

Ethics Awareness As A Moderating Factor In Generative AI Adoption Among Business School Students

Aivars Spilbergs^{1*}, Biruta Sloka², Gunta Innuse-Breidaka³, Laima Čable⁴, Ginta Tora⁵, Kristīne Liepiņa⁶

¹ Department of Economics and Finance, BA School of Business and Finance, University of Latvia, Riga, Latvia ORCID ID_0000-0003-2537-8053, aivars.spilbergs@lu.lv

² Faculty of Economics and Social Sciences, University of Latvia, Riga, Latvia ORCID ID_0000-0003-2129-053X, biruta.sloka@lu.lv

³ Department of Economics and Finance, BA School of Business and Finance, University of Latvia, Riga, Latvia ORCID ID_0009-0007-4771-6873, gunta.innuse-breidaka@lu.lv

⁴ Department of Economics and Finance, BA School of Business and Finance, University of Latvia, Riga, Latvia ORCID ID_0009-0003-5027-7366, laima.cable@lu.lv

⁵ Faculty of Economics and Social Sciences, University of Latvia, Riga, Latvia ORCID ID_0000-0003-0427-72102, ginta.tora@lu.lv

⁶ Faculty of Economics and Social Sciences, University of Latvia, Riga, Latvia ORCID ID_0009-0002-6505-08962 kristine.liepina@lu.lv

*Corresponding Author: aivars.spilbergs@lu.lv

Abstract- The rapid proliferation of generative artificial intelligence (GAI) tools has transformed higher education, raising urgent questions about their ethical use and acceptance. This study examines the moderating effect of ethics awareness on the adoption of GAI among business school students in the Baltic Sea region. Designing on the Unified Theory of Acceptance and Use of Technology (UTAUT2) and its extensions, the research integrates constructs of performance expectancy, effort expectancy, social influence, study value, habit, and ethics awareness. A survey of 441 students across Baltic Sea region business schools was analyzed using partial least squares structural equation modeling (PLS-SEM).

Results indicate that performance expectancy, social influence, study value, habit, and ethics awareness significantly predict GAI use, whereas effort expectancy has a limited influence. Habit emerged as the strongest driver, underscoring the importance of routinized engagement. Moderation analyses reveal that ethics awareness amplifies the effects of social influence and habit but attenuates the impacts of performance expectancy, effort expectancy, and study value. These findings suggest that ethical sensitivity does not discourage adoption but channels it toward socially validated and responsible practices.

The study contributes to theory by extending UTAUT2 with ethics awareness as a critical construct and offers practical implications for business schools. Embedding ethical literacy alongside technical proficiency is crucial to ensure the responsible integration of AI. Limitations include regional sampling; future research is encouraged to explore cross-cultural contexts and longitudinal adoption patterns.

Keywords— Adoption Determinants, Artificial Intelligence, Business Schools, Ethics Awareness, Moderating Factor

I. INTRODUCTION

The rapid proliferation of generative artificial intelligence (GAI) tools has ushered in a transformative era across various sectors, necessitating a critical examination of its implications, particularly within higher education. The unprecedented adoption rates of these AI tools, despite their controversial nature, underscore the urgency for comprehensive research into their ethical dimensions and user acceptance within academic environments. Specifically, within business education, the integration of AI tools presents a dual challenge: fostering technical proficiency while simultaneously cultivating a robust ethical awareness to navigate the complex landscape of AI-integrated professional roles [1].

This research aims to explore the moderating role of ethics awareness in the adoption of GAI among business school students, recognizing that while AI offers opportunities, it also poses significant ethical challenges. This investigation is particularly pertinent given the rising concerns about the ethical use of GAI in academic assignments and the broader professional sphere [2]. Indeed, while AI tools like large language models are increasingly incorporated into daily academic tasks, including those of business school students, concerns persist regarding issues such as copyright, authorship, transparency, and academic integrity [3]. These concerns underscore the need for a nuanced insight into how students perceive and interact with AI tools, particularly in relation to ethical considerations that may influence their adoption behaviors. This study handles a notable gap in the literature by focusing on the specific challenges within the academic environment related to ethical implications and user trust in AI, particularly among distinct academic segments, such as business school students. It aims to elucidate how ethical awareness among business school students may mitigate or exacerbate the adoption of GAI tools. This approach is critical, as ethical concerns regarding AI tools can vary significantly across academic disciplines. For instance, business students face distinct considerations compared to those in STEM or humanities fields. The nuanced ethical landscape of AI adoption necessitates a continuous dialogue on best practices, especially considering the evolving capabilities of AI and its potential to challenge foundational principles in the digital age.

Furthermore, cultural and geographical contexts significantly influence the perception and adoption of AI technologies, with studies indicating varying ethical considerations and utilization trends across different regions [4]. For example, varying institutional responses to AI integration in academia, ranging from outright prohibition to active encouragement, reflect these diverse ethical perspectives and regulatory environments. This understanding is crucial for developing pedagogical strategies that promote both technological literacy and ethical reasoning in future business leaders. Moreover, examining the influence of ethical perceptions and academic integrity concerns on AI adoption is crucial for developing robust frameworks of technology acceptance.

II. LITERATURE REVIEW

A literature review is essential to synthesize existing research on GAI adoption, ethical considerations, and the unique dynamics within business education contexts. This review aims to create a theoretical foundation by exploring established models of technology acceptance and integrating insights from ethical frameworks relevant to AI, thereby addressing the identified gap in understanding how ethical considerations interact with traditional technology adoption factors.

The Unified Theory of Acceptance and Use of Technology model (UTAUT), along with its extended version, UTAUT2, provides a robust theoretical foundation for analyzing technology adoption in various contexts, including higher education. These models integrate several influential theories of technology acceptance, e.g., the Theory of Reasoned Action, the Technology Acceptance Model, and Social Cognitive Theory, providing a comprehensive framework for assessing factors that influence user adoption [5]. However, given the unique characteristics of GAI, such as its autonomous content generation capabilities and potential ethical implications, an enhanced version has been developed to address these nuances in educational settings specifically [6]. This revised framework incorporates additional constructs, such as perceived ethical risk, AI literacy, and institutional support, which are crucial for a nuanced understanding of GAI adoption among students. This expanded theoretical lens enables a more nuanced examination of how ethical considerations, alongside traditional technology acceptance drivers, influence students' engagement with AI tools in academic settings. This refined

framework is particularly pertinent for investigating the adoption of GAI among business school students, where ethical considerations and the responsible application of technology are paramount.

Performance expectancy (PER) refers to the extent to which an individual considers that using a system will help them attain rewards in job performance, a concept consistently found to be a significant predictor of behavioral intention across various technology adoption studies [5]. In the context of GAI, this translates to students' perceptions of how tools like ChatGPT can enhance their academic output, streamline tasks, or improve learning outcomes [6]. Specifically, students are more inclined to utilize GAI if they perceive it as enhancing the quality of their work or increasing their efficiency in completing assignments.

Effort expectancy (EFF) refers to the degree of ease associated with using a particular technology, which, for GAI, encompasses the perceived simplicity of its interface and the minimal cognitive load required for effective operation [5]. This factor is critical for the initial acceptance of new technologies, as a high perceived effort can deter even motivated users. Thus, if students find GAI tools intuitive and straightforward to operate, they are more likely to integrate them into their learning processes. Conversely, a complex or unintuitive GAI platform could significantly impede its adoption, regardless of its potential performance benefits.

Social influence (SOC) refers to the degree to which an individual captures that important others believe they should use the technology [5]. In the context of GAI adoption among students, this translates to how peer recommendations, instructor endorsements, or institutional mandates regarding AI tool usage shape an individual's intention to engage with these technologies. This collective perception may significantly sway students' decisions to adopt or reject GAI tools, especially within collaborative learning environments. Moreover, the perceived expectations from significant individuals, such as faculty and peers, about the utility of generative AI in academic work are crucial in shaping students' adoption intentions.

Study values (STV) refer to the personal significance students attribute to the ethical implications of GAI use, reflecting their intrinsic beliefs about responsible technology engagement. This construct, unlike other adoption factors, delves into the moral compass of students, exploring how their ethical frameworks shape their receptiveness to AI tools, particularly when considering issues such as academic integrity and data privacy. This dimension captures how students weigh the benefits of GAI against potential ethical pitfalls, thereby influencing their willingness to adopt these technologies in their academic pursuits [7].

Habit (HA) refers to the extent to which individuals automatically use a technology due to learning and repeated usage [5]. In the context of GAI, habit formation implies that as students repeatedly use these tools for academic tasks, their engagement becomes less deliberate and more automatic, influencing long-term adoption. This automaticity, rooted in consistent positive experiences and perceived utility, reinforces the integration of GAI into students' academic routines, making it an indispensable part of their educational toolkit.

Ethics awareness (ETC) refers to an individual's capacity to recognize, analyze, and reflect upon the moral implications of their actions and the technologies they employ, particularly within the nascent and evolving landscape of GAI. This awareness extends beyond mere knowledge of ethical guidelines to encompass a deeper understanding of potential biases, privacy concerns, and academic integrity issues inherent in AI applications [8] (Holzmann et al., 2025). In academic settings, ethical awareness surrounding GAI is particularly salient, as students frequently encounter ethical

dilemmas related to plagiarism, accountability, and the originality of work. This heightened ethical sensitivity significantly influences students' decisions to adopt or refrain from using GAI, acting as a crucial moderating factor [8].

The literature review supports the following hypotheses:

H1: Business school students' adoption of GAI is positively influenced by their PER.

H2: The EFF of GAI tools fosters greater uptake among business school students.

H3: SOC plays a significant role in encouraging the adoption of GAI among business school students.

H4: The perceived STV of GAI strengthens its adoption among business school students.

H5: Established HAB has a positive impact on the likelihood of GAI adoption among business school students.

H6: ETC enhances the adoption of GAI among business school students.

H7: ETC moderates the effect of performance expectancy on GAI adoption among business school students.

H8: ETC moderates the influence of effort expectancy on GAI adoption among business school students.

H9: ETC moderates the impact of social influence on GAI adoption among business school students.

H10: ETC moderates the relationship between study value and GAI adoption among business school students.

H11: ETC moderates the effect of habit on GAI adoption among business school students.

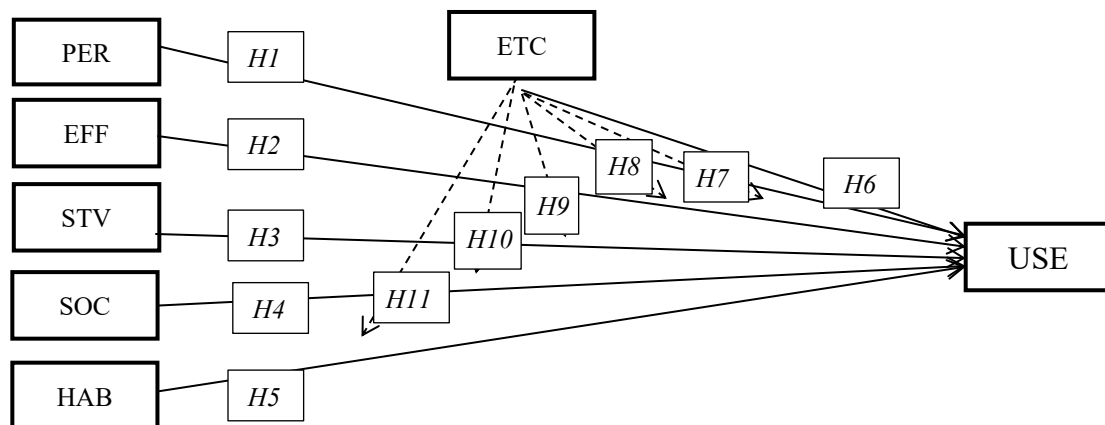


Fig. 1. Conceptual model for testing business school students' adoption of GenAI in the study process

III. DATA AND METHODS

To test the suggested hypotheses, a survey instrument was designed following a comprehensive review of scholarly literature to identify the key factors influencing GAI adoption. Independent variables were measured using a 10-point Likert scale, ranging from "disagree" to "strongly agree", while GAI usage (USE) was assessed on a 5-point scale from "never" to "daily". Before full deployment, the questionnaire was pilot-tested in Autumn 2024 with a small subset of the target population to ensure clarity of items and estimate completion time, leading to minor adjustments based on participant feedback. Demographic information, including age, level of study, and region, was also collected. The finalized survey was distributed through academic networks affiliated with business schools across the Baltic Sea region, and data collection took place between January and March 2025. A total of 452 responses were received, of which 11

incomplete submissions were excluded, resulting in a final dataset of 441 valid cases for analysis.

In terms of age distribution, the largest group was students under 23 years old (43.3%), followed by those aged 23–27 (32.7%). Smaller proportions were represented in the 28–32 (11.8%), 33–37 (5.2%), 38–42 (2.9%), and 43–47 (2.7%) age brackets, while only a handful of respondents were aged 48–52 (0.2%) or 53–57 (1.1%). Regarding gender, the bulk of respondents were female (61.2%), with males accounting for 38.8%. Study level was predominantly at the bachelor's level (51.8%), followed by master's (18.3%) and doctoral studies (9.5%), while 20.4% did not specify their level of study. Geographically, most respondents were based in Latvia (59.2%), with additional representation from Lithuania (12.7%), Denmark (7.9%), Estonia (7.5%), and other regions (12.7%).

This convenience sample largely reflected the demographic composition of business school students in Baltic higher education institutions with respect to age, gender, and study level. Table 1 presents a summary of the survey responses at the construct level.

TABLE I Construct-level summary of the survey responses

Construct	Mean range	Median range	SD range	Notes on Distribution
PER	8.04 - 8.71	8–9	1.39–1.62	High agreement, negatively skewed, leptokurtic
EFF	8.01 – 8.66	8–9	1.33–1.41	Strong positive ratings, low variability
SOC	6.37 – 7.59	6–8	1.72–1.97	Moderate ratings, more balanced distributions
STV	7.58 – 8.65	8–9	1.52–1.92	Positive perceptions, clustered at the upper end
HAB	6.06 – 8.93	7–9	1.61–2.32	Mixed results
ETC	7.39 – 8.56	8–9	1.37–2.08	Consistently positive, strong consensus
USE	3.03 – 4.03	3–4	0.82–1.13	Moderate adoption, regular but not daily use

The descriptive statistics indicate generally high agreement across most constructs (see Table I). PER items showed strong endorsement, with means ranging from 8.04 to 8.71 and medians of 8–9. The distributions were negatively skewed (skew values between –1.65 and –2.60) and highly leptokurtic, suggesting clustering at the upper end of the scale. EFF items also scored highly (means between 8.01 and 8.66), with low variability (SD $\approx$ 1.3–1.6) and similarly negative skewness, reflecting favorable perceptions of ease of use. SOC items displayed more moderate ratings, with means ranging from 6.37 to 7.59. Variability was higher (SD $\approx$ 1.7–1.9), and skewness values were less pronounced, indicating more balanced distributions compared to expectancy constructs. STV items were rated positively (means 7.58–8.65), with medians of 8–9 and strong negative skewness, again reflecting favorable perceptions. HAB items showed mixed results, suggesting weaker habitual use among some respondents. ETC items were consistently positive, with means ranging from 7.39 to 8.56 and medians of 8 to 9. Distributions were negatively skewed and leptokurtic, indicating strong consensus on ethical considerations. USE items, measured on a 5-point scale, reflected moderate levels of adoption. Means ranged from 3.03 to 4.03. Skewness values were moderately negative,

suggesting that while daily use was less common, regular engagement was evident among respondents.

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 [6], [7], [9], [10], [11], [12].

IV. Results

Construct validity was evaluated through measurement model analysis, which included indicator loadings, internal consistency (as measured by Cronbach's alpha and composite reliability), and validity (convergent and discriminant). All items exceeded the recommended loading threshold of 0.708 [13], see Table II, and were statistically significant ($p < 0.001$).

TABLE II CONSTRUCT-LEVEL SUMMARY OF THE MEASUREMENT MODEL LOADINGS

Construct	Loadings range	Notes
PER	0.836–0.917	All items are very strong, highly significant
EFF	0.880–0.913	Consistently strong loadings
SOC	0.717–0.839	Acceptable
STV	0.804–0.897	Strong loadings
HAB	0.804–0.875	Solid loadings
ETC	0.702–0.810	Moderate to strong
USE	0.705–0.825	Good reliability across items

The reliability and validity of the constructs were confirmed through multiple indicators. PER and EFF demonstrated excellent internal consistency, with Cronbach's alpha values of 0.904 and 0.878, composite reliability (ρ_{c}) above 0.92, and average variance extracted (AVE) exceeding 0.77, indicating strong reliability and convergent validity. STV also showed high reliability ($\alpha = 0.864$, $\rho_{\text{c}} = 0.907$, AVE = 0.710), while HAB achieved acceptable levels ($\alpha = 0.787$, $\rho_{\text{c}} = 0.876$, AVE = 0.702). SOC and USE constructs demonstrated satisfactory reliability, with Cronbach's alpha values of 0.798 and 0.793, ρ_{c} values of 0.867 and 0.866, and AVE values of 0.621 and 0.618, respectively, all above the recommended threshold of 0.50. ETC demonstrated moderate reliability ($\alpha = 0.839$, $\rho_{\text{c}} = 0.884$, AVE = 0.605), confirming acceptable measurement quality despite a slightly lower variance extraction compared to expectancy-based constructs. Overall, all constructs met or exceeded the recommended thresholds ($\alpha > 0.70$, $\rho_{\text{c}} > 0.70$, AVE > 0.50), supporting the robustness of the measurement model.

Discriminant validity was evaluated using the Fornell–Larcker ratio, with the square root of each construct's AVE exceeding its correlations with other constructs, thereby confirming validity, see Table III below.

TABLE III FORNELL–LARCKER RATIOS

Construct	PE	EF	SI	SV	HA	ET	USE
PER	0.881						
EFF	0.478	0.894					
SOC	0.364	0.215	0.788				
STV	0.627	0.381	0.389	0.843			
HAB	0.666	0.445	0.444	0.662	0.838		
ETC	0.177	0.275	0.159	0.324	0.207	0.778	
USE	0.538	0.380	0.431	0.542	0.653	0.227	0.786

Multicollinearity was evaluated by variance inflation factors (vif), all of which ranged from 1.332 to 3.017, well below the threshold of 3.3, confirming its absence.

The structural model demonstrated moderate explanatory power ($R^2 = 0.489$; adjusted $R^2 = 0.476$), with habit exerting the most potent effect on GAI use ($\beta = 0.416$), followed by social influence ($\beta = 0.140$) and performance expectancy ($\beta = 0.113$).

TABLE IIIV BOOTSTRAPPED PATHS STATISTICS

Paths	Orig.E st.	Boot.Me an	Boot.S D	t-stat	2.5% CI	97.5% CI	H tests
PER → USE	0.113	0.112	0.057	1.996	0.001	0.223	H1 Yes
EFF → USE	0.063	0.067	0.045	1.400	-0.021	0.155	H2 No
SOC → USE	0.140	0.142	0.048	2.930	0.046	0.234	H3 Yes
STV → USE	0.104	0.103	0.052	1.985	0.000	0.206	H4 Yes
HAB → USE	0.416	0.415	0.063	6.629	0.290	0.538	H5 Yes
ETC → USE	0.048	0.051	0.025	1.897	0.014	0.101	H6 Yes
PER*ETC → USE	-0.051	-0.051	0.068	-0.753	-0.186	0.080	H7 No
EFF*ETC → USE	-0.031	-0.032	0.037	-0.845	-0.107	0.036	H8 No
SOC*ETC → USE	0.017	0.019	0.009	1.961	0.002	0.036	H9 Yes
STV*ETC → USE	-0.018	-0.017	0.056	-0.315	-0.129	0.092	H10 No

HAB*ETC → USE	0.094	0.095	0.048	1.97 5	0.017	0.188	H11 Yes
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Bootstrapped path analysis ($n = 10,000$) revealed that PER, SOC, STV, HAB, ETC significantly predicted GAI use, with hypotheses H1, H3, H4, H5, H6, H9, and H11 supported at a confidence level greater than 95%. In contrast, EFF, the interaction terms PER*ETC, EFF*ETC, and STV*ETC were not significant, providing insufficient evidence for H2, H7, H8, and H10 at a confidence level greater than 95%.

As shown in Table IV, the interaction term PER*ETC negatively influences US (-0.051), while the direct effect of PER → USE is positive (0.113). Taken together, these results indicate that the relationship between PER and USE is 0.113 at the average level of ETC. At higher levels of ETC (i.e., one standard deviation above the mean), the effect of PER on USE decreases by the size of the interaction term, yielding an adjusted effect of 0.062. Conversely, at lower levels of ETC (i.e., one standard deviation below the mean), the effect increases by the same amount, resulting in an adjusted effect of 0.164.

The relationship between PER and USE is positive for all levels of ETC. Due to the adverse moderating effect, at a high level of ETC, the impact of PER on the use of GAI is weaker. In contrast, at lower levels of ETC, the effect of PER on the use of GAI is stronger. In turn, as shown in Table IV, the t-statistic (-0.753) for the path linking the interaction term PER*ETC and USE points out that this ratio is not statistically significant at the desired confidence level of 95%, and should therefore be considered with caution.

As shown in Table IV, the interaction term EFF*ETC negatively influences USE (-0.031), while the direct effect of EFF → USE is positive (0.063). Taken together, these results indicate that the relationship between EFF and USE is 0.063 at the average level of ETC. At higher levels of ETC (i.e., one standard deviation above the mean), the effect of EFF on US decreases by the size of the interaction term, yielding an adjusted effect of 0.032. Conversely, at lower levels of ETC (i.e., one standard deviation below the mean), the effect increases by the same amount, resulting in an adjusted effect of 0.094. The moderating role of ETC is further clarified through slope analysis.

The relationship between EFF and USE is positive for all levels of ETC, as indicated by the positive slopes of their regression lines. Due to the adverse moderating effect, at a high level of ETC, the impact of EFF on the use of GAI is weaker. In contrast, at lower levels of ETC, the effect of EFF on the use of GAI is stronger. In turn, as shown in Table IV, the t-statistic (-0.845) for the path linking the interaction term EFF*ETC and USE points out that this ratio is not statistically significant at the desired confidence level of 95%, and should therefore be considered with caution.

The interaction term SOC*ETC has a positive effect on USE of 0.017, whereas the simple effect of SOC on USE is 0.140. Jointly, the results indicate that the relationship between SOC and USE is 0.140, corresponding to an average level of ETC. For higher levels of ETC, i.e., for every standard deviation unit increase of ETC, the relationship between SOC and USE increases by the size of the interaction term, i.e., $0.140 + 0.017 = 0.157$. On the contrary, for lower levels of ETC, i.e., for every standard deviation unit decline of ETC, the relationship between SOC and USE shrinks by the extent of the interaction term, i.e., $0.140 - 0.017 = 0.123$.

The relationship between SOC and USE is positive for all levels of ETC, as indicated by the positive slopes of their regression lines. Due to the positive moderating effect, at a high level of ETC, the impact of SOC on the use of GAI is more substantial. In contrast, at lower levels of ETC, the effect of SOC on the use of GAI is weaker. As shown in Table IV, the t-statistic (1.961) for the path linking the interaction term SOC*ETC and USE indicates that this relationship is statistically significant at a confidence level >95%.

The interaction term STV*ETC has a negative influence on USE (-0.018), while the direct effect of STV on USE is positive (0.104), as shown in Table IV. Taken together, these results indicate that the relationship between STV and USE is 0.104 at the average level of ETC. At higher levels of ETC (i.e., one standard deviation above the mean), the effect of STV on USE decreases by the size of the interaction term, yielding an adjusted effect of 0.086. Conversely, at lower levels of ETC (i.e., one standard deviation below the mean), the effect increases by the same amount, resulting in an adjusted effect of 0.122.

The relationship between STV and USE is positive for all levels of ETC, as indicated by the positive slopes of their regression lines. Due to the adverse moderating effect, at a high level of ETC, the impact of STV on the use of GAI is weaker. In contrast, at lower levels of ETC, the effect of STV on the use of GAI is stronger. In turn, as shown in Table IV, the t-statistic (-0.315) for the path linking the interaction term STV*ETC and USE indicates that this ratio is not statistically significant at the 95% confidence level, and should therefore be considered with caution.

The interaction term HAB*ETC has a positive effect on USE of 0.094, whereas the simple effect of HAB on USE is 0.416. Jointly, the results indicate that the relationship between HAB and USE is 0.416, corresponding to an average level of ETC. For higher levels of ETC, i.e., for every standard deviation unit increase of ETC, the relationship between HAB and USE increases by the size of the interaction term, i.e., $0.416 + 0.094 = 0.510$. On the contrary, for lower levels of ETC, i.e., for every standard deviation unit decline of ETC, the relationship between HAB and USE reduces by the size of the interaction term, i.e., $0.416 - 0.094 = 0.322$.

The relationship between HAB and USE is positive for all levels of ETC, as indicated by the positive slopes of their regression lines. Due to the positive moderating effect, at a high level of ETC, the impact of HAB on the use of GAI is more substantial. In contrast, at lower levels of ETC, the effect of HAB on the use of GAI is weaker. The t-statistic (1.975), as shown in Table IV, for the path linking the interaction term HAB*ETC and USE indicates that this relationship is statistically significant at a confidence level > 95%.

V. DISCUSSIONS AND CONCLUSIONS

This study advances understanding of generative AI (GAI) adoption in business education by highlighting the role of ethics awareness. Consistent with prior research on technology acceptance [6], [10], performance expectancy, social influence, study value, habit, and ethics awareness significantly predicted GAI use. Habit exerted the most potent effect, underscoring the importance of repeated exposure and routinized practices in embedding AI into academic routines [11], [12]. Social influence also proved influential, reflecting the weight of peer and faculty endorsement in shaping adoption decisions [9]. Effort expectancy, despite high descriptive ratings, did not significantly predict adoption. This suggests that usability is no longer a decisive factor when tools are already intuitive; instead, perceived utility and social validation are the dominant factors. This finding diverges from traditional UTAUT assumptions, indicating a shift in adoption dynamics in contexts where ease of use is often taken for granted.

Ethics awareness played a dual role. Its direct effect on adoption was positive, but moderation analyses revealed divergent outcomes. Ethics awareness amplified the effects of social influence and habit, indicating that ethically sensitive students are more responsive to collective norms and deliberate in the routinization of AI use. Conversely, it attenuated the effects of performance expectancy, effort expectancy, and study value, suggesting that heightened ethical concerns temper reliance on purely instrumental drivers. This selective filtering aligns with [8], who argue that ethical awareness can both enable and constrain technology adoption depending on context.

These findings underscore the need to integrate ethics into technology acceptance frameworks [14], [15], [16], [17]. Ethical awareness does not discourage adoption; instead, it channels it toward socially validated and responsible practices [18], [19], [20], [21], [22]. For business schools, this highlights the importance of embedding ethical literacy alongside technical proficiency, ensuring that future leaders engage with AI tools critically and responsibly [23], [24], [25], [26], [27]. The Baltic Sea regional context further illustrates how institutional and cultural environments shape adoption, echoing the influence of regulatory and cultural variation.

This study demonstrates that ethics awareness is a crucial factor in the adoption of generative AI among business school students. Performance expectancy, social influence, study value, habit, and ethics awareness were significant predictors of use, while effort expectancy was less relevant. Moderation analyses revealed that ethics awareness strengthens social and habitual drivers but weakens instrumental ones, extending UTAUT2 by showing how ethical sensitivity reshapes adoption pathways.

Theoretical contributions include positioning ethics awareness as a critical construct in technology acceptance models. Practically, the findings suggest pedagogical strategies that strike a balance between technological literacy and ethical reasoning, thereby fostering responsible adoption. Policy implications include embedding ethical guidelines into institutional frameworks to mitigate risks related to plagiarism, authorship, and transparency.

Limitations include reliance on a convenience sample from the Baltic Sea region, which may constrain generalizability. Future research should examine other cultural contexts, employ longitudinal designs to capture the evolution of habits, and refine measurement instruments for ethics awareness.

In summary, ethics awareness moderates adoption in complex ways, ensuring that the use of generative AI in higher education is not only widespread but also aligned with ethical imperatives. Business schools must therefore cultivate both technical competence and ethical sensitivity to prepare students for professional roles that incorporate AI.

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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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