Generative AI for Undergraduate Thesis Writing: An Extended Theory of Planned Behavior Perspective

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Abstract: In the academic and higher education setting, generative artificial intelligence (GenAI) systems have emerged as a revolutionary tool for generating meaningful content and assisting students in academic work, especially among undergraduate students completing their thesis as a final requirement to complete their studies. While research has been published on adopting GenAI for academic writing and research writing, most studies have focused on postgraduate students and faculty. This gap highlights the need to study the factors influencing undergraduate students to use GenAI systems as a supporting tool for their academic writing and workload. Building upon the theory of planned behavior (TPB) model, the study explores the effects of guilt and hedonic motivation on undergraduate students' intention to use GenAI systems. A validated instrument was administered to 100 undergraduate students across Greater Manila, and responses were analyzed using partial least squares structural equation modeling (PLS-SEM). The findings revealed that attitude and subjective norms positively and significantly influenced intention to use GenAI systems. However, contrary to the established TBP model, perceived behavioral control did not significantly predict this intention. Additionally, hedonic motivation significantly impacted students' intention to use the technology. Guilt influenced students' attitude toward GenAI, but not their intention. Subjective norms were found to influence this feeling of guilt inversely. We discuss and analyze our findings, their implications for existing research, and recommendations for future studies.

Keywords: generative artificial intelligence, thesis writing, theory of planned behavior, technology adoption, hedonic motivation

1. Introduction

Generative artificial intelligence (GenAI) systems such as ChatGPT emerged rapidly as a transformative tool across various domains, changing how people perform various tasks because of their capability to produce meaningful text and other kinds of content (Feuerriegel et al., 2024). Its adoption and use have extended to the academic and higher education settings, where it has proven to be a viable and valuable tool for academic writing (Garcia, 2025; Strzelecki, 2024). GenAI use has become prominent and is perceived as a valuable assistant for the structured, complex, and empirical nature of research writing (Garcia, 2025; Khalifa & Albadawy, 2024).

Thesis writing, a common requirement for undergraduate and graduate students, often causes frustration due to limited experience and guidance (Quinto, 2022; Rizwan & Naas, 2022; Garcia, 2025; Habibi, 2025). To cope, students increasingly use GenAI tools to support various writing stages (Garcia, 2025; Habibi, 2025; Khalifa & Albadawy, 2024; Kim et al., 2025; Rodafinos, 2025). However, most research focuses on postgraduates, leaving undergraduates underexplored. Emotional and ethical aspects, such as guilt from ethical concerns and enjoyment from GenAI use, are often overlooked in existing models (Ajzen, 2011; Ren et al., 2025).

This study addresses existing gaps by examining factors influencing undergraduates' intention to use GenAI for thesis writing. An extended theory of planned behavior (TPB) model was tested, incorporating guilt and hedonic motivation. Specifically, it explored how attitude, subjective norms, and perceived behavioral control affect intention, along with guilt's direct and indirect effects and the role of enjoyment (Ajzen, 2011).

2. Related Literature

Generative AI (GenAI) produces content in formats like text, images, and audio, offering multimodality, interactivity, and productivity (Feuerriegel et al., 2024). GenAI "models" (e.g., GPT-4) are embedded in systems (e.g., ChatGPT) and used in applications such as academic writing. This review examines GenAI's role in research writing, its ethical and emotional implications, and identifies research gaps and the study's theoretical foundation.

Academic writing demands cognitive effort and structured formats like literature reviews and empirical data (Al Fadda, 2012; Anani et al., 2025; Garcia, 2025; Khalifa & Albadawy, 2024), often causing frustration among thesis writers (Habibi, 2025). GenAI tools help generate questions, summarize literature, manage data, and refine drafts (Garcia, 2025; Kim et al., 2025; Rodafinos, 2025). Adoption is growing among postgraduates and faculty, driven by task-technology fit and trust (Garcia, 2025; Al-Bukhrani et al., 2025; Zou & Huang, 2023).

Ethical concerns, plagiarism, authenticity, and institutional policies affect GenAI use (Khalifa & Albadawy, 2024; Ren et al., 2025). Students may hesitate to disclose usage due to fear of judgment, leading to guilt and discomfort (Ren et al., 2025; Y. Cui, 2025; Kim et al., 2025). However, GenAI also brings positive emotions like enjoyment and reduced anxiety (Kim et al., 2025; Lin & Chang, 2020; Pavone, 2025; Hawanti & Zubaydulloevna, 2023), showing emotional factors influence adoption beyond utility.

Despite valuable insights, research often overlooks undergraduates and relies heavily on TAM and UTAUT, with limited use of TRA and TPB. Ren et al. (2025) noted TPB's limitations in capturing negative emotions like guilt. The study adopts an extended TPB model to examine undergraduates' intention to use GenAI, incorporating attitude, subjective norms, perceived behavioral control, guilt, and enjoyment (Ajzen, 2011).

3. Theoretical Foundations and Hypotheses Development

The theory of planned behavior (TPB), developed by Ajzen (1985), explains intention through three factors: attitude (beliefs about outcomes), subjective norms (perceived social pressure), and perceived behavioral control (confidence in performing the behavior despite obstacles). TPB extends the theory of reasoned action (TRA) by adding control to account for non-volitional behaviors (Ajzen, 2020b). Ajzen (2011) later clarified that emotions can influence these factors indirectly, and sometimes directly affect intention or behavior, adding up to 7% variance in intention and 1% in behavior. Based on this, we propose extending TPB with emotional constructs like guilt and hedonic motivation to better understand undergraduate students' intention to use GenAI for thesis writing. The following sections present and justify our hypotheses.

3.1 Theoretical Model

Figure 1 – Theoretical Model presents our extended theoretical model, combining the core TPB constructs, attitude, subjective norms, perceived behavioral control, intention, and behavior (Ajzen, 1991), with two emotional factors: guilt and hedonic motivation. Curved bidirectional arrows indicate possible correlations among TPB constructs (Ajzen, 2020b; Rajeh, 2022), while the dashed arrow suggests a potential direct influence. These correlations and the direct control-to-behavior path are outside this study's scope, aligning with prior

research focused on the predictive relationships shown by solid arrows. The following sections justify each construct's role in the model.

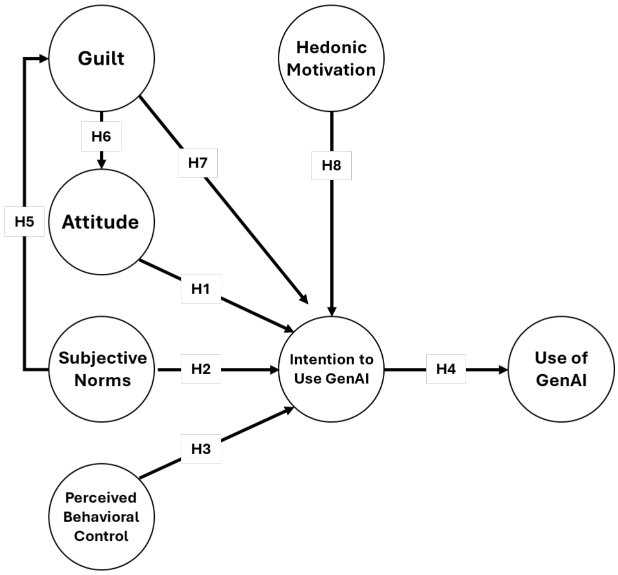

Figure 1. Theoretical Model.

3.2 Core Constructs of TPB

TPB has been widely applied to technology adoption (Ajzen, 2020a), including GenAI use in academia. Studies show that students' attitudes, peer and instructor influence (subjective norms), and perceived ability to use GenAI tools significantly predict adoption (Lenart et al., 2025; Nurtanto et al., 2025; Wang et al., 2025). Anani et al. (2025) link positive attitudes to perceived benefits, while Al-Bukhrani et al. (2025), using TRA, found that attitudes and subjective norms also shape researchers' intentions. Given this evidence, we propose that TPB constructs similarly predict undergraduates' intention to use GenAI for thesis writing. The following hypotheses reflect this:

> *H1: Attitude positively and significantly influences the intention to use GenAI for thesis writing.*
> *H2: Subjective norms positively and significantly influence the intention to use GenAI for thesis writing.*
> *H3: Perceived behavioral control positively and significantly influences the intention to use GenAI for thesis writing.*
> *H4: Intention to use GenAI for writing a thesis positively and significantly influences its usage.*

3.3 Guilt

Guilt, defined as remorse for wrongdoing (Hoppen et al., 2022), is increasingly studied in GenAI contexts. Chan (2024) introduced "AI guilt," describing moral discomfort when using AI for tasks traditionally done by humans, especially in academic settings where integrity is a concern (Chan, 2024; Qu & Wang, 2025). Researchers have called for deeper exploration of these ethical issues (Garcia, 2025; Papakonstantinidis et al., 2024; Zou & Huang, 2023). Personal values and social norms shape guilt—students fear judgment from peers and educators (Chan, 2024). They may face "AI shaming" for perceived laziness or dishonesty (Giray, 2024). These norms influence emotional responses (Jo, 2025; Qu & Wang, 2025). Qu and Wang (2025) found guilt reduces ChatGPT use for higher-order tasks, while Jo (2025) noted it lowers perceived benefits, negatively affecting attitude. Based on these findings and Ajzen's (2011) view that emotions can shape intention directly or indirectly, we propose the following hypotheses:

H5: Subjective norm negatively and significantly influences guilt associated with using GenAI for thesis writing.
H6: Guilt negatively and significantly influences the attitude toward using GenAI for thesis writing.
H7: Guilt negatively and significantly influences the intention to use GenAI for thesis writing.

3.4 Hedonic Motivation

Hedonic motivation, the enjoyment or pleasure from using a technology, is a key factor in technology adoption (Venkatesh et al., 2012). Marikyan and Papagiannidis (2025) found that it predicts behavioral intention in consumer tech use. In GenAI contexts, students are drawn to its engaging, chatbot-like interface, which enhances writing experiences (Lin & Chang, 2020; Kim et al., 2025). This enjoyment reduces cognitive load, boosts confidence, and increases intention to use GenAI for thesis writing (Y. Cui, 2025). Strzelecki (2024) also noted that undergraduates value enjoyment more than postgraduates. Based on these findings, we propose the following hypothesis:

H8: Hedonic motivation positively and significantly influences the intention to use GenAI for thesis writing.

4. Methodology

This study empirically investigates the factors influencing undergraduate students' intention to utilize GenAI for thesis writing. A survey instrument was adapted and validated to gather data, then distributed through convenience sampling among undergraduate students. Data analysis employed partial least squares structural equation modeling (PLS-SEM), following the methodology described by Hair et al. (2019). In the following sections, we detail our process for developing the data collection instrument, gathering data, analyzing that data, and interpreting the results.

4.1 Instrument Development

The survey included 28 items (excluding demographics) and was administered via Google Forms. It was distributed through convenience snowball sampling among undergraduates in thesis or capstone stages, using in-person outreach, online chats, and social media. A pilot test with 50 students from the target group was conducted to assess the instrument’s validity and reliability, with results presented in the following sections.

4.1.1 TPB Constructs.

The TPB constructs, namely attitude, subjective norms, perceived behavioral control, behavioral intention, and behavior, were adapted from Cui (2025). The proponent of TPB, Ajzen (2020b), noted that there is no standardized survey instrument for the theory’s core constructs. Hence, we selected Cui’s instrument for its clear and straightforward phrasing and reported reliability and validity. The items were each rephrased to refer specifically to using GenAI for thesis writing.

4.1.2 Guilt

Guilt was evaluated using an adapted six-item instrument from the Positive and Negative Affect Schedule (PANAS) developed by Watson and Clark (1999). The original instrument listed words and phrases associated with guilt, and respondents rated the extent to which they have felt these emotions on a seven-point Likert scale, ranging from "very slightly" to "extremely." However, to ensure consistency with measurement items in other constructs, these emotions were reformulated into statements such as "I feel (emotion or feeling) when I use generative AI for thesis writing." A five-point Likert agreement scale ranging from "strongly agree" to "strongly disagree" was also used instead.

4.1.3 Hedonic Motivation.

Hedonic motivation was measured using items adapted from Venkatesh et al. (2012), reworded from Elnaem et al. (2025) to fit the thesis writing context (e.g., "Using GenAI for thesis writing is [emotion]"). While the original used a seven-point Likert scale, we applied a five-point agreement scale for consistency, as also used by Elnaem et al.

4.2 Reliability and Convergent Validity Test

The internal consistency and convergent validity of the survey instrument's items were assessed using Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE). These metrics, standardized testing methods in information systems research, were calculated using the PLS-SEM algorithm within the SmartPLS software.

Table 1. *Instrument Reliability and Validity*

Construct	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted**
Attitude (A)	0.907	0.910	0.781
Guilt (G)	0.928	0.942	0.733
Hedonic Motivation (HM)	0.926	0.946	0.871
Intention (I)	0.930	0.931	0.827
Perceived Behavioral Control (PB)	0.865	0.956	0.636
Subjective Norms (SN)	0.747	0.764	0.564
Actual Use (U)	0.886	0.886	0.898

As presented in Table 1 – Instrument Reliability and Validity, all constructs demonstrated strong internal reliability, meeting the minimum threshold of 0.70 for acceptability in Cronbach's α and CR (Al-Emran et al., 2019; Bayaga & Kyobe, 2021). The lowest recorded value was 0.747 for subjective norms, while the highest was 0.928 for guilt. The lowest recorded value for CR was 0.764 for subjective norms, while the highest was 0.956 for perceived behavioral control. The constructs also demonstrated strong convergent validity as they all satisfied the minimum value of 0.50 for AVE (Al-Emran et al., 2019). The lowest recorded value was 0.564 for subjective norms, while the highest was 0.898 for actual use.

4.3 Discriminant Validity Test

The distinctiveness of the survey instrument's items from one another was also assessed using the Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratio scores, which are standardized metrics used to measure discriminant validity and ensure that constructs are not measuring the same concept (Hair et al., 2019). These metrics were also computed using the PLS-SEM algorithm within the SmartPLS software.

Fornell-Larcker criterion scores were used to establish discriminant validity and assess the intercorrelations of all constructs in the survey instrument (Hair et al., 2019). Table 2 - Fornell – Larcker Criterion Scores showcases that discriminant validity was substantiated by comparing the diagonal values, highlighted in bold, to the values of the inter-construct correlations within the same row and column.

Table 2. *Fornell – Larcker Criterion Scores*

Construct	A	G	HM	I	PB	SN	U
A	**0.884**	-	-	-	-	-	-
G	–0.458	**0.856**	-	-	-	-	-
HM	0.572	–0.345	**0.933**	-	-	-	-
I	0.748	–0.454	0.614	**0.909**	-	-	-
PB	0.282	–0.149	0.380	0.482	**0.797**	-	-
SN	0.443	–0.286	0.417	0.560	0.474	**0.751**	-
U	0.627	–0.226	0.470	0.789	0.388	0.527	**0.948**

However, recent literature has shown that the Fornell-Larcker criterion scores cannot be used to establish discriminant validity alone. To address this limitation, the HTMT ratio scores were also obtained using the PLS-SEM algorithm to corroborate the discriminant validity of the survey instrument. In Table 3 – HTMT Ratio and Scores, all calculated values fall below the threshold value of 0.90 for the HTMT ratio metric set by Henseler (2015), validating the distinctiveness of the constructs.

Table 3. *HTMT Ratio and Scores*

Construct	A	G	HM	I	PB	SN	U
A	-	-	-	-	-	-	-
G	0.478	-	-	-	-	-	-
HM	0.615	0.353	-	-	-	-	-
I	0.811	0.465	0.650	-	-	-	-
PB	0.262	0.193	0.361	0.466	-	-	-
SN	0.524	0.337	0.481	0.647	0.499	-	-
U	0.696	0.247	0.508	0.868	0.393	0.618	-

5. Results and Discussion

5.1 Participants' Profile

The sample included 148 participants from higher education institutions in Metro Manila. Most were aged 20 to 24 years old. The gender split was fairly balanced, 52% female and 45% male. ChatGPT was the most used GenAI tool (90%), followed by Google Gemini (37%), DeepSeek (16%), Claude (14%), NotebookLM (13%), and Copilot (9%), with 21% using other tools. Based on Khalifa and Albadawy (2024), everyday use cases included idea development (69%), content structuring (59%), literature synthesis (56%), and editing (53%). Data analysis (26%) and ethical compliance (19%) were less frequent, with 3% reporting other uses.

5.2 Structural Model Testing

The structural model was assessed using PLS-SEM with bootstrapping to test the hypothesized relationships. The results of the hypothesis testing, summarized through standard path coefficients, t statistics, and corresponding p values for each hypothesis, are presented in Table 4 – Hypotheses Testing Results. Six of the eight proposed hypotheses were confirmed to be statistically significant and empirically supported.

The results indicate that attitude exerted a strong, statistically significant influence on intention ($\beta = 0.446$, $t = 5.074$, $p = 0.000$), to use GenAI for thesis writing, supporting H1. Similarly, subjective norms ($\beta = 0.227$, $t = 3.208$, $p = 0.001$), and hedonic motivation ($\beta = 0.227$, $t = 2.800$, $p = 0.005$) were significant positive predictors of intention, supporting H2 and H8. Crucially, intention demonstrated a strong, positive, and significant effect on actual use of GenAI for thesis writing ($\beta = 0.803$, $t = 18.605$, $p = 0.000$).

Table 4. *Hypotheses Testing Results*

Hypotheses	Path Coefficient	t Statistics	p Values	Decision
H1: A → I	0.446	5.074	0.000	Accepted
H2: SN → I	0.227	3.208	0.001	Accepted
H3: PB → I	0.108	**1.449**	**0.147**	**Rejected**
H4: I → U	0.803	18.605	0.000	Accepted
H5: SN → G	–0.255	2.377	0.018	Accepted
H6: G → A	–0.392	4.076	0.000	Accepted
H7: G → I	0.036	**0.502**	**0.616**	**Rejected**
H8: HM → I	0.227	2.800	0.005	Accepted

The model also revealed significant negative relationships involving the guilt construct. Subjective norms had a significant negative relationship with guilt ($\beta = –0.255$, $t = 2.377$, $p = 0.018$), supporting H5. Guilt, in turn, significantly negatively influenced attitude ($\beta = –0.392$, $t = 4.076$, $p = 0.000$), supporting H6.

Two hypotheses were found to be statistically non-significant, and therefore not supported. Perceived behavioral control did not have a statistically significant influence on intention ($\beta = 0.108$, $t = 1.449$, $p = 0.147$), leading to the rejection of H3. Additionally, guilt did not exhibit a significant direct effect on intention ($\beta = 0.36$, $t = 0.502$, $p = 0.616$), resulting in the rejection of H7.

5.3 Discussion

5.3.1 Attitude and subjective norms predict intention to use GenAI for thesis writing

Structural model results show that two core TPB constructs, attitude (H1) and subjective norms (H2), significantly and positively influenced intention to use GenAI for thesis writing. Attitude was the strongest predictor, consistent with Anani et al. (2025) and Lenart et al. (2025), who linked positive attitudes to perceived benefits and usefulness. Subjective norms also had a significant effect, supported by Al-Bukhrani et al. (2025), who emphasized the role of social influence from peers, supervisors, and the academic community.

5.3.2 Perceived behavioral control does not predict intention to use GenAI for thesis writing

The hypothesis that perceived behavioral control predicts intention (H3) was not supported. Similar findings in GenAI adoption studies suggest this may be due to “technological optimism” among students (Wu & Dong, 2025). Our data also showed a high mean and low variance for perceived control, indicating students generally feel confident using GenAI—making it a weak predictor. Although the result was marginally significant ($\beta = 0.121$, $t = 1.674$, $p = 0.094$), it did not meet the statistical threshold. A larger sample may reveal a more apparent effect, but perceived control did not significantly influence intention in this study.

5.3.3 Hedonic motivation predicts intention

The results supported the model’s hypothesis regarding hedonic motivation as a positive and significant influence on intention to use GenAI systems (H8). Recent research has confirmed this influence. Cui (2025) deduced that the enjoyment is derived from the reduced cognitive load on students as they use GenAI to assist in academic writing. Likewise, Strzelecki (2024) notes that undergraduate students are more likely to enjoy using GenAI than postgraduate students, which is corroborated by the findings of this study, which focused on undergraduate students.

5.3.4 Guilt influences attitude toward the use of GenAI for thesis writing, but does not predict the intention to use it

Results showed guilt significantly affected attitude (H6) but not intention (H7). This supports Jo (2025), who found guilt lowers students' positive views of GenAI's usefulness, and aligns with Ajzen's (2011) view that emotions can indirectly shape intention via beliefs. However, Ajzen's suggestion of a direct emotional effect was not supported. Jo (2025) also noted that students may prioritize GenAI's practical benefits over emotional discomfort. Chan (2024) adds that students often view GenAI as a supportive tool, especially for research and idea generation, reducing the impact of guilt on intention.

5.3.5 Subjective norms inversely predict feelings of guilt toward the use of GenAI for thesis writing

The hypothesis that subjective norms negatively influence guilt (H5) was supported. Participants reported mild peer and academic approval (M = 3.29, SD = 0.87) and correspondingly low guilt levels (M = 2.79, SD = 1.39). This aligns with Qu and Wang (2025), who noted that students internalize community norms around GenAI use. At De La Salle University (2025), where responsible GenAI use is encouraged, institutional support likely reduces guilt. Chan's (2024) "fear of judgment" appears less relevant here, suggesting that clear, supportive policies can ease emotional barriers and explain why guilt affected attitude (H6) but not intention (H7).

6. Conclusion and Recommendations

GenAI systems are rapidly adopted in academic research, especially for thesis writing (Garcia, 2025; Habibi, 2025; Khalifa & Albadawy, 2024; Kim et al., 2025; Rodafinos, 2025). This study surveyed undergraduates to explore their motivations, using TPB as a framework with core constructs—attitude, subjective norms, and perceived behavioral control—and added guilt and hedonic motivation. Findings show intention is mainly driven by attitude and subjective norms, while perceived control was insignificant. Hedonic motivation also significantly influenced intention and was linked to reduced cognitive load. Guilt affected attitude but not intention, and was lowered by supportive peer norms and institutional policies.

Future research can address several limitations. First, the sample was mostly from computing and liberal arts, offering a general view of GenAI use. A more discipline-specific study could reveal differences in perception, especially between creativity-based and routine-based thesis tasks (Qu & Wang, 2025). Subjective norms may also vary by field. Second, expanding the theoretical model with frameworks like technology continuance theory could help explain long-term GenAI use, as thesis writing spans multiple semesters (Quinto, 2022). Third, since most participants were from De La Salle University, where GenAI use is encouraged, future studies could explore institutions with stricter policies to assess the impact on subjective norms and guilt. Fourth, research could focus on specific GenAI tools or tasks, as perceptions and guilt vary by use case (Chan, 2024; Qu & Wang, 2025). Lastly, the non-significance of perceived behavioral control may be due to sample size; larger studies could clarify its role.

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