular and institutional interventions should be developed to encourage recurring, integrity-focused practices. Building legitimate, repeated classroom and research uses, combined with explicit norms and value-aligned workflows, will be the most effective path to mainstreaming GenAI in ways that enhance learning and research while preserving academic standards.

While this study is situated in the Baltic region, the central finding that habit is the dominant driver of GenAI adoption has broader relevance. In higher education systems worldwide, repeated and structured exposure to GenAI tasks is likely to foster routine use, regardless of local institutional cultures. Nevertheless, contextual factors such as resource availability, policy frameworks, and pedagogical traditions may condition the strength of these effects. By highlighting habit formation as a transferable mechanism, our findings contribute to international debates on responsible and sustainable integration of GenAI in higher education, [50].

A. Practical implications and recommendations

The statistical results directly inform the practical recommendations of this study. The dominant role of habit suggests that curricular design should prioritize repeated, scaffolded GenAI tasks that encourage responsible use and verification practices. The study's findings highlight the importance of interventions that emphasize demonstrable academic benefits for both students and staff, such as improved workflow efficiency and enhanced learning outcomes. By directly linking these recommendations to empirical results, the study offers actionable guidance for educators and administrators seeking to promote responsible, sustained adoption of GenAI.

Faculty engagement is also essential. Institutions should prioritize workflow-aligned interventions for staff, such as time-saving templates, reproducible pipelines for data cleaning and analysis, and collaboratively developed teaching materials. These interventions demonstrate tangible study and research value, facilitating the transition from trial use to routine practice. Early adopter faculty members can accelerate the diffusion of responsible habits by providing practical examples and participating in peer-to-peer mentoring.

Policy and infrastructure should be structured to support habitual use rather than merely providing access. Facilitating conditions that reduce barriers to routine use, including single sign-on systems, approved tool lists, and integration with learning management systems, should be complemented by pedagogical routines that encourage habitual engagement. Institutional policies should emphasize transparency, define acceptable practices, and establish assessment standards that reward responsible GenAI-enabled workflows.

Reform in training and assessment is also required. Institutions should replace binary bans or unrestricted use with scaffolded skill-building approaches that foster prompt literacy, verification strategies, and reproducible reporting. Assessment criteria should be updated to evaluate students' critical engagement with AI outputs, requiring explanations of how outputs are used, evidence of verification, and demonstration of original contributions.

B. Limitations and future research

Several limitations of this study should be acknowledged. First, reliance on cross-sectional survey data limits the ability to establish causal relationships between constructs. Although habit was identified as the strongest predictor of GenAI use, it is unclear whether repeated use fosters habit or if pre-existing routines drive adoption. Reverse causality and reciprocal effects are recognized challenges in technology adoption research; thus, longitudinal or experimental designs are needed to clarify these dynamics and establish causal pathways. Second, the use of a convenience sample, while broadly representative of Baltic social science institutions, may restrict generalizability to other disciplines or geographic contexts with different cultural norms and institutional infrastructures. Third, the measurement of habit within the UTAUT2 framework may reflect broader aspects of professional routinization among academic staff, raising concerns about construct validity. Previous critiques have suggested that habit may overlap with constructs such as workflow or professional identity, especially in academic settings.

Future research should utilize mixed-method approaches, such as qualitative interviews and diary studies, to refine the operationalization of habit and differentiate it from related constructs. Additionally, although predictive validity analysis indicated strong out-of-sample performance, further research is required to test the model in diverse educational settings and with alternative behavioral indicators of GenAI use. Out-of-sample prediction techniques, including PLSpredict, are intended to assess predictive accuracy. Replication across varied contexts will increase confidence in the model's practical utility. Addressing these limitations will improve theoretical precision and provide stronger evidence to guide the development of policies and curricula for responsible AI integration in higher education.

REFERENCES

[1]. C. A. Bail, “Can Generative AI improve social science?” *Proc. Natl. Acad. Sci.*, vol. 121, no. 21, p. e2314021121, 2024, doi: 10.1073/pnas.2314021121.

[2]. L. Hughes, T. Malik, S. Dettmer, A. S. Al-Busaidi, and Y. K. Dwivedi, “Reimagining Higher Education: Navigating the Challenges of Generative AI Adoption,” *Inf. Syst. Front.*, pp.1-13, 2025, doi: 10.1007/s10796-025-10582-6.

[3]. Q. Wu, J. Tian, and Z. Liu, “Exploring the usage behavior of generative artificial intelligence: a case study of ChatGPT with insights into the moderating effects of habit and personal innovativeness,” *Curr. Psychol.*, vol. 44, pp. 8190–8203, 2025, doi: 10.1007/s12144-024-07193-w.

[4]. A. Yusuf, N. Pervin, and M. R. González, “Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives,” *Int. J. Educ. Technol. High. Educ.*, vol. 21, no. 21, pp.1-29, 2024, doi: 10.1186/s41239-024-00453-6.

[5]. C. Stöhr, A. W. Ou, and H. Malmström, “Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study,” *Comput. Educ. Artif. Intell.*, vol. 7, p. 100259, 2024, doi: 10.1016/j.caeai.2024.100259.

[6]. K. H. Arar, H. Özen, G. Polat, and S. Turan, “Artificial intelligence, generative artificial intelligence and research integrity: a hybrid systemic review,” *Smart Learn. Environ.*, vol. 12, no. 44, pp.1-29, 2025, doi: 10.1186/s40561-025-00403-3.

[7]. R. J. Eddine, E. Gide, and A. Al-Sabbagh, “Generative AI in higher education: A cross-sector analysis of ChatGPT's impact on STEM, social sciences, and healthcare,” *STEM Educ.*, vol. 5, no. 5, pp. 757–801, 2025, doi: 10.3934/steme.2025035.

[8]. B. G. Acosta-Enriquez, E. V. R., Farroñan, L. I. V., Zapata, F. S. M., Garcia, H. C., Rabanal-León, J. E. M., Angaspilco, and J. C. S. Bocanegra, “Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory,” *Heliyon*, vol. 10, no. 19, p. e38315, 2024, doi: 10.1016/j.heliyon.2024.e38315.

[9]. J. Kim, M. Klopfer, J. R. Grohs, H. Eldardiry, J. Weichert, L. A. Cox, and D. Pike, “Examining Faculty and Student Perceptions of Generative AI in University Courses,” *Innov. High. Educ.*, vol. 50, pp. 1281–1313, 2025, doi: 10.1007/s10755-024-09774-w

[10]. C. Ambrosio, C. C. De Falco, and D. Trezza, “Artificial social research? AI’s capabilities and risks in predicting values and attitudes,” *Sicurezza e scienze sociali*, vol. 13, no. 2, pp. 167–182, 2025, doi: 10.5281/zenodo.17297559.

[11]. E. Đerić, D. Frank, and D. Vuković, “Exploring the Ethical Implications of Using Generative AI Tools in Higher Education,” *Informatics*, vol. 12, no. 2, pp. 1-22, 2025, doi: 10.3390/informatics12020036.

[12]. T. Yu, Y. Tian, Y. Chen, Y. Huang, Y. Pan, and W. Jang, “How Do Ethical Factors Affect User Trust and Adoption Intentions of AI-Generated Content Tools? Evidence from a Risk-Trust Perspective,” *Systems*, vol. 13, no. 6, p. 1-32, 2025, doi: 10.3390/systems13060461.

[13]. L. Reiter, M. Jörling, C. Fuchs, and R. Böhm, “Student (Mis)Use of Generative AI Tools for

University-Related Tasks," *Int. J. Hum.-Comput. Interact.*, vol, 41, no. 19, pp. 12390-12403, 2025, doi: 10.1080/10447318.2025.2462083.

[14]. M. A. Nadim and R. D. Fuccio, "Unveiling the Potential: Artificial Intelligence's Negative Impact on Teaching and Research Considering Ethics in Higher Education," *Eur. J. Educ.*, vol. 60, no. 1, pp.1-6, 2025, doi: 10.1111/ejed.12929.

[15]. J. Jeon, L. Kim, and J. Park, "The Ethics of Generative AI in Social Science Research: A Qualitative Approach for Institutionally Grounded AI Research Ethics," *Technol. Soc.*, vol. 81, pp. 1-11, 2025, doi: 10.1016/j.techsoc.2025.102836.

[16]. A. Hazzan-Bishara, O. Kol, and S. Levy, "The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants," *Educ. Inf. Technol.*, vol. 30, pp. 15043–15069, 2025, doi: 10.1007/s10639-025-13393-z.

[17]. A. Shata and K. Hartley, "Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative AI," *Int. J. Educ. Technol. High. Educ*, vol. 22, no. 14, pp.1-22, 2025, doi: 10.1186/s41239-025-00511-7.

[18]. V. Venkatesh, M. Morris, G. Davis, and F. Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Q.*, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.

[19]. S. Grassini, M. L. Aasen, and A. Møgelvang, "Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model," *Appl. Artif. Intell.*, vol. 38, no. 1, pp. 1-24, 2024, doi: 10.1080/08839514.2024.2371168.

[20]. M. I. Baig and E. Yadegaridehkordi, "Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 5, pp.1-23, 2025, doi: 10.1186/s41239-025-00506-4.

[21]. M. Faraon, K. Rönkkö, M. Milrad, and E. Tsui, "International perspectives on artificial intelligence in higher education: An explorative study of students' intention to use ChatGPT across the Nordic countries and the USA," *Educ. Inf. Technol.*, vol. 30, pp. 17835–17880, 2025, doi: 10.1007/s10639-025-13492-x.

[22]. F. G. K. Yılmaz, R. Yılmaz, and M. Ceylan, "Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study," *Int. J. Hum. - Comput. Inter.*, vol. 40, no. 24, pp. 8703–8715, 2023, doi: 10.1080/10447318.2023.2288730.

[23]. P. M. Cortez, A. K. S. Ong, J. F. T. Diaz, J. D. German, and S. J. Jagdeep, "Analyzing Preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool," *Heliyon*, vol. 10, no. 3, pp. 1-18, 2024, doi: 10.1016/j.heliyon.2024.e25896.

[24]. L. Zhao, M. H. Rahman, W. Yeoh, S. Wang, and K. B. Ooi, "Examining factors influencing university students' adoption of generative artificial intelligence: a cross-country study," *Stud. High. Educ.*, vol. 50, no.12, pp. 2646–2668, 2024, doi: 10.1080/03075079.2024.2427786.

[25]. K. Lavidas, I. Voulgari, S. Papadakis, S. Athanassopoulos, A. Anastasiou, A. Filippidi, V. Komis, and N. Karacapilidis, "Determinants of Humanities and Social Sciences Students' Intentions to Use Artificial Intelligence Applications for Academic Purposes," *Information*, vol. 15, no. 6, pp. 1-15, 2024, doi: 10.3390/info15060314.

[26]. M. Al-Okaily, W. Mater, N. Matar, and F. S. Shiyyab, "Understanding of ChatGPT adoption among business school students," *Comput. Educ. Artif. Intell.*, vol. 9, pp. 1-15, 2025, doi: 10.1016/j.caeai.2025.100441.

[27]. A. Shuhaiber, M. A. Kuhail, and S. Salman, "ChatGPT in higher education: A Student's perspective," *Comput. Hum. Behav. Rep.*, vol. 17, pp. 1-12, 2025, doi: 10.1016/j.chbr.2024.100565.

[28]. V. Venkatesh, J. Thong, and X. Xu, "Unified theory of acceptance and use of technology: A synthesis and the road ahead," *J. Assoc. Inf. Syst.*, vol. 17, no. 5, pp. 328–376, 2016, doi: 10.17705/1jais.00428.

[29]. A. Strzelecki, "Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology," *Innov. High. Educ.*, vol. 49, no. 2, pp. 223-245, 2024, doi: 10.1007/s10755-023-09686-1.

[30]. C. Kim, "Understanding Factors Influencing Generative AI Use Intention: A Bayesian Network-Based Probabilistic Structural Equation Model Approach," *Electronics*, vol. 14, no. 3, pp. 1-18, 2025, doi: 10.3390/electronics14030530.

[31]. J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to Use and How to Report the Results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[32]. X. Tang, Z. Yuan, and S. Qu, "Factors Influencing University Students' Behavioural Intention to Use Generative Artificial Intelligence for Educational Purposes Based on a Revised UTAUT2 Model," *J. Comput. Assist. Learn.*, vol. 41, no. 1, pp. 1-15, 2025, doi: 10.1111/jcal.13105.

[33]. A. Lampo, "The Role of Habit in UTAUT-2 Research: A Study of BEV Users," in *Proc. 2023 9th Int. Conf. Ind. Bus. Eng.*, Beijing, China, ICIBE 2023, pp. 449–453, doi: 10.1145/3629378.3629384.

[34]. S. Rashid, "Habit Predicting Higher Education EFL Students' Intention and Use of AI: A Nexus of UTAUT-2 Model and Metacognition Theory," *Educ. Sci.*, vol. 15, no. 6, pp. 1-20, 2025, doi: 10.3390/educsci15060756.

[35]. P. Holzmann, P. Gregori, and E. J. Schwarz, "Students' little helper: Investigating continuous-use determinants of generative AI and ethical judgment," *Educ. Inf. Technol.*, vol. 30, pp. 24991-

25011, 2025, doi: 10.1007/s10639-025-13708-0.

[36]. A. Aristovnik, K. Karampelas, L. Umek, and D. Ravšelj, "Impact of the COVID-19 pandemic on online learning in higher education: a bibliometric analysis," *Front. Educ.*, vol. 8, pp. 1-13, 2023. doi: 10.3389/feduc.2023.1225834.

[37]. X. Zhou, C. J. M. Smith, and H. Al-Samarraie, "Digital technology adaptation and initiatives: a systematic review of teaching and learning during COVID-19," *J. Comput. High. Educ.*, vol. 36, pp. 813–834, 2024, doi: 10.1007/s12528-023-09376-z.

[38]. J. N. Montes and J. Elizondo-García, "Faculty acceptance and use of generative artificial intelligence in their practice," *Front. Educ.*, vol. 10, pp. 1-11, 2025, doi: 10.3389/feduc.2025.1427450.

[39]. H. Zheng, F. Han, Y. Huang, Y. Wu, and X. Wu, "Factors influencing behavioral intention to use e-learning in higher education during the COVID-19 pandemic: A meta-analytic review based on the UTAUT2 model," *Educ. Inf. Technol.*, vol. 30, pp. 12015–12053, 2025, doi: 10.1007/s10639-024-13299-2.

[40]. B. Bervell, J. A. Kumar, V. Arkorful, and E. M. Agyapong, "Remodelling the role of facilitating conditions for Google Classroom acceptance: A revision of UTAUT2," *Australas. J. Educ. Technol.*, vol. 8, no. 1, pp. 115–135, 2024, doi: 10.14742/ajet.7178.

[41]. J. Cordero, J. Torres-Zambrano, and A. Cordero-Castillo, "Integration of Generative Artificial Intelligence in Higher Education: Best Practices," *Educ. Sci.*, vol. 15, no. 1, pp. 1-16, 2024, doi: 10.3390/educsci15010032.

[42]. G. Kurtz, M. Amzalag, N. Shaked, Y. Zaguri, D. Kohen-Vacs, E. Gal, G. Zailer, and E. Barak-Medina, "Strategies for Integrating Generative AI into Higher Education: Navigating Challenges and Leveraging Opportunities," *Educ. Sci.*, vol. 14, no. 5, p. 1-11, 2024, doi: 10.3390/educsci14050503.

[43]. K. Kanont, P. Pingmuang, T. Simasathien, S. Wisnuwong, B. Wiwatsiripong, K. Poonpirome, N. Songkram, and J. Khlaisang, "Generative-AI, a Learning Assistant? Factors Influencing Higher-Ed Students' Technology Acceptance," *Electron. J. E-Learn.*, vol. 22, no. 6, pp. 18-33, 2024, doi: 10.34190/ejel.22.6.3196.

[44]. A. E. Korchak, G. Al Murshidi, A. Getman, N. Raouf, M. Arshe, N. Al Meheiri, G. Shulgina, and J. Costley, "The role of social influence in generative artificial intelligence ChatGPT adoption intentions among undergraduate and graduate students," *Innov. Educ. Teach. Int.*, vol. 62, no. 5, pp. 1559–1573, 2025, doi: 10.1080/14703297.2025.2496942.

[45]. J. Cabero-Almenara, A. Palacios-Rodríguez, M. I. Loaiza-Aguirre, and P. S. Andrade-Abarca, "The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2," *Front. Artif. Intell.*, vol. 7, pp. 1-11, 2024, doi: 10.3389/frai.2024.1497705.

[46]. X. Bai and L. F. Yang, "Research on the influencing factors of generative artificial intelligence usage intent in post-secondary education: an empirical analysis based on the AIDUA extended model," *Front. Psychol.*, vol. 16, pp. 1-18, 2025, doi: 10.3389/fpsyg.2025.1644209.

[47]. G. Shmueli, M. Sarstedt, J. F. Hair, J. H. Cheah, H. Ting, S. Vaithilingam, and C. M. Ringle, "Predictive model assessment in PLS-SEM: guidelines for using PLSpredict," *Eur. J. Mark.*, vol. 53, no. 11, pp. 2322–2347, 2019, doi: 10.1108/EJM-02-2019-0189.

[48]. C. McGrath, A. Farazouli, and T. C. Pargman, "Generative AI chatbots in higher education: a review of an emerging research area," *High. Educ.*, vol. 89, pp. 1533–1549, 2024, doi: 10.1007/s10734-024-01288-w.

[49]. N. J. Francis, S. Jones, and D. P. Smith, "Generative AI in Higher Education: Balancing Innovation and Integrity," *Br. J. Biomed. Sci.*, vol. 81, no. 14048, pp. 1-9, 2025, doi: 10.3389/bjbs.2024.14048.

[50]. J. Dalle, H. Aydin, and C. X. Wang, "Cultural dimensions of technology acceptance and adaptation in learning environments," *J. Form. Des. Learn.*, vol. 8, pp. 99–112, 2024, doi: 10.1007/s41686-024-00095-x.

Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Aivars Spilbergs carried out the conceptualization, investigation, writing of the original draft, review, and editing.

Sources of funding for research presented in a scientific article

This research is supported by Project No.5.2.1.1.i.0/2/24/I/CFLA/007 "Internal and external consolidation of the University of Latvia" (RRF project), Project No. LU-BAPA-2024/1–0052, UL and BA SBF consolidation grant project.

Conflicts of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this article, the authors utilized Grammarly to correct grammatical errors and refine the academic writing style. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.