

Generative AI Adoption Among Business School Students: Drivers Of Use And Policy Implications

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Abstract— The rapid integration of generative Artificial Intelligence (GenAI) tools into higher education presents both transformative potential and pedagogical challenges. This study researches the key factors influencing the adoption of GenAI among business school students, utilizing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as its theoretical framework. Drawing on survey data from 441 students across the Baltic Sea region, the research employed partial least squares structural equation modeling (PLS-SEM) to estimate the relationships between performance expectancy, effort expectancy, social influence, study value, habit, facilitating conditions, and hedonic motivation in predicting the use of GenAI.

The findings reveal that habit, social influence, and study value significantly impact students' adoption of GenAI tools. At the same time, performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation do not show statistically significant effects. These results suggest a behavioral-intention gap: positive perceptions of GenAI do not consistently translate into actual use. The study highlights the importance of fostering habitual engagement and peer-driven norms to encourage meaningful integration of GenAI in academic settings. By offering empirical insights into student behavior, this study contributes to the discourse on digital transformation in higher education. It provides actionable recommendations for educators and policymakers to support the ethical, practical, and student-centered adoption of GenAI, aligning with the conference's mission to advance innovation and quality in higher education studies.

Keywords— artificial intelligence, business school students, drivers of use, policy implications, UTAUT2

I. INTRODUCTION

The advent of generative Artificial Intelligence (GenAI) has significantly impacted various sectors, and its proliferation within academic institutions, particularly business schools, presents both transformative opportunities and considerable challenges [8]. This burgeoning technology necessitates an examination of the factors influencing its adoption among business school students, who are poised to leverage these tools in their future professional landscapes. The rapid integration of sophisticated GenAI tools, such as ChatGPT, into daily academic and professional life necessitates a deeper grasp of the factors that drive or hinder their acceptance among this critical demographic. Despite the growing ubiquity of GenAI in educational settings, a notable disparity exists between student and instructor adoption rates, with students often leading in experimental usage [7], [16], [21]. This phenomenon stresses the importance of examining the behavioral intentions and motivations underlying student adoption, particularly given the potential for these technologies to transform learning processes and professional competencies. The widespread use underscores the need for empirical research to identify the specific psychological, technological, and environmental factors

that facilitate or hinder the integration of generative AI into higher education, particularly in business curricula. Understanding these factors is important for educators and policymakers to develop effective strategies that promote beneficial integration while mitigating associated risks, ensuring the ethical and academically sound use of these powerful tools [20], [22]. Consequently, a comprehensive analysis of students' perceptions, behavioral intentions, and the contextual factors influencing the adoption of GenAI is imperative to foster its practical and ethical deployment in business education. This paper aims to explore these multifaceted factors by drawing on established theoretical frameworks to provide a comprehensive analysis of the drivers of GenAI adoption among business school students. Specifically, this study incorporates the Unified Theory of Acceptance and Use of Technology (UTAUT) factors, which have been identified as crucial to the adoption of advanced technologies in higher education. The UTAUT2 model allows for a more nuanced understanding of how students' perceptions of AI's usefulness, ease of use, social norms, availability of resources and support, and other determinants influence their willingness to integrate these tools into their academic practices [5]. Furthermore, by examining these variables, we can differentiate student adoption patterns from those of faculty, highlighting unique challenges and opportunities specific to the student demographic in business education. This holistic technique aims to provide a comprehensive analysis of students' experiences with GenAI in higher education, thereby informing educators and institutions about the opportunities and barriers associated with integrating these technologies into educational practices. Moreover, this investigation aims to provide practical implications for educational institutions, guiding them in judiciously balancing the transformative benefits of GenAI tools with essential safeguards to uphold academic integrity. By understanding students' perceptions and experiences, universities can better harness AI's potential for high-quality teaching and learning while also guiding its safe and effective adoption in higher education. This comprehensive understanding will empower the development of pedagogical strategies that effectively integrate AI tools, while addressing ethical considerations and fostering responsible innovation among future business leaders. Thus, this study addresses a critical gap by investigating the interplay among performance expectancy, effort expectancy, and perceived risk, which fundamentally shape students' attitudes toward AI in academic contexts.

II. LITERATURE REVIEW

Previous research, frequently employing frameworks such as the Technology Acceptance Model (TAM) [2], [13] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [18], has identified constructs including perceived usefulness, perceived ease of use, performance expectancy (PE), effort expectancy (EF), and social influence (SI) as significant predictors of technology adoption. These foundational models are often extended to incorporate additional factors such as perceived trust, ethical considerations, and perceived risks, which are especially relevant for advanced AI technologies in educational contexts. Performance expectancy (PE) refers to a student's belief that using generative AI (GenAI) will improve academic performance and efficiency, thereby directly influencing behavioral intention to adopt these tools [18]. Effort expectancy (EF) refers to the perceived ease of using GenAI, which can substantially impact students' willingness to integrate these tools into their academic routines [18]. Facilitating conditions (FC), defined as the organizational and technical support available, are also crucial in enabling the effective utilization of GenAI in academic settings [17]. Social influence (SI), reflecting the impact of peers and instructors on students' adoption decisions, remains a critical determinant [9]. These frameworks collectively facilitate a comprehensive examination of the multidimensional factors influencing the adoption of generative AI among business

school students, considering both individual perceptions and external environmental factors. The UTAUT and its extension, UTAUT2, offer robust frameworks for understanding technology adoption and acceptance, particularly in educational environments [4], [7].

The UTAUT model, developed by Venkatesh et al., synthesizes eight prior models and has been empirically validated across diverse user groups and contexts, demonstrating strong explanatory power for technology acceptance [12]. Its extension, UTAUT2, incorporates additional constructs such as hedonic motivation, price value, and habit (HA), providing a more comprehensive perspective for examining technology adoption in consumer and educational settings [10], [14], [15], [19]. Hedonic motivation (HM), which captures the enjoyment derived from using AI, and learning value, defined as the perceived educational benefits, are important antecedents of students' intention to use GenAI [11]. In this context, price value is replaced by study value (SV), which represents the perceived enhancements that GenAI tools offer to the educational experiences of business school students. Habit (HA) describes the extent to which individuals perceive the use of GenAI tools as automatic within their routine activities [18].

Within higher education, UTAUT2 has been effectively applied to examine students' intentions to use various technological tools, including e-learning platforms, mobile applications, and immersive virtual reality systems [4], [17]. This expanded model is particularly valuable for understanding voluntary technology adoption, where factors beyond organizational mandates, such as enjoyment from AI tools and perceived personal learning value, become prominent [3]. UTAUT2 thus offers a robust framework for investigating the diverse determinants influencing business school students' voluntary adoption of GenAI, encompassing both utilitarian and experiential dimensions of technology use [5]. Habit and performance expectancy have emerged as especially influential predictors of GenAI adoption, alongside hedonic motivation, social influence, and perceived study value, all of which positively shape behavioral intention [17]. Performance expectancy is consistently identified as the most impactful construct on behavioral intention, followed by habit, in the context of students' engagement with generative AI technologies [5]. However, some studies suggest that effort expectancy and social influence may not always have a direct, significant effect on behavioral intention, highlighting nuances that depend on the user group and technological context [17]. Despite these variations, research consistently demonstrates that performance expectancy, effort expectancy, and social influence have a significant and positive impact on students' behavioral intention to use AI in educational settings, as shown in studies employing the core UTAUT framework. This evidence supports the hypotheses that PE, EF, and SI positively influence students' intention to use AI in education [12].

Additionally, the perceived usefulness of AI tools for academic tasks and the ease of their integration into existing learning workflows are critical determinants of adoption, often mediating the effects of other influencing factors [10]. Furthermore, perceived quality and the level of institutional support from higher education institutions have been shown to positively influence students' intentions to adopt generative AI [11]. Therefore, a comprehensive analysis of business school students' adoption of generative AI should address these multifaceted determinants to inform the optimization of pedagogical strategies and technological integration in higher education.

The literature review supports the following hypotheses:

H1: Performance expectancy of GenAI contributes to its adoption among business school students.

H2: Effort expectancy associated with GenAI tools positively impacts their uptake by business school students.

H3: Social influence and prevailing academic norms encourage the adoption of GenAI by business school students.

H4: Study value of GenAI enhances its adoption among business school students.

H5: Habit has a positive effect on the likelihood of GenAI adoption among business school students.

H6: Availability of supportive infrastructure facilitates the adoption of GenAI by business school students.

H7: Enjoyment and intrinsic motivation derived from using GenAI positively influence its adoption among business school students.

III. DATA AND METHODS

This section outlines the research design, data collection procedures, and analytical techniques used to examine factors influencing GenAI adoption among business school students. To evaluate the proposed hypotheses, a survey questionnaire was developed based on a comprehensive literature review to identify key determinants of GenAI adoption. Independent variables were measured using a 10-point Likert scale from "strongly disagree" to "strongly agree," while GenAI usage (USE) was assessed on a 5-point scale from "never" to "daily."

The survey was pilot tested in Autumn 2024 with a small group from the target population. This stage assessed the clarity of items and estimated completion time. Minor revisions were made in response to feedback. Demographic data, such as age, level of study, and region, were also collected.

The finalized survey was distributed through academic networks associated with business schools in the Baltic Sea region. Data collection ran from January to March 2025 and yielded 452 responses. After removing 11 incomplete submissions, the final dataset included 441 valid responses.

The sample included 295 undergraduate students, 104 master's students, and 42 doctoral candidates. About 33.7% of respondents were under 23 years old. Another 25.8% were in the 23-27 age range. Fewer older students participated than expected, considering the usual age distribution in higher education across the Baltic Sea region. These demographic details provide context for interpreting geographic and academic representation in the following section.

Building on the demographic overview, the geographic distribution of participants shows that most (56.9%) resided in Latvia, followed by Denmark (10.9%), Lithuania (10.5%), and Estonia (6.5%). Overall, this convenience sample closely reflected the demographic and academic composition of social science students and faculty in the region's higher education sector.

Turning to the analysis of perceptions presented in Table I, most constructs (PE, EF, FC, SV) have means above 7.5, reflecting strong positive perceptions. In contrast, Social Influence (SI2–SI4) and Usage (US1–US4) exhibit lower means, suggesting weaker peer influence and moderate actual usage. Standard deviations range from 1.3 to 2.3, indicating moderate variability; notably, the highest values for HA2, FC4, and HA1 highlight diverse habits and support conditions.

Further detailing these findings, additional analysis of response distributions reveals that most items are negatively skewed, indicating that responses are concentrated at the higher end of the scale. Specifically, items such as PE3 (8.89), HA3 (6.56), and SV4 (5.97) display leptokurtic distributions, characterized by pronounced peaks and heavy tails, suggesting strong consensus with some outliers.

Moreover, the close agreement between the trimmed mean and the sample mean suggests minimal impact from outliers, while the median absolute deviation (MAD), consistently around 1.48, reinforces a moderate spread around the median.

Key Observations:

- The highest rated item was HA3 (Mean = 8.92), indicating that students strongly agree that using GenAI has become habitual.
- In contrast, the lowest rated item was US1 (Mean = 3.03), indicating that actual usage remains relatively low despite high expectancy and motivation.
- Among distribution patterns, PE3 was the most skewed (Skew = -2.59), reflecting strong agreement with performance benefits.
- Regarding distribution shape, HA2 (Kurtosis = -0.13) exhibited the flattest distribution, with responses more evenly spread.

TABLE I DESCRIPTIVE STATISTICS ON SURVEY RESPONSES

Item	Mean	SD	Median	Trimmed	MAD	Min	Max	Skew	Kurtosis	SE
PE1	8.28	1.37	8.00	8.41	1.48	1	10	-1.64	5.58	0.07
PE2	8.04	1.52	8.00	8.21	1.48	1	10	-1.74	5.09	0.07
PE3	8.70	1.55	9.00	8.98	1.48	1	10	-2.59	8.89	0.07
PE4	8.55	1.62	9.00	8.83	1.48	1	10	-2.03	5.53	0.08
EF1	8.01	1.33	8.00	8.10	1.48	1	10	-1.11	3.09	0.06
EF2	8.10	1.41	8.00	8.22	1.48	1	10	-1.49	4.64	0.07
EF3	8.66	1.34	9.00	8.87	1.48	1	10	-1.77	4.95	0.06
SI1	7.59	1.72	8.00	7.78	1.48	1	10	-1.62	3.80	0.08
SI2	6.49	1.97	7.00	6.77	1.48	1	10	-1.21	1.09	0.09
SI3	6.51	1.91	7.00	6.70	1.48	1	10	-1.05	1.59	0.09
SI4	6.37	1.85	6.00	6.43	0.94	1	10	-0.45	0.88	0.09
FC1	7.92	1.59	8.00	8.10	1.48	1	10	-1.53	4.17	0.08
FC2	7.63	1.48	8.00	7.74	1.48	1	10	-1.42	4.40	0.07
FC3	7.73	1.52	8.00	7.88	1.48	1	10	-1.40	3.38	0.07
FC4	7.86	2.02	8.00	8.19	1.48	1	10	-1.61	2.58	0.10
SV1	7.71	1.70	8.00	7.95	1.48	1	10	-1.59	2.94	0.08
SV2	7.58	1.74	8.00	7.88	1.48	1	10	-1.80	3.81	0.08
SV3	8.17	1.92	9.00	8.51	1.48	1	10	-1.80	3.47	0.09
SV4	8.65	1.52	9.00	8.90	1.48	1	10	-2.00	5.97	0.07
HM1	8.05	1.65	8.00	8.29	1.48	1	10	-1.81	4.63	0.08
HM2	7.10	1.71	7.00	7.21	1.48	1	10	-0.95	1.92	0.08
HM3	8.45	1.72	9.00	8.77	1.48	1	10	-1.88	4.12	0.08
HA1	7.49	2.01	8.00	7.78	1.48	1	10	-1.52	2.30	0.10
HA2	6.06	2.32	7.00	6.26	1.48	1	10	-0.77	-0.13	0.11
HA3	8.92	1.61	9.00	9.26	1.48	1	10	-2.31	6.56	0.08
US1	3.03	1.13	3.00	3.12	1.48	1	5	-0.67	-0.62	0.05
US2	3.12	0.92	3.00	3.22	1.48	1	5	-0.61	0.23	0.04
US3	3.51	0.82	4.00	3.55	1.48	1	5	-0.66	1.02	0.04
US4	4.03	1.01	4.00	4.17	1.48	1	5	-1.12	1.12	0.05

To further explore these findings, the relationships among variables in the measurement model were evaluated using a two-stage partial least squares-structural equation modelling (PLS-SEM) approach, given the specific characteristics of the collected data and the established efficacy in comparable studies [1], [5], [17].

IV. RESULTS

The quality of the constructs PE, EF, SI, SV, HA, HM, FC, and USE is assessed through evaluation of the measurement model. The assessment of the measurement model includes analysing indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), and validity (convergent and discriminant).

Factor loading indicates how strongly each item is associated with its underlying construct. All items in this study had factor loadings higher than the recommended value of 0.708 [6], with only one exception, and all were statistically significant at $p < 0.001$. Factor loadings are presented in Table II.

TABLE III Measurement model factor loadings confidence intervals

Items	Orig.e st.	Bootstr. mean	SD	t-stat	2.5% CI	97.5% CI
PE1→PE	0.836	0.833	0.031	26.89 1	0.761	0.884
PE2→PE	0.917	0.916	0.014	64.33 9	0.885	0.940
PE3→PE	0.898	0.896	0.021	42.57 4	0.849	0.932
PE4→PE	0.872	0.871	0.024	36.83 7	0.818	0.912
EF1→EF	0.880	0.876	0.023	37.51 0	0.823	0.914
EF2→EF	0.889	0.887	0.024	37.26 0	0.833	0.926
EF3→EF	0.913	0.914	0.015	59.09 8	0.880	0.940
SI1→SI	0.717	0.715	0.047	15.41 8	0.614	0.794
SI2→SI	0.839	0.839	0.025	34.22 2	0.786	0.881
SI3→SI	0.838	0.836	0.026	31.76 5	0.776	0.878
SI4→SI	0.751	0.748	0.040	18.59 2	0.656	0.815
SV1→SV	0.804	0.803	0.031	25.85 8	0.736	0.857
SV2→SV	0.837	0.836	0.026	32.63 3	0.782	0.881
SV3→SV	0.897	0.897	0.014	63.73 5	0.867	0.922
SV4→SV	0.830	0.830	0.024	34.44 5	0.778	0.872
HA1→H A	0.875	0.874	0.020	44.00 2	0.830	0.907
HA2→H A	0.803	0.804	0.022	36.58 3	0.757	0.843

HA3→H A	0.834	0.833	0.024	34.32 8	0.781	0.874
FC1→FC	0.648	0.644	0.073	8.924	0.474	0.759
FC2→FC	0.709	0.709	0.057	12.44 8	0.577	0.797
FC3→FC	0.815	0.814	0.035	23.35 1	0.738	0.874
FC4→FC	0.782	0.780	0.048	16.13 2	0.668	0.860
HM1→H M	0.883	0.882	0.019	46.86 7	0.840	0.914
HM2→H M	0.763	0.761	0.047	16.22 6	0.655	0.837
HM3→H M	0.810	0.808	0.038	21.57 7	0.722	0.869
US1→US E	0.710	0.711	0.031	22.68 4	0.639	0.761
US2→US E	0.803	0.803	0.023	35.65 1	0.754	0.842
US3→US E	0.808	0.807	0.026	30.94 2	0.752	0.854
US4→US E	0.824	0.823	0.019	42.71 2	0.780	0.857

As shown in Table II, the majority of items exhibit strong loadings (≥ 0.80), have high t-statistics and tight confidence intervals, indicating robust significance and stability. Strong loadings across most constructs support the convergent validity of the measurement model.

Reliability is typically assessed using two key metrics: Cronbach's alpha and composite reliability (ρ_{oc}). Cronbach's alpha provides a conservative estimate, representing the lower bound of internal consistency, while composite reliability (ρ_{oc}) offers an upper bound. Positioned between these two, the reliability coefficient (ρ_{oA}) serves as a balanced indicator of a construct's internal consistency.

Convergent validity reflects the degree to which a construct successfully accounts for the variance observed in its indicators. This is commonly evaluated using the average variance extracted (AVE), which quantifies the proportion of variance captured by the construct relative to measurement error. An AVE value of 0.50 or higher is considered acceptable, indicating that the construct explains at least half of the variance in its indicators. As shown in Table III, all AVE values exceed this threshold, confirming strong convergent validity for the reflectively measured constructs.

TABLE IIII Reliability ratios

Construct	alpha	ρ_{oc}	AVE	ρ_{oA}
PE	0.904	0.933	0.777	0.911
EF	0.878	0.923	0.799	0.922
SI	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

Discriminant validity refers to the extent to which constructs that are conceptually distinct exhibit low correlations with one another. In other words, when constructs are theoretically different, their respective measurement indicators should not overlap significantly. According to the Fornell and Larcker (FL) criterion, discriminant validity is confirmed when the square root of each construct's average variance extracted (AVE), represented on the diagonal of the correlation matrix, exceeds its correlations with all other constructs. As shown in Table IV, the diagonal FL values for each construct are consistently higher than their corresponding inter-construct correlations, thereby providing robust evidence of discriminant validity.

TABLE IVV FL ratios

Construct	PE	EF	SI	SV	HA	FC	HM	USE
PE	0.881							
EF	0.478	0.894						
SI	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

The structural model's evaluation includes assessing the absence of multicollinearity, R-squared, adjusted R-squared, and path coefficients. Variance inflation factor (vif) test values five or above denote the possibility of collinearity [6]. The absence of multicollinearity was established for the studied model, as the vif values ranged from 1.322 to 3.213 (see Table V), which is lower than the cut-off value.

TABLE V vif ratios

Ratio	PE	EF	SI	SV	HA	FC	HM
vif	2.462	1.634	1.322	2.178	2.852	1.639	3.213

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. The observed R-squared value for GenAI use was 0.479, and the adjusted R-squared value was 0.471, providing

moderate predictive power. Among the independent variables, habit shows the highest influence (0.420) on the use of GenAI, followed by social impact (0.152) and study value (0.133), as shown in Table VI.

TABLE VI Bootstrapped paths statistics

Paths	Orig.Es t.	Boot.Me an	Boot.S D	t-stat	2.5% CI	97.5% CI	H tests
PE → USE	0.109	0.108	0.066	1.651	-0.023	0.239	H1 No
EF → USE	0.083	0.086	0.049	1.697	-0.008	0.185	H2 No
SI → 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	H7 No

Path coefficients represent the structural model's estimates of the relationships among factors and dependent variables in the model under investigation. To evaluate the effect of the independent variables on GenAI adoption, we use bootstrapped (nboot = 10000) path statistics. The original estimates of path coefficients, bootstrapping results, and hypothesis test results are summarized in Table 6. It is observed that the path coefficients for PE, EF, SI, SV, and HA have a positive effect on the use of GenAI, which aligns with expectations. Estimates for SI → USE, SV → USE, and HA → USE are statistically significant at a confidence level >95%, thus supporting hypotheses H3, H4, and H5, respectively. Regarding estimates for PER → USE, EF → USE, FC → USE, and HM → USE, the survey results do not provide enough evidence to support hypotheses H1, H2, H6, and H7 at a confidence level > 95%.

V. DISCUSSIONS

This study offers a comprehensive analysis of factors influencing GenAI adoption among business school students. It uses the UTAUT2 framework [17]. The results show a complex interaction among behavioral, technological, and contextual variables. These findings advance the literature on AI integration in higher education [5], [10], [23].

The findings show that, of seven hypothesized relationships, three constructs, habit, social influence, and study value, were significant predictors of GenAI usage. Habit had the strongest effect ($\beta = 0.420$, $t = 6.633$), highlighting the role of routine engagement with AI tools. This aligns with research showing habitual behavior often overrides rational evaluation, especially when these tools are part of academic routines [10].

In addition to habit, social influence ($\beta = 0.152$, $t = 3.220$) significantly affected GenAI usage. Peer norms and academic culture influenced student behavior. This result corroborates Korchak et al. (2025), who highlighted the role of institutional and peer encouragement in promoting AI adoption. Likewise, study value ($\beta = 0.133$, $t = 2.264$) reflects the perceived educational benefit of GenAI. This supports that students are motivated by concrete academic gains, such as improved efficiency and learning outcomes [11].

In contrast, while performance expectancy and effort expectancy are usually strong predictors in technology acceptance models [18], they did not significantly influence GenAI usage in this study. Both constructs showed high mean scores and strong factor loadings; however, their path coefficients (PE → USE: $\beta = 0.109$; EF → USE: $\beta = 0.083$) were not statistically significant. As a result, this suggests that students perceive GenAI as useful and easy to use, yet do not consistently use it. Potential reasons for this discrepancy include ethical concerns, unclear academic guidelines, or perceived risks [7].

Similarly, facilitating conditions and hedonic motivation were not significant predictors of GenAI usage. The minimal effect of facilitating conditions ($\beta = -0.016$) may indicate that students rely more on personal initiative than on institutional support for GenAI adoption, as Strzelecki [17] also found. Furthermore, the non-significant influence of hedonic motivation ($\beta = -0.031$) suggests that enjoyment alone does not drive adoption, which is especially relevant in academic settings that prioritize credibility and utility [5].

Lastly, the measurement model showed strong reliability and validity across constructs. All factor loadings were above 0.708 [6], with high t-statistics and narrow confidence intervals. Composite reliability and average variance extracted (AVE) confirmed internal consistency and convergent validity. The Fornell-Larcker criterion supported discriminant validity. Together, these metrics affirm the instrument's robustness and the theoretical soundness of the UTAUT2-based framework [12].

VI. Conclusions

This study provides empirical evidence on the determinants of GenAI adoption among business school students, offering a timely contribution to the discourse on digital transformation in higher education. By applying the UTAUT2 framework and analyzing survey data from 441 students across the Baltic Sea region, the research identifies habit, social influence, and study value as the most influential factors driving the use of GenAI. These findings underscore the importance of behavioral and contextual factors, particularly routine engagement and peer norms, in shaping technology adoption in academic settings.

Performance expectancy and effort expectancy received high ratings. However, their lack of statistical significance in predicting actual usage shows a behavioral-intention gap. This gap suggests that, while students recognize GenAI as useful and easy to use, they may hesitate to incorporate it into their routines due to ethical concerns, institutional ambiguity, or lack of structured guidance. Similarly, the non-significant effects of facilitating conditions and hedonic motivation indicate that infrastructure and enjoyment alone are insufficient to promote meaningful adoption.

Given these results, the implications for higher education are clear. To support responsible GenAI integration, educators should do more than emphasize utility and ease of use. Priorities should be fostering habitual engagement through curriculum design, reinforcing positive social norms, and highlighting GenAI's academic value. Institutions must also promote ethical literacy, establish clear usage guidelines, and support students in managing the complexities of AI-enhanced learning.

Future research should track GenAI adoption over time, compare cross-cultural student behaviors, and assess ethical awareness and the impacts of institutional policies. Qualitative work can reveal motivations and barriers that quantitative models miss. As GenAI evolves, ongoing research will help ensure it improves, rather than undermines, the quality, equity, and integrity of higher education.

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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.

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