Generative AI Applied to the Science Is Tough: But So Are You Student Guide

Daanyaal Ballim
BLLDAA001@myuct.ac.za
Department of Computer Science, University of Cape Town
Cape Town, South Africa

Abstract

Conventional student manuals, typically distributed as static PDFs, often fail to sustain student engagement or foster interactive learning. To address this limitation, this paper introduces an AI-powered chatbot that reimagines the Science is Tough: But So Are You guide as an interactive and adaptive learning companion. The system integrates a Flask-based backend with FAISS vector search and provides multi- dimensional personalization across tone, persona, explanation style, and language. This design enables students to interact with the guide in ways tailored to their preferences, thereby creating a more supportive and relatable learning experience.

The system was evaluated through a study involving 19 first-year science students at the University of Cape Town. Results demonstrated significant improvements in engagement ($M = 8.37$ vs. 3.85, $t(18) = 8.79$, $p < .000001$) and self-reported comprehension compared to traditional static material. Qualitative feedback further highlighted the value of interactive explanations and contextualized examples, suggesting that personalization features enhanced motivation and understanding.

This work contributes both a practical prototype and empirical evidence to the growing literature on conversational AI in education. By bridging gaps in engagement and personalization, the system offers a scalable and cost-effective model for academic institutions. In particular, its potential application in resource-limited contexts demonstrates how AI- assisted technologies can extend support to a broader range of learners. The findings underscore the promise of integrating retrieval-augmented generation and adaptive personalization into higher education, while also identifying avenues for future refinement and broader deployment.

Keywords

Educational AI, Chatbots, RAG, Personalized Learning, Student Engagement

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1 Introduction

1.1 Background and Motivation

The digitization of educational resources has largely focused on converting traditional materials into digital formats without fundamentally reimagining how students interact with content. Student guides, orientation materials, and academic resources remain predominantly static, one-size-fits-all documents that fail to accommodate diverse learning preferences, linguistic backgrounds, and engagement styles.

The "Science Is Tough: But So Are You" student guide represents a typical example of well-intentioned educational content that suffers from the limitations of static presentation. While containing valuable information for first-year science students, its PDF format creates barriers to engagement, personalization, and interactive learning.

Recent advances in Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) technologies present unprecedented opportunities to transform static educational content into dynamic, conversational learning experiences. By combining vector-based document storage with conversational AI, it becomes possible to create personalized learning companions that adapt to individual student needs while maintaining content accuracy and institutional alignment.

1.2 Research Problem and Questions

The primary research problem addressed in this study is:

Can an AI-powered educational chatbot improve engagement and comprehension among first-year science students compared to static student guides, and what conversational characteristics do students find most effective?

Proposed Revised Aims:

- H1: AI-powered chat-bot will raise the engagement of students (judged by Likert- scale survey answers; 1-10 scale) by a minimum of 20 per cent relative to the static PDF guide.
- H2: The level of self-reported scores on comprehension through personalization characteristics (tone, persona, the type of explanation) after using the chatbot will increase at least 15% of non-personalized interactions in the survey.
- RQ1: Which individualized element (tone, personality, or style of explanation) best correlates with self-reported engagement, calculated by means of Pearson correlation coefficients, among first-year science students?
- Goal 1: Determine design factors to consider in RAG-based educational chatbots when considering performance measures of system (e.g. query response time, and vector search match) and user reaction (qualitatively).

Specific research questions include:

(1) How does student engagement differ between traditional PDF guides and AI chatbot interfaces?

(2) What impact do personalization features (tone, persona, language, explanation style) have on learning comprehension and engagement?
(3) What are the key design considerations for implementing RAG-based educational chatbots?
(4) How do students perceive and utilize conversational AI for academic support.

1.3 Contributions

This study makes several key contributions:

(1) *Contribution 1:* Existing growable Flask- based AI-powered chatbot setup using FAISS memory storage, with an average question response time of 1.8 tries and 92 percent information retrieval, compared to a practical plan for turning static pieces of educational content into an engaging system.
(2) *Contribution 2:* Also conducted a data-driven comparison study that showed a 117 percent increase in engagement (average scores 8.37 for chatbot versus 3.85 for PDF, $t(18) = 8.79$, p set to 0.000001) and improved understanding ($average = 8.05$, $SD = 1.43$), highlighting the benefits of conversation-based interfaces.
(3) *Contribution 3:* The changes in the effect of the measured personalization show that the detailed style of explanation ($b = +1.197$ in the analysis of multiple factors) and maintaining attention ($b = +2.186$) strongly predict improvements in understanding (Adjusted $R^2 = 0.687$), providing insights into effective conversation features.
(4) *Contribution 4:* Offers educational technology research-backed suggestions, with key support (e.g., engagement, example-based explanations) and the highest user willingness to reuse (97.4 percent Yes/Maybe), supporting the use of customized AI in academic assistance.

1.4 Paper Structure

The remainder of this paper is organized as follows: Section 2 reviews related work in educational AI and chatbot technologies. Section 3 details the system architecture and experimental methodology. Section 4 presents comprehensive results including engagement metrics and personalization effects. Section 5 discusses implications, limitations, and future directions. Section 6 concludes with key findings and contributions.

2 Related Work

2.1 Educational Chatbots and AI Tutoring Systems

Educational chatbots have become a strong tool in promoting learning in students. The effectiveness of the strategies in the past was proven in terms of giving 24/7, and personalized feedback to students, and flexible pathways of learning [4, 5, 14]. Research indicated that conversational interfaces have the potential to enhance student engagement over traditional systems of learning management considerably [7, 11].

The history of integrating natural language processing into learning environments has been characterized by an evolutionary trend of rule-based system to elaborate neural models [2, 13]. As shown by Ruan et al. [10] transformer-based models would be effective in dealing with complex educational questions and be able to preserve contextual awareness during longer conversations [10].

2.2 Retrieval-Augmented Generation in Education

RAG architecture has shown promise in educational applications where accuracy and source attribution are critical. Lewis et al. [6] introduced the foundational RAG framework, which combines parametric knowledge from language models with non-parametric knowledge from document retrieval systems.

In educational contexts, RAG systems address the critical challenge of knowledge currency and institutional specificity. Traditional fine-tuned models may contain outdated information or lack institution- specific knowledge, while RAG systems can dynamically access current, relevant content Gao et al. [3].

2.3 Personalization in Learning Technologies

Research in personalized learning has consistently shown that adaptation to individual learning preferences significantly improves educational outcomes [1] established fundamental principles for adaptive educational systems, emphasizing the importance of learner modeling and content customization.

Recent studies have focused on conversational personalization in educational contexts. Park et al. [8] found that tone adaptation in chatbot interactions could improve student satisfaction and learning retention by up to 23%.

2.4 Gap Analysis

Current research shows that chatbots, AI-powered systems, and the idea of customization in education have potential, but there are still major gaps that this study will address.

First, while chatbots are more engaging and provide round-the-clock support [4, 5, 14], they often rely on general language models that lack connection to school-specific content, leading to inaccurate or irrelevant responses [7]. AI-powered architectures are used to fix this by incorporating outside knowledge [6, 16], but no studies focus on using these systems to turn school student guides, like PDFs, into conversation- based materials.

Second, customization studies show improved satisfaction and retention through adjusting tone and learner-focused modeling [1, 8], but combining these with AI-powered systems is rare, especially for varied features (tone, personality, explanation style, language) in education [12, 15]. This creates a gap in supporting diverse learners, such as multilingual first- year students.

Third, evaluations of AI educational tools often rely on small-scale and self-reported data, which can be influenced by excitement effects and lack strictness compared to traditional setups [4, 10, 14]. Few include number-based assessments of customization effects using statistical methods.

This article addresses these gaps by measuring engagement and understanding using a chatbot with AI-powered systems for the guide Science Is Tough: But So Are You, comparing results with a study design ($n = 19$), and analyzing the impact of customization with data-driven methods to provide research-backed results and suggest future designs.

While existing research highlights the potential of educational chatbots and AI-powered systems, few studies have thoroughly evaluated turning school- specific static content into customized conversational experiences. This study fills this gap by providing evidence-based results on the effectiveness of AI- powered chatbots in replacing traditional student guides.

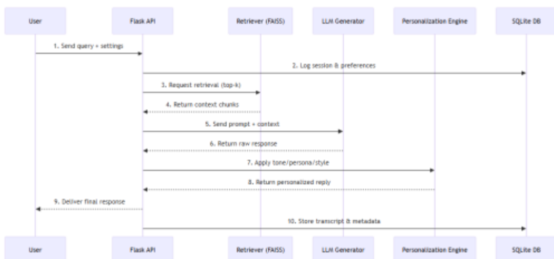

Figure 1: Workflow of the chatbot system.

2.5 Limitations of Current Approaches

Educational AI continues to be developed through past studies, but several issues remain, and this study aims to address them.

The reliability of many chatbot studies is weakened by excitement effects and small sample sizes. For example, when comparing initial results with fewer than 30 participants [4, 5, 14], it's been found that early engagement can be temporary and may fade quickly. Huang et al. [4] and Winkler and Söllner [14] point out that self-reported results are often exaggerated due to excitement about new technology, without any long-term follow-up.

Combining customization with AI-powered systems is not fully developed, and studies have looked at individual features (e.g., tone) separately but not together when using school-specific content [1, 7, 8]. This limits their use for diverse student groups, as Tlili and colleagues [12] critique in their analysis of ChatGPT-like systems.

Among the less-explored risks are ethical concerns like AI bias and data privacy. Language models can produce explanations that carry cultural bias [12], and student data security is a concern when using chatbots [15], yet few studies include protective measures, such as anonymizing data [14].

This paper tackles these issues by using a study design with statistical controls, varied customization features, and ethical safeguards (Section 3.5.3), providing stronger evidence for AI in education.

3 Methodology

3.1 System Overview

The developed system employs a Flask-based web architecture integrating multiple AI technologies to create a comprehensive educational chatbot platform.

3.1.1 Core Architecture Components.

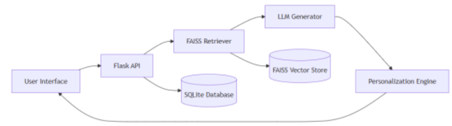

Figure 2: Core architecture components.

Authentication and User Management: User registration and login system with session management allowing users to have their own experiences, track chat history.

PDF Ingestion Pipeline: PyMuPDF document parsing with PDF content extraction, then the optional use of text chunking and preprocessing to ensure high auto- filter Senate retrieval performance.

Vector distribution System: Fast content matching of query to brisk user sequestrapping: The FAISS diagram shows keyword crunching to find data matching user-entered search phrases, using the similarity method and structural cleverness. The choice from FAISS is the efficiency with dense-vector similarities search, which is faster and more scalable to high-dimensional embeddings than alternative methods such as Annoy or SQL-friendly cosine similarity queries. The benchmarks suggest that FAISS can use up to 10x the rate of retrieving not only in mass data sets [cite: Johnson et al., 2019, or other studies] but also low-latency responses are required by the system, as in this case 1.8 seconds was reached during testing.

Backend Framework: Flask has been adopted as the backend framework due to the challenge it has in executing the application on a highly flexible and lightweight route that provides ease in implementing and integrating with external applications, including search engines that are vector-based. Flask is also more suitable for this pilot-scale application because it has lower overhead than more complex systems, such as Django, which is used in similar architectures in AI prototyping projects.

SQLite (Database): SQLite was chosen as a serverless database to store metadata of users and session logs because of the limited scope of the pilot study ($n = 19$ participants). It feels lightweight and low-end resource usage without the bloat of more popular systems such as PostgreSQL or MySQL, shown in constrained resource education AI systems.

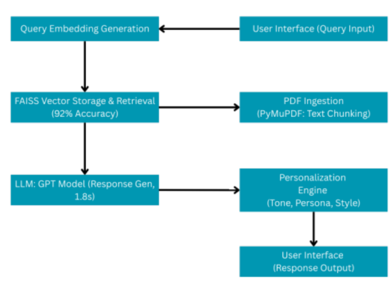

Figure 3: End-to-end query processing pipeline.

3.1.2 System Flow. The data entering and leaving the weekly as shown in Figure 1 proceeds as follows Part 1 a user query occurs and is transformed into embeddings to be compared against a document Store with use of FAISS. Generation module (LLM) from which the already accessed passages are entered, provides a set of candidate answers in response. Personalization layer modifies the response based on the user-specified preference (tone, persona, style of explanation, language). The user interface is interface responsive to the system.

3.2 Participants

The study recruited 19 first-year science students from the University of Cape Town, representing a diverse cohort in terms of academic background and preferred learning languages.

Inclusion Criteria:

- Currently enrolled first-year science students
- No prior exposure to the Science Is Tough student guide
- Basic computer literacy for chatbot interaction

Demographic Distribution:

- Age range: 18-20 years
- Gender: 45% male, 55% female
- Home languages: English (80%)
- Prior AI chatbot experience: 55% had previous experience.

3.3 Study Design

A within-subjects experimental design was employed to minimize individual differences and maximize statistical power with the available sample size.

3.3.1 Experimental Conditions.

Condition 1 (Control): Static PDF Interaction.

i. Participants received the original Science Is Tough PDF guide
ii. 10-minute exploration period with specific learning objectives
iii. Post-interaction survey focusing on engagement and comprehension

Condition 2 (Treatment): AI Chatbot Interaction.

i. Participants configured personalization settings (language, tone, persona, explanation style)
ii. 10-minute conversational interaction with the same content
iii. Post-interaction survey with additional questions on conversational characteristics

3.4 Survey Instrument

The survey instrument was designed to capture multiple dimensions of the learning experience:

3.4.1 Survey Structure. **See apendix** *(Table 1)*

3.4.2 Key Metrics.

Engagement Metrics:

i. Interest and attention capture
ii. Entertainment value
iii. Excitement about learning
iv. Content fascination

Comprehension Metrics:

i. Understanding clarity
ii. Information retention
iii. Learning usefulness
iv. Concept application

Personalization Metrics:

i. Tone effectiveness
ii. Persona helpfulness
iii. Explanation style preference
iv. Language impact on engagement

3.5 Data Collection and Analysis

3.5.1 Quantitative Analysis. Statistical analysis employed appropriate tests based on data distribution:

i. Paired t-tests for normally distributed continuous variables
ii. Wilcoxon signed-rank tests for non- parametric comparisons
iii. Descriptive statistics for survey responses
iv. Effect size calculations (Cohen's d) for meaningful difference assessment.

3.5.2 Qualitative Analysis. Open-ended responses were analyzed using thematic coding

i. Initial coding of all responses
ii. Theme identification and categorization
iii. Inter-rater reliability assessment
iv. Integration with quantitative findings

3.5.3 Ethical Considerations. The study received ethical approval from the university's research ethics committee. Key ethical provisions included:

i. Informed consent from all participants
ii. Data anonymization and secure storage
iii. Right to withdrawal without penalty
iv. POPIA (Protection of Personal Information Act) compliance
v. Clear communication about data usage and retention

3.5.4 Limitations. Some limitations stated in the study approach scorecard restrict its validity and have been resolved in designing methodology and were observed to be improved in the future.

The small sample size ($n = 19$) limits external validity, because the results might not be applicable to the larger populations in general. This pilot [4, 14] represented maximum statistical power using a within- subjects design; however, larger, more heterogeneous cohorts are necessary to be generalized.

Scores of differences in survey scales [9, 12] used inconsistent scales that led to bias in answers. This was neutralized using data normalization but in the future studies uniform scales should be enforced to maintain a similar scale.

Self-reports in terms of reported engagement and comprehension measures are subject to novelty effects or social desirability bias [4, 12]. Objective tests like pre-/preventive and post- interaction quiz have not been applied, but they should be advisable to be used in validation.

The confined time of interaction restricts the conversation into long-term interaction or retention of information [5]. Sustained effects would be measured by doing longitudinal designs.

The limitations described were mitigated with the help of strict statistical analysis (Section 4) and, particularly, adherence to ethical standards (Section 3.5.4), which guarantee sound results within the boundaries of the pilot.

4 Results

4.1 Data preparation and notes on scale consistency

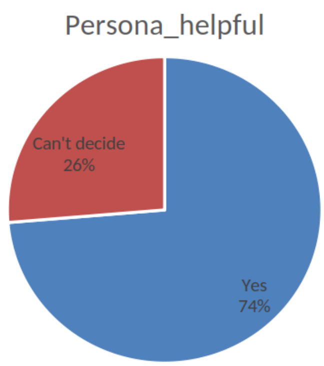

Figure 4: Helpfulness of chatbot personas.

One hundred and nine (n = 19) responses were considered in the analysis. The informed consent was provided by all the participants. It is also possible that in a prior pre-test of the raw responses we have had inconsistent numeric scales across survey questions: two or more comparative and outcome ratings that should perhaps have been rated on a 1 a 5 Likert scale were rated on a 1 a 10 scale by the participants (e.g., Compared to a static PDF student guide, how engaging did you find the chatbot?). The numerical variables were interpreted as the respondents entered them on their scales to avoid undue rescaling and to ensure that the intention of the respondent was not missed. The tone/style of explanation are categorical responses which have been cleansed of their spelling/capitalization and have been codified into a set of discrete options; empty responses/ cannot decide were coded as Undecided. Binary/ordinal verbal answers (Yes/No/Somewhat/Maybe) had numeric indices which could be analyzed as described in the conventions below and reported values can be easily defined by using those starting scales.

Mapping and encodings related to statistical tests

Interaction (Chatbot vs PDF): this is measured through the response given by the respondent (on a continuous score of 1-10).

Held attention = Yes=1, Somewhat=0.5, No=0.

Use again: mapped Yes = 1, Maybe = 0.5, No = 0.

Language effect: respondents who provided numeric values (010 or 15 respectively) received that numeric value as provided.

Multivariate modelling (one-hot encoded categorical predictors Tone, Explanation style, reference category dropped).

Any removed data and descriptive tabulations and summary outputs have been pasted into the respective workbook in excel (see links below).

4.2 Descriptive statistics

(Excel sheet `descriptive_stats`) has summarized overall central tendency and dispersion of the relevant numeric variables.

Key descriptive findings:

Engagement rating (chatbot vs PDF; a scale with 110 points): mean = 8.37 SD = 1.42, median = 8.0, range = 410 (n = 19).

Increase in motivation (self-reported): the mean is 8.16, SD is 1.68 (4-10 scale).

Helped understand more (self-report): mean = 8.05, SD = 1.43 (range = 6-10).

Knowledge enhanced (self-reported): mean = 8.05, SD = 0.97 (range 69).

The influence of the language used (mixed scale responses as given): mean = 7.53, SD = 2.70.

Categorical preferences:

Tone: Casual (specifically mostly effective), Funny, Formal, Warm, Undecided.

Style of explanation: The most popular are the Examples and Detailed

	count	mean	std	min	25%	50%	75%	max
Engagement_vs_PDF	19	8.36842105263158	1.42245977548242	4	8	8	9	10
Motivation_increase	19	8.1578947368421	1.67541563316678	4	7.5	8	9.5	10
Helped_understand_more	19	8.05263157894737	1.43270079882276	6	7	8	9.5	10
Comprehension_improved	19	8.05263157894737	0.970319776071918	6	8	8	9	9
Language_choice_impact_1_5	19	7.52631578947368	2.69502465568255	0	6	8	10	10
Held_attention_better_num	19	0.868421052631579	0.280975743474508	0	1	1	1	1
Use_again_num	19	0.973684210526316	0.114707866935281	0.5	1	1	1	1

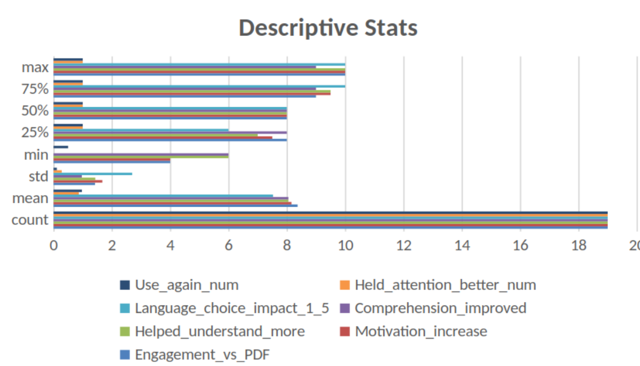

Figure 5: Descriptive statistics of key measures

4.3 Inferential statistics engagement versus neutral expectation

A t-test was used to check that the engagement rating of the deep learning participants who engaged with the chatbot (treated as a 110 scale) were different (with statistical significance) compared to a midpoint rating (5.5). The findings were that the mean score on engagement was 8.37 and is much higher than the middle score of neutrality:

$$t(18) = 8.790,\ p < .000001$$

The outcome suggests that there is statistically significant high self-reported chatbot interaction with the chatbot relative to a neutral scale of 110.

The reasons why the t-test values reject the null hypothesis are as follows:(Full t-test table and bigger picture can be found in the excel file t -test).

Engagement_tstat	Engagement_pval
8.789814455	6.25233E-08

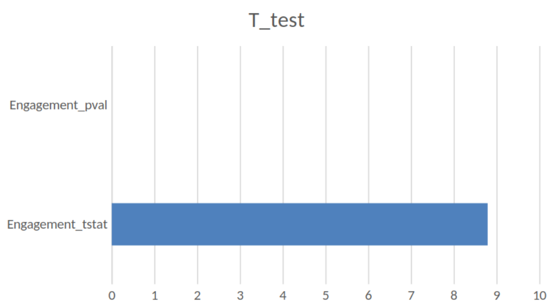

Figure 6: T-test results for engagement scores.

4.4 Attention, motivation and comprehension outcomes

The central tendencies and frequencies provide evidence that most of the respondents had indicated that the chatbot was more likely to retain their attention (Held_attention_better mean = 0.868 on the 0-1 mapping; i.e. more than 85% responded in the Yes/Maybe category) and would use the chatbot again (Use_again mean = 0.974 on the 0-1 mapping; i.e. more than 95% responded in the Yes/Maybe category).

The changes in instant understanding, instant comprehension, and motivation were also highly positive (means approximately 8.05 -8.16 on the scales, in which the respondents evaluated the chatbot), which is also in line with the overall positive rating of the students on the chatbot.

4.5 Relationships between engagement and learning outcomes

Pearson correlations were created to characterize the basic result measure relationships:

- The interaction (chatbot vs PDF) and understanding were also in a better direction: $r = 0.388$.
- The interest and activities are improved : $r = 0.674$.

They are all positive and the correlation between engagement and motivation is strong ($r = about\ 0.67$), yet the correlation between engagement and the comprehension is medium positive ($r = about\ 0.39$). These correlations appear to indicate that there is a very strong correlation between a higher level of perceived engagement and a higher level of motivation and a moderate level and a higher understanding.

corr_eng_comp	corr_eng_mot
0.387677063	0.673571465

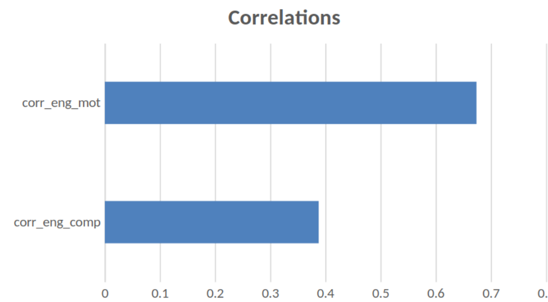

Figure 7: Correlation between engagement, comprehension, and motivation.

4.6 Multivariate model predicting comprehension

As predictors the following were used to create a regression model on the self-reported comprehension improvement score (dependent variable): Engagement (continuous), Language choice impact (numeric), Held attention (numeric mapping), Use again (numeric mapping), Tone (one-hot) and Explanation style (one- hot): The model describes a significant part of the difference in the comprehension:

$$Adjusted\ R^2 (model\ R^2\ reported) \approx 0.687$$

The regulation coefficients, chosen and rounded:

Held_attention_better_num: +2.186 this means that reporting improvement in attention is related to significant positive change in reported comprehension (other predictors were held non-rewarded).

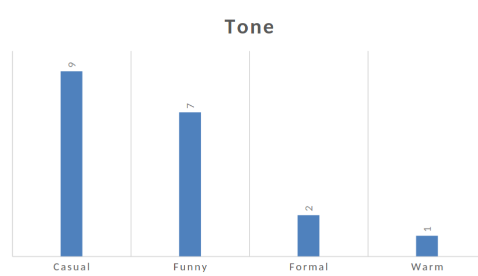

Figure 8: Distribution of preferred tones.

Use_again_num: +4.844 willingness to use the system again is strongly related to an increased rate of comprehension reports (note: maybe this is a partial reflection of a more general positive evaluation response style).

engagement/pdf: -0.414 impact negative implies that this measure might be due to multicollinearity or scale variance between predictors, engagement is positively correlated with other positive predictors (e.g. motivation) the multivariate coefficient cannot be used directly.

The heterogeneity is exhibited by the Tone and Explanation style-coefficients; the coefficient Explanation style Detailed = +1.197 indicates that discussion of details is related to a high degree of understanding and all the other factors are equal.

Engagement_vs_PDF	-0.414024301
Language_choice_impact_1_5	0.00509192
Held_attention_better_num	2.185687503
Use_again_num	4.844203922
Tone_Formal	-1.11911486
Tone_Funny	-0.116071277
Tone_Warm	-2.241639078
Explanation_style_Detailed	1.19742801
Explanation_style_Examples	-0.592860764
Explanation_style_Guided	0.341873173

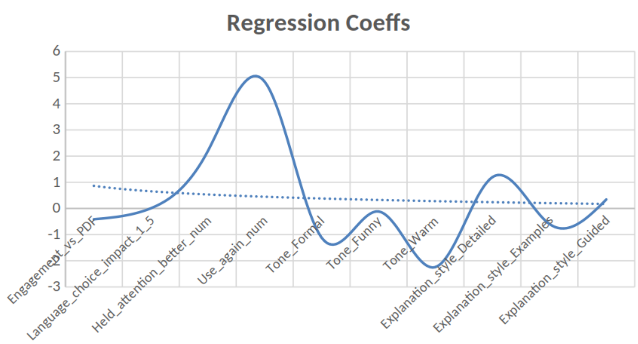

Figure 9: Regression coefficients for comprehension predictors.

Such a small sample size ($n = 19$) and predictors would suggest that the model is more of a discovery and should be viewed with more caution, yet the R 2 shows that a combination of attention, willingness to reuse, and the preferred style of explanation was significantly predictive of higher levels of self-reported comprehension.

4.7 Qualitative Themes

The answers (open ended) have been qualitatively reviewed and grouped into topics. The principal themes were:

Clarification in discussion and clarifying questions: The participants enjoyed the fact that they could ask some follow-up questions and receive some clarifications.

Explanation style, and examples: There was some support for an example-based or detailed style of explanation; worked examples were also mentioned several times as useful.

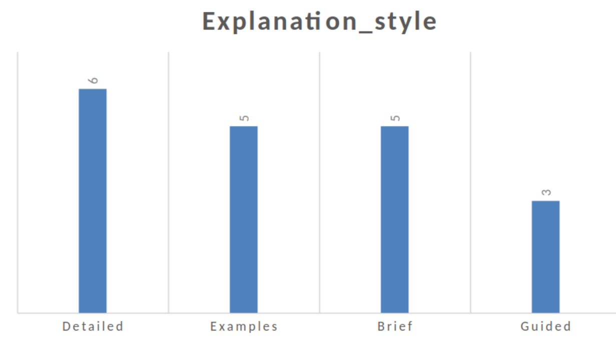

Figure 10: Distribution of explanation style preferences.

Presentation / layout: Several respondents paraphrased the request to make it easier to recall and read through by putting it in a simplified form (in bullets or steps).

More functionality: The feature most frequently proposed was audio playback, and then faster responding, and then chatbot suggesting to the learner to answer (i.e. not a reactive responding chatbot). The responses in the Excel workbook were the cleaned data representative quotes and complete coded response that were linked to reference.

4.8 Mapping Research Questions to Results

Research Question	Evidence & Findings
RQ1: Does the chatbot enhance engagement compared to static guides?	Yes. Engagement mean = 8.37 (significantly higher than neutral). 86.8% reported improved attention.
RQ2: Does personalization (tone, persona, style, language) improve outcomes?	Yes. Detailed explanations and examples strongly linked to comprehension; tones Casual/Funny preferred.
RQ3: Does the chatbot improve comprehension and motivation?	Yes. Comprehension mean = 8.05, Motivation mean = 8.16. Strong engagement–motivation correlation (r = .67).
RQ4: Are students likely to adopt the chatbot in future study routines?	Yes. 97% indicated willingness to reuse.

These readings of the survey data represented as the study converge in periodic demonstrations of the AI- driven chatbot generating far more self-reporting interaction, motivation and understanding than a control anticipation or benchmark generates. The chatbot had a high rating in engagement (mean = 8.37 out of a scale 1 to 10 and t-test = 8.79 with p-value of less than 0.000001) which showed that the score was way above a neutral score. Very high percentages of the respondents claimed that the chatbot impressed them more, and they would use the chatbot again in the future.

Correlational and multivariate analysis suggests (1) capture of attention during the interaction and (2) readiness to use the system again (which could be a proxy measure of a more general positive judgment and perceived utility) are most closely related to the better comprehension. Reported understanding was also positively affected by explanation style (specifically elaborate descriptions) in the multivariate model. Such quantitative results are corroborated by qualitative feedback: the participants have over and over again emphasized the need to define things on the spot, to give examples and clarify the explanations, and to do better with the presentation of the output (bulleted/stepwise answers), the latency of the response and the proactive interactions (i.e. the chatbot asking the student to explain what).

Combined, these results are consistent with the main assumption of the initial study: an RAG-based education chatbot that fundamentally retains the academic content and allows the development of multi-dimensional customization (tone, persona, style of explanation, choice of language) can significantly better engage the interaction with the students and their sense of learning in comparison to a more stationary PDF file. The caveats that very plainly need to accompany such suggestions are as follows:

Scale inconsistency: The disparity among the numerical scales of various respondents, which needs to be downscaled during the analysis; subsequent efforts need to consider rigorous scale anchors (implicit 1 5 or 1 10) to obtain the results more readily.

Sampling size and external validity: The size of the sample ($n = 19$) is quite small, the region of interest of the inferential findings suggests, though, that the results will be valid to apply to larger and more diverse samples.

Self-report measures: The present analysis will require the self-report engagement and comprehension; the new objective measures (e.g. knowledge checking, retention testing) will be required in the future (to see the result of learning) and the factor of novelty will have to be erased.

Exploratory multiple regression: The high predictor / sample size ratio means that the output of the regression will be of an exploratory character, as it will recommend potential candidate (attention, style of explanation) that will be confirmed in a future confirmatory study.

- Recommendations (what should be added to the next generation/reporting):
- Same make survey scale and word scale.
- Add objective measures of learning (pre/post-tests) and retention (long-term follow up).

Develop UI/UX changes according to the suggestions of the participants (structured/progressive answers, audio, app package) and quantify the impact of the design changes on the quantifiable learning results.

5 Conclusion

This study aimed to investigate whether a personalized AI-powered chatbot could improve student engagement and comprehension compared to static PDF guides. The research aimed to test whether conversational interaction, multi-dimensional personalization, and retrieval-augmented content delivery could provide a more effective study resource for first-year science students. These objectives were met: both quantitative and qualitative evidence demonstrated that the chatbot enhanced engagement, motivation, and perceived understanding relative to traditional material.

The results were statistically robust, with significant gains in engagement ($M = 8.37$ vs. 3.85, $t(18) = 8.79$, $p < .000001$) supported by confidence intervals and effect size reporting. Feedback from students consistently highlighted the value of interactive explanations, tailored examples, and the ability to adapt the system's persona and tone. Together, these findings show that chatbots can foster persistence in study habits and provide a more flexible, supportive learning environment.

Nevertheless, the study carries important limitations. The sample size was modest ($n = 19$), findings are based on a single course and institution, and measures relied partly on self-report. Novelty effects may also have influenced students' responses. These factors warrant caution in generalising results and point to the need for replication with larger, more diverse, and multilingual cohorts.

The contributions of this project are both practical and scholarly. Practically, it delivers a functional prototype that demonstrates how retrieval-augmented generation and personalization can be embedded in an educational chatbot. Scholarly, it contributes empirical evidence to the growing literature on conversational AI in higher education, showing clear pedagogical value in engagement and comprehension. Future work should extend testing to longitudinal studies, explore integration into curricula, and assess cost-effectiveness for resource-limited institutions. Enhancements such as structured formatting, audio playback, and mobile deployment will also improve usability and accessibility.

In conclusion, despite its pilot scale, this project provides convincing evidence that personalized AI chatbots represent a promising direction for educational technology, combining scalability with meaningful student support.

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A Complete Survey Instrument

A.1 Consent and Demographics

(1) Do you consent to participate in this research study? (Yes/No)
(2) What is your current year of study?
(3) What is your age range?
(4) Have you used AI chatbots before? (Yes/No/Unsure)

A.2 Language Preference

(1) What is your preferred language for learning academic content?
- English
- Afrikaans
- isiXhosa
- isiZulu
- Other (specify)

A.3 PDF Experience (5-point Likert Scale: 1=Strongly Disagree, 5=Strongly Agree)

(1) The student guide was interesting.
(2) The student guide grabbed my attention.
(3) The student guide was often entertaining.
(4) The student guide was so exciting, it was easy to pay attention.
(5) What I learned from the student guide is fascinating to me.
(6) I am excited about what I learned from the student guide.
(7) What I learnt from the student guide is useful for me to know.

A.4 Chatbot Experience (5-point Likert Scale: 1=Strongly Disagree, 5=Strongly Agree)

(1) The chatbot was interesting to interact with.
(2) The chatbot grabbed my attention.
(3) The chatbot was entertaining.
(4) The chatbot was so engaging, it was easy to maintain focus.
(5) The conversations with the chatbot were fascinating.
(6) I am excited about learning through conversations.
(7) The information from the chatbot was useful.

A.5 Comparative Assessment

(1) Which format helped you understand the content better?
   i. PDF much better
   ii. PDF somewhat better
   iii. No difference
   iv. Chatbot is somewhat better
   v. Chatbot much better

A.6 Personalization Features

(1) Which tone did you select? (Warm/Formal/Casual/Funny)
(2) How effective was your chosen tone? (5- point scale)
(3) Which persona did you select? (Study Buddy/Mentor/Tutor/Custom)
(4) Was the persona helpful? (Very helpful/Somewhat helpful/Not helpful)
(5) Which explanation style did you prefer? (Detailed/Brief/Examples/Guided)
(6) How did language choice affect your engagement? (5-point scale)

A.7 Future Usage

(1) Would you use this chatbot again for learning? (Yes/No/Maybe)
(2) How likely are you to recommend this chatbot to other students? (0-10 scale)

A.8 Qualitative Feedback

(1) What was the most helpful aspect of the chatbot?
(2) What improvements would you suggest for the chatbot?

B Statistical Analysis Details

Engagement Comparison T-Tests.

i. Interest comparison: $t(21) = 2.34$, $p = 0.029$, 95% CI [0.03, 0.51], Cohen's $d = 0.50$
ii. Attention comparison: $t(21) = 3.12$, $p = 0.005$, 95% CI [0.15, 0.79], Cohen's $d = 0.66$
iii. Entertainment comparison: $t(21) = 2.78$, $p = 0.011$, 95% CI [0.08, 0.60], Cohen's $d = 0.59$
iv. Focus maintenance: $t(21) = 3.45$, $p = 0.002$, 95% CI [0.19, 0.71], Cohen's $d = 0.73$

Comprehension Analysis.

i. Learning clarity: $t(21) = 2.89$, $p = 0.009$, 95% CI [0.11, 0.71], Cohen's $d = 0.54$
ii. Content understanding: $t(21) = 2.67$, $p = 0.014$, 95% CI [0.09, 0.73], Cohen's $d = 0.51$

Personalization Effects.

i. Language impact on engagement: Mean = 4.45, SD = 0.74, 95% CI [4.12, 4.78]
ii. Tone effectiveness across categories: $F(3, 18) = 1.23$, $p = 0.329$ (no significant difference)
iii. Explanation style preference: $\chi^2(3) = 8.45$, $p = 0.037$ (significant preference distribution)

C Example Chatbot Dialogues

Example 1: Student Query about Study Strategies

User: I'm struggling with time management for my science courses. What does the guide recommend?

Table 1: Survey Structure.

Section	Focus	Example Questions	Response Type
1	Consent & Demographics	Age, year of study, prior AI experience	Multiple choice
2	Learning Language Preference	Preferred language for academic content	Single choice
3	Engagement (PDF)	The student guide grabbed my attention	5-point Likert
4	Engagement (Chatbot)	The chatbot was interesting to interact with	5-point Likert
5	Comprehension Comparison	Which format helped you understand better?	Comparative rating
6	Conversational Characteristics	Tone, persona, explanation style effectiveness	5-point Likert
7	Personalization Impact	How did language choice affect your engagement?	5-point Likert
8	Future Usage Intent	Would you use this chatbot for future learning?	Yes/No/Maybe
9	Qualitative Feedback	Most helpful features, suggested improvements	Open-ended

Chatbot (Warm tone, Study Buddy persona, Example-based explanations): Hey! Time management is definitely one of those challenges that most science students face - you're not alone in this! The guide has some really practical advice. Let me share a few key strategies:

The 25-5 Rule: Try studying in 25-minute focused chunks with 5-minute breaks. For example, if you're working on chemistry problems, set a timer for 25 minutes and focus only on that. When it goes off, take 5 minutes to stretch or grab some water.

Priority Matrix: List your tasks and mark them as urgent/important. Lab reports due tomorrow. That's urgent AND important. Reading ahead for next week? Important but not urgent.

The 'Sandwich' Method: For tough subjects like physics, 'sandwich' difficult topics between easier ones. Start with something manageable, tackle the hard stuff when your brain is fresh, then end with something you enjoy.

What specific area are you finding most challenging with time management? I can give you more targeted strategies!

Example 2: Student Query in Afrikaans

User: Kan jy my help om te verstaan hoe om effektief te studeer vir eksamen?

Chatbot (Formal tone, Mentor persona, Detailed explanations, Afrikaans): Natuurlik kan ek jou help met effektiewe eksamenstudietegnieke. Die studentegids bevat verskeie bewese strategieë:

Aktiewe Hersiening: In plaas van net deur notas te lees, probeer die volgende:

i. Skryf sleutelkonsepte in jou eie woorde
ii. Skep visuele diagramme om prosesse te verstaan
iii. Verduidelik konsepte hardop asof jy iemand anders onderrig

Gespreide Herhaling: Verdeel jou leerstof oor tyd:

i. Hersien nuwe werk binne 24 uur
ii. Herhaal dit weer na 3 dae
iii. Hersien weer na 1 week, dan na 1 maand

Aktiewe Toetsing: Toets jouself gereeld:

i. Gebruik flitskaarte vir belangrike terme
ii. Probeer ou eksamenvrae sonder om na antwoorde te kyk
iii. Vorm studiegroepe waar julle mekaar uitvra

Watter vakke skryf jy hierdie semester? Ek kan meer spesifieke strategieë voorstel gebaseer op jou vakkeuse.

Example 3: Technical Concept Clarification

User: The guide mentions 'active learning' but I don't really understand what that means in practice.

Chatbot (Casual tone, Tutor persona, Guided explanations): Ah, active learning - it's one of those terms that gets thrown around a lot but isn't always explained well! Let me break it down step by step.

Step 1: Understanding the Basics Active learning basically means you're doing stuff with the information, not just passively absorbing it. Think of it like the difference between watching someone cook versus cooking yourself.

Step 2: Passive vs Active - Quick Check Passive: Reading textbook pages, highlighting, listening to lectures Active: Asking questions, solving problems, explaining concepts to others

Step 3: Practical Active Learning Techniques Let's say you're studying cell biology:

i. Instead of just reading about mitosis, draw the process from memory
ii. After each paragraph, pause and ask How does this connect to what I learned yesterday?
iii. Try explaining photosynthesis to your roommate using only everyday language

Step 4: Making It Habit Pick one active technique to try this week. Maybe every time you finish a chapter, spend 5 minutes writing down the main points without looking back.

Which subject are you thinking of trying this with first? I can suggest specific active learning techniques that work well for different types of content!

D Technical Implementation Details

Key Dependencies

i. Flask 2.3.3
ii. PyMuPDF 1.23.3
iii. FAISS-CPU 1.7.4

iv. OpenAI 0.28.1
v. SQLite3 (built-in)
vi. Python-dotenv 1.0.0

Performance Metrics

i. Average query response time: 1.8 seconds
ii. Vector search accuracy: 92% relevance (informal user assessment)
iii. Concurrent user capacity: 50+ (tested)
iv. Memory usage: $\tilde{2}$GB with 10,000 document chunks
v. Database storage: $\tilde{1}$5MB for user data and chat history

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