

Askeptbot: A Machine-Learning Chatbot Companion for Disseminating English Placement Test Information

Muhammad Haziq Abd Rashid^{1*}, Hairul Azhar Mohamad², Amir Lukman Abd Rahman³, Hidayat Rahmah Hassan⁴, Nurhafeza Mohd Akhir⁵, Rasyiqah Batrisya Md Zolkapli⁶, Venny Karolina⁷

¹⁻⁵Akademi Pengajian Bahasa, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia

⁶Centre of Foundation Studies, Universiti Teknologi MARA, Cawangan Selangor, Kampus Dengkil, Selangor, Malaysia

⁷Fakultas Keguruan dan Ilmu Pendidikan (FKIP), Universitas Tanjungpura, Pontianak, Kalimantan Barat, Indonesia

*Corresponding Author

DOI: <https://doi.org/10.47772/IJRISS.2026.100700577>

Received: 24 July 2026; Accepted: 29 July 2026; Published: 07 August 2026

ABSTRACT

The English Placement Test (EPT) allows first-semester diploma students at Universiti Teknologi MARA (UiTM) to be exempted from the compulsory first-level English proficiency course if they sit and pass it. Communicating accurate and timely information about the test across the university's branch campuses has long been difficult, because there has been no single, centralised information hub, and important materials were often lost among the many messages exchanged between lecturers and students. This study introduces AskePTbot, a machine-learning Telegram chatbot developed to act as a one-stop centre for EPT information that is accessible to both lecturers and students. Building the chatbot involved integrating EPT information into its knowledge database and enabling a machine-learning feature designed to return increasingly accurate responses as more users interact with it. The aim was to coordinate the EPT communication system and to ease the workload of the lecturers in charge (LICs) at 22 UiTM branches nationwide, who had previously answered hundreds of enquiries individually or through WhatsApp groups. A two-pronged quantitative design combined secondary data analysis of user analytics with a user satisfaction survey. Analytics from 5,067 users showed a high volume of repeat sessions and interactions per user, and the chatbot returned accurate responses in 94.61% of the sampled cases during a single evaluation week. Survey respondents also reported high satisfaction with the chatbot's usefulness, its ability to meet expectations, its response speed, the clarity of its replies, and its ease of use. AskePTbot therefore functioned as a practical, well-used information hub and was designed to reduce the administrative burden on LICs.

Keywords: AskePTbot; machine learning; English Placement Test (EPT); information dissemination; user engagement

INTRODUCTION

English is the medium of instruction in tertiary education at most Malaysian universities, so students who wish to understand how the academic system works are expected to keep improving their command of the language once they enrol. At Universiti Teknologi MARA (UiTM), first-semester diploma students must take an English proficiency course, either ELC121: Integrated Language Skills I or LCC111: English for Communicative Competence I. Both are compulsory first-level courses intended to strengthen students' core skills in reading, writing, listening, speaking and grammar, and to encourage them to use English in an academic setting. This preparation also supports their readiness for the Malaysian University English Test (MUET) and their subsequent

enrolment in a bachelor's degree programme. Ariastuti and Wahyudin (2022) stressed the value of such courses in producing credible, high-quality graduates and in widening career prospects, given that many leading companies use English as their main language of communication, and that proficiency in the language can improve employability at home and abroad. Related work by Gustanti and Ayu (2021) and Gultom and Oktaviani (2022) reached similar conclusions, noting that most academic resources are written in English, that the shift towards Education 5.0 has made English-language programming languages, software documentation and technical materials more central, and that a good command of English helps students sit standardised tests such as TOEFL, IELTS, GRE and GMAT when they pursue studies abroad. These findings are consistent with the objectives of UiTM and Akademi Pengajian Bahasa (APB) in offering English proficiency courses to diploma and degree students.

Students may be exempted from the proficiency course if they sit and pass an English proficiency assessment known as the English Placement Test (EPT). The administration of the EPT has shifted considerably, moving from a manual pen-and-paper test to a technology-based format delivered through UFUTURE, the university's student-instructor portal. The test assesses three language skills: reading, listening and grammar. Disseminating information about the EPT, however, has remained a challenge because there is no centralised hub, and materials tend to be lost among the many messages exchanged between lecturers and students. Members of the EPT team had to maintain a continuous flow of information to branch campus coordinators, from the briefing stage through to the release of results, so that every branch received accurate updates. Many nationwide UiTM APB assessments, including the EET, ELC and LCC diploma codes as well as the EPT, still lack a single, shared communication tool.

The contribution of this study is an account of a nationwide, multi-campus deployment of a single-purpose information chatbot at scale, spanning 5,067 users across 22 UiTM campuses. Rather than testing a controlled intervention, it documents how students used the chatbot to obtain EPT information and how they rated their experience of it, offering a practitioner-oriented picture of what a coordination tool of this kind looks like in real use.

The study was guided by two objectives: to coordinate and streamline the communication system surrounding the EPT, and to ease the workload of the lecturers in charge (LICs) of the EPT at 22 UiTM branches nationwide. To address these objectives, the study set out to answer the following research questions:

1. What are users' engagement levels with the AskePTbot application, in terms of their user-interaction ratio and the frequency of their enquiries?
2. What are users' satisfaction levels with their overall experience of AskePTbot and with its specific, descriptive satisfaction aspects?

LITERATURE REVIEW

Chatbot Users' Engagement

Chatbots have increasingly been used to support learning, and several studies report positive effects on how actively students engage with them. Hew et al. (2023) found that a learning-buddy chatbot helped students acquire English-as-a-foreign-language (EFL) listening materials and improved their understanding of listening exercises; students found the chatbot easy to communicate with, which encouraged positive engagement. In a related investigation of how a chatbot supports goal setting, seven students reported that the activity helped them clarify their learning goals by giving direction and helping them visualise objectives they had only loosely sketched in their minds (Hew et al., 2023). The same body of work suggests that a lack of guidance is a common source of frustration during self-regulated learning, which a responsive chatbot can help to reduce.

The freedom to ask repeatedly, without social cost, appears to be an important driver of engagement. Richardson et al. (2017) observed that students preferred chatbots because they could raise the same query many times

without fear of being reprimanded or of straining a relationship. Social presence in an educational setting refers to establishing an environment that encourages open and cohesive communication, one in which participants feel at ease asking questions without worrying about causing offence or damaging relationships (Singh et al., 2019). More recent evidence reinforces this picture. In a systematic review of educational chatbots, Kuhail et al. (2023) found that well-designed conversational agents can sustain learner engagement, especially when they personalise their responses, and a systematic review by Lo et al. (2024) reported that generative-AI chatbots such as ChatGPT can raise behavioural and emotional engagement when they offer timely, tailored support. In the specific context of language learning, a meta-synthesis by Koç and Savaş (2025) concluded that AI chatbots can strengthen learners' motivation and willingness to communicate, which is directly relevant to a tool designed to support an English proficiency assessment.

Users' Satisfaction with Chatbot Applications

A second strand of research examines what makes users satisfied with chatbots. Industry and academic surveys alike point to ease of use, speed and convenience as the main reasons users give for preferring chatbots; users are particularly impressed when a chatbot saves them time or makes help easier and quicker to reach, such as through effective customer support or a well-signposted set of frequently asked questions. In the Indonesian market, Sanny et al. (2020) identified a relationship between four factors, namely usefulness, brand image, personality and ease of use, and customer satisfaction with chatbots, and argued that developers should weigh these factors when designing for that market.

Satisfaction has also been documented in service-oriented settings. In healthcare, the Your.MD chatbot offers patients relevant health information, helps them assess possible symptoms and points them to appropriate professionals, and has achieved a high level of user satisfaction (Your.MD, n.d.). Tezcan and Zhang (2014) reported that chatbots are often prioritised in customer service because they are seen as an effective channel, especially when several requests must be handled at once alongside other support channels. Rieke (2018) found that offering a chatbot as an alternative support option during periods when other channels are unavailable increased customer satisfaction. Evidence from mobile users likewise suggests that a brand can shape users' confidence in a chatbot, with perceptions of a chatbot's effectiveness producing more favourable sentiment among younger customers towards their mobile devices (Følstad & Taylor, 2020). Contemporary higher-education studies converge on similar determinants. Yu et al. (2024) found that perceived usefulness was the strongest predictor of satisfaction with an AI chatbot, which in turn shaped users' intention to keep using it, while in the Malaysian context most relevant to the present study, Yahaya et al. (2024) applied the technology acceptance model and found that ease of use was the strongest predictor of students' acceptance of an AI chatbot, followed by perceived usefulness.

METHODOLOGY

Research design

A quantitative approach was adopted to provide structured, numerical evidence on how the chatbot was used and received. The study used a two-pronged design that combined secondary data analysis with a survey. Secondary data analysis draws on data already collected by other researchers or organisations (Weston et al., 2019). In this study, quantitative secondary data in the form of user analytics was used to describe users' reliance on AskePTbot. Neuman (2014) noted that secondary data analysis is a cost-effective and time-saving way of gathering information, particularly for large-scale studies, and that the resulting datasets can help explain events relevant to the research question. This suited the present study, in which roughly 5,000 users across all UiTM campuses in Malaysia interacted with the chatbot.

The second component was a survey. Survey questionnaires collect data from a population or sample through self-reported answers to a set of questions (Rea & Parker, 2014), offering a structured and efficient way to gather information from a large group. As Gehlbach and Brinkworth (2011) observed, surveys can cover a broad range

of topics and are well suited to measuring attitudes, opinions and behaviours. With close to 5,000 users, a survey embedded in the chatbot was the most practical way to gauge perceptions of its overall usefulness.

Sampling

Selecting appropriate participants is central to the validity and generalisability of research findings. This study used convenience sampling, a non-probability technique in which participants are chosen on the basis of their availability and ease of access (Etikan et al., 2016). The approach offers clear advantages in time and resources, since recruiting participants can otherwise be slow and costly, especially when a population is geographically dispersed (Neuman, 2014). This fitted the context of the study, in which AskEPTbot users came from various states and districts across Malaysia, following the locations of the university's 22 campuses. Convenience sampling allows data to be gathered quickly from readily available participants, which makes it well suited to exploratory or pilot work (Sekaran & Bougie, 2016).

The technique does, however, carry limitations that must be acknowledged. The main concern is selection bias, where the sample may not accurately represent the target population (Etikan et al., 2016); this can arise if the readily available participants share characteristics that are not typical of the wider population. In this study, the user satisfaction survey was attached to the chatbot and was easily accessible to any user who wished to respond, which reinforced the logic of using convenience sampling. The total population was 5,067 AskEPTbot users, a figure drawn from Dialogflow Analytics on the back end of the development platform over a one-month period, from 24 September 2025 to 24 October 2025. Comparable windows have been used elsewhere; for example, Ait-Mlouk and Jiang (2020) reported that KBot, a chatbot specialising in graph-based queries, used one month of user data to run its statistical tests, and the process was repeated across several cycles to ensure accurate reporting.

From this population of 5,067 users, smaller samples were drawn to answer the two research questions. The first sample was taken from a specific week within the study month that included several triggered stages of the EPT process, and was used to measure the accuracy of AskEPTbot's responses to user prompts; this segment contained 2,487 users. A second segment of 454 users answered the satisfaction survey embedded in the chatbot. The samples narrow progressively as the data-collection goals become more specific, so segmenting the population in this way was necessary to address each objective properly.

Instruments

The study developed a customised chatbot application, AskEPTbot, and combined two research instruments to build a fuller picture of the research questions: user data analytics and a user satisfaction questionnaire.

AskEPTbot Application and Its Features

AskEPTbot is a machine-learning Telegram chatbot powered by DialogFlow that serves as a one-stop centre for sharing EPT information with both lecturers and students through the Telegram application. Its development involved integrating EPT information into the chatbot's knowledge database alongside a machine-learning feature designed to improve the accuracy of responses as the number of user prompts grows. The wider educational setting is changing quickly, particularly with the growing use of artificial intelligence (AI) in education. Avisyah et al. (2023) explained that chatbot technology uses natural language processing (NLP) together with AI to respond quickly and produce relevant answers, while Manullang et al. (2023) noted that Telegram is a convenient platform for an AI chatbot because its data are stored in the cloud, which makes it easier to train the bot to give appropriate responses. Telegram has already served as a base for educational chatbots; Khalil and Rambech (2022), for example, developed Eduino, a Telegram-based learning chatbot for higher education, and reported that the platform's accessibility supported student use. AskEPTbot was therefore implemented on Telegram for the convenience of both developers and users.

Students reach the EPT Telegram channel through a unique link or by scanning a QR code, after which they are directed to the chatbot to ask questions about the EPT, such as "When can we take the EPT?". The system analyses each prompt against keywords linked to readily available responses; in the example above, the words "when" and "take EPT", or similar keywords, are automatically matched to the stored response on the dates of the test. The application also carries a machine-learning (ML) capacity that improves the accuracy of responses as more prompts are received. One notable feature is that it suggests further prompts closely related to the user's most recent question. Figure 1 shows the further prompts generated after the ML feature interprets an earlier prompt.



Figure 1: Suggested further prompts generated by AskePTbot

AskePTbot is also an adaptive ML model. It can respond to personalised requests, provide a step-by-step guide to each stage of the EPT process, and offer detailed explanations. Where a simpler explanation is helpful for students, it can reply with relevant visual aids or infographics, and it supports continuous conversational exchanges so that users do not have to start a new conversation each time. Together, these features are intended to give AskePTbot informative, human-like interactions. In its current form, the system works through intent and keyword matching alongside an adaptive suggested-prompt feature, and its machine-learning capability improves response accuracy through ongoing background calibration of the knowledge base as more prompts are received. The accuracy reported later is a snapshot from a single evaluation window rather than a longitudinal measure of this improvement.

User data analytics

User data analytics refers to the collection, analysis and interpretation of data generated by users as they interact with a system or platform (Ha et al., 2022). For a chatbot, this can include intent data, session data and interaction data, all of which offer insight into user behaviour and help researchers identify areas for improvement (Zheng et al., 2009). In this study, user data analytics was used to examine the interactions between users and the chatbot, focusing on the volume and accuracy of the responses AskePTbot returned. This provided an objective picture of user behaviour that complemented the subjective insights from the satisfaction questionnaire. Because these metrics are generated automatically by the system as telemetry rather than self-reported, they provide an objective behavioural record that does not rely on respondent recall. To address the objectives, enquiries were grouped into two categories, focusing on a predefined set of enquiry types so that the analytics could be compared consistently. The categories and types of enquiries are shown in Table 1.

Table 1: Categories and types of enquiries

No.	Enquiry category	Type of enquiry
1	Significant event-based enquiries on AskePTbot	Telegram group link sharing
		Payment procedures
		Payment status validation
		Trial test paper access
2	Significant non-event-based (general) enquiries on AskePTbot	EPT test format
		Tutorials on EPT
		Important dates for EPT
		Introduction to EPT

As Table 1 shows, the analytics distinguished two enquiry categories: significant event-based enquiries and significant non-event-based (general) enquiries. Each category was broken down into four types. Event-based enquiries comprised Telegram group link sharing, payment procedures, payment status validation and trial test paper access. General enquiries comprised the EPT test format, tutorials on the EPT, important dates for the EPT and an introduction to the EPT.

User Satisfaction Survey

A user satisfaction survey is an instrument designed to measure users' perceptions of, and attitudes towards, a system or service (Pramatari & Theotokis, 2009). It usually asks users to rate their satisfaction with various aspects of the system and is valuable for understanding user perspectives and identifying where a system may fall short of user needs (Sauro & Lewis, 2016). For this study, a survey used by Segura et al. (2019) was adapted to capture users' perceptions of AskePTbot's ease of use, functionality and overall satisfaction. The questionnaire was designed to be clear, concise and easy to complete. Its items evaluated the chatbot's ease of use, accuracy, appropriateness, responsiveness and overall usefulness. Each aspect was captured with a single categorical item rather than a multi-item scale, so the responses are reported as descriptive proportions.

Using both instruments together provided complementary perspectives on the research questions. The analytics offered objective insight into user behaviour, while the questionnaire provided subjective, scale-based feedback on users' experiences and perceptions.

Data Collection and Analysis

The data came from the two instruments, and each followed its own collection procedure. For the analytics, Google Dialogflow was used to obtain a range of metrics related to AskePTbot. Dialogflow supplies developers with a large volume of data across several dimensions. One user may create more than one session at different times; one session may contain one or more interactions; and a session is treated as complete once no further prompt is received within two minutes.

To align the data with the objectives, several back-end settings were adjusted. For the first segmentation, the analytics were set to display input from 24 September 2025 to 24 October 2025, a one-month window that gave an overview of users' reliance on the chatbot. For the second segmentation, the window was narrowed to one week of interactions so that the accuracy of the responses could be evaluated in detail.

The second instrument, which captured satisfaction data, followed a different procedure. The survey was embedded within a series of follow-up questions supported by the chatbot's natural language processing. Once the relevant intent was triggered, users were invited to complete a short survey hosted on Quizizz, which used

gamification elements to encourage the target users to take part. Participation was voluntary and responses were collected anonymously, with no personally identifiable information recorded.

Once collection was complete, the data from both instruments were tabulated and summarised into statistical charts and diagrams. The analytics and survey results were analysed using standard descriptive statistics, including ratios and percentages. The analytics produced a user-interaction ratio made up of three values, namely the number of users, the number of sessions and the number of interactions, which accumulate in a top-down manner. A user is identified when a person enters the chatbot with at least one prompt, and later entries from the same person are matched to that user through their use of the same device. Once no further prompt is received after an idle interval of two minutes, the system records one complete session; sessions therefore refer to the total number of completed sessions generated by the cumulative number of users at different points in time. On this basis, one user may generate more than one session on the same day or on different days, and each session may contain more than one interaction, where an interaction is one complete prompt-and-response pair, or one prompt-response frequency. A user could thus create one or more sessions, each with one or more interactions. Given this mechanism, the overall engagement results were expected to appear in a top-down form and to increase from smaller to larger figures along the user-interaction ratio.

For the satisfaction survey, which used a five-point or four-point categorical scale, the data were analysed as percentages within each category. This simple, descriptive approach made it easy to see whether the survey findings reflected the earlier analysis of engagement, without over-complicating the analytical process.

RESULTS

This section presents two broad sets of findings that correspond to the two forms of analysis: users' engagement statistics and the usefulness of AskePTbot to its users.

User-interaction Ratio for One Month

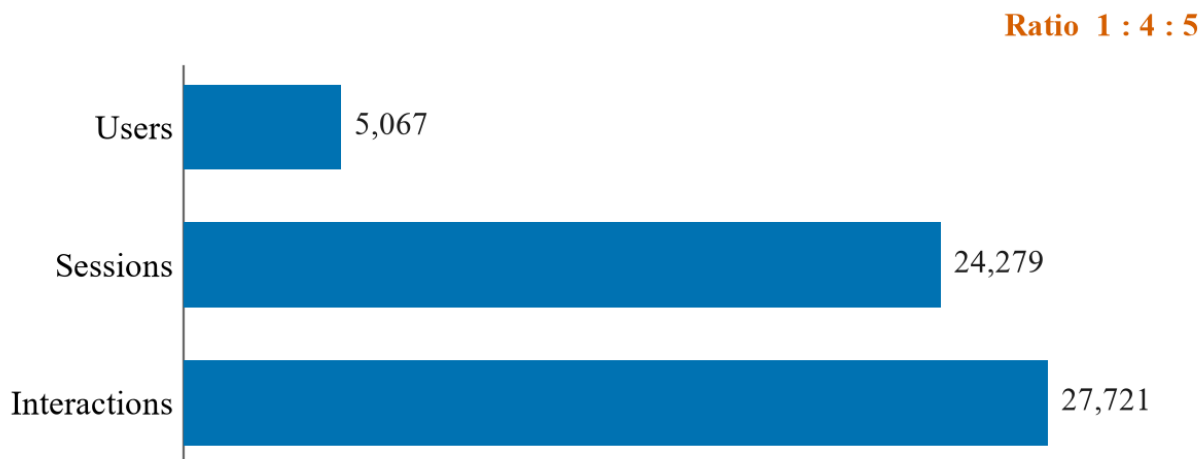


Figure 2: User-interaction ratio for one month

Figure 2 presents the user-interaction ratio for the one-month period from 24 September 2025 to 24 October 2025 among AskePTbot users. It describes the users' behaviour in terms of the number of sessions and interactions they generated. The 5,067 users cumulatively created 24,279 sessions and 27,721 interactions. Expressed as a ratio, this averages approximately four sessions and five interactions per user across the month, a ratio of about 1:4:5. On average, each session contained close to one prompt-and-response pair (roughly 1.14), which suggests that users typically returned for short, targeted look-ups rather than extended single sessions. The interpretation of this usage pattern is taken up in the Discussion.

Overall enquiries by event and non-event type

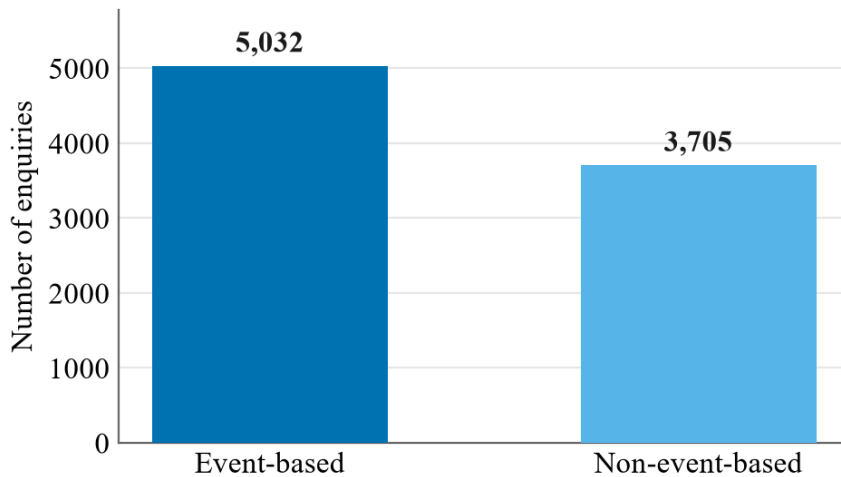


Figure 3: Number of enquiries by event and non-event type

Figure 3 shows the overall number of enquiries by event type (specific, occasion-based enquiries) and non-event type (general enquiries). Of the 8,737 enquiries received in one month, event-based enquiries accounted for 5,032, which was higher than the 3,705 non-event-based enquiries. This suggests that when an announcement was made about a specific occasion within the EPT workflow, users were more inclined to send enquiries through AskEPTbot to learn more about that event than to send general enquiries unconnected to any announcement. The 8,737 categorised enquiries fall within the eight predefined enquiry types and are therefore a subset of the total interactions, which also include prompts outside these categories.

Engagement by type of event-based and general enquiry

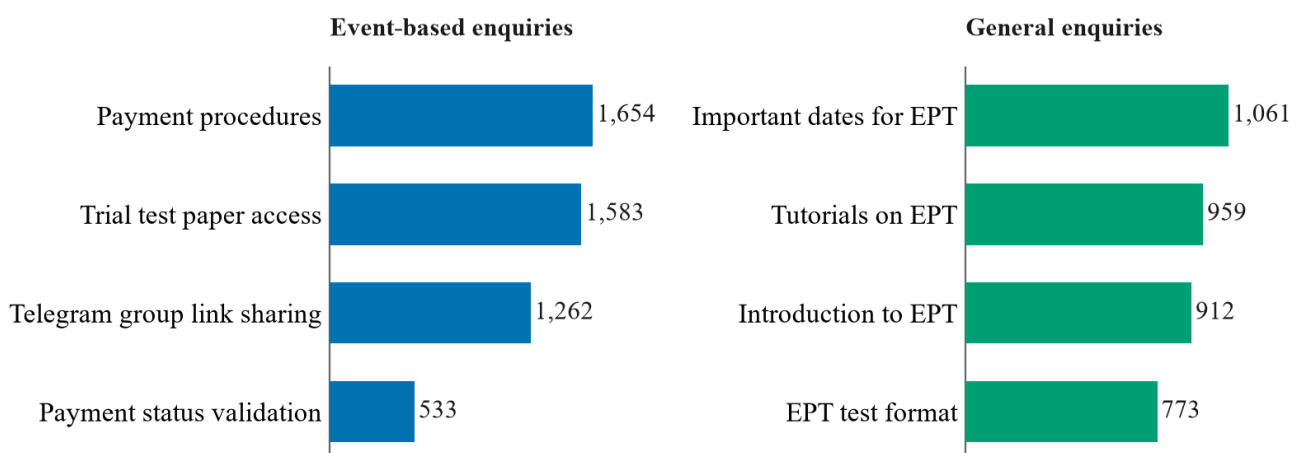


Figure 4: Frequencies of event-based enquiries (left) and general enquiries (right)

Figure 4 breaks the two categories down by type and helps to explain the pattern in Figure 3. Among the four most common event-based enquiries, namely Telegram group link sharing, payment procedures, payment status validation and trial test paper access, payment procedures drew the highest number of enquiries with 1,654 counts, while payment status validation drew the lowest with 533. This indicates that when the fee-payment window was announced, students turned to AskEPTbot to ask about payment procedures more than about other events, which is consistent with the higher event-based total shown in Figure 3. Among the four most common general enquiries, namely the EPT test format, tutorials on the EPT, important dates for the EPT and an introduction to the EPT, important dates drew the highest number with 1,061 counts, while the test format drew

the lowest with 773. This suggests that students used AskEPTbot mainly to check the important dates they needed to keep in mind, rather than the format of the test questions.

Accuracy of AskEPTbot's responses



Figure 5: Percentage of response accuracy by AskEPTbot for one week

Figure 5 presents the accuracy of AskEPTbot's responses over one week, from 1 October 2025 to 6 October 2025, within the wider month of data. Accuracy was determined from the system's response logs and verified by the EPT management team, using a simple dichotomous classification of accurate and inaccurate responses. AskEPTbot returned accurate responses in 94.61% of cases, against 5.39% that were inaccurate. Accuracy over this one-week window was therefore high, although it reflects a single evaluation period rather than performance across the full month.

Overall satisfaction with AskEPTbot and its component ratings

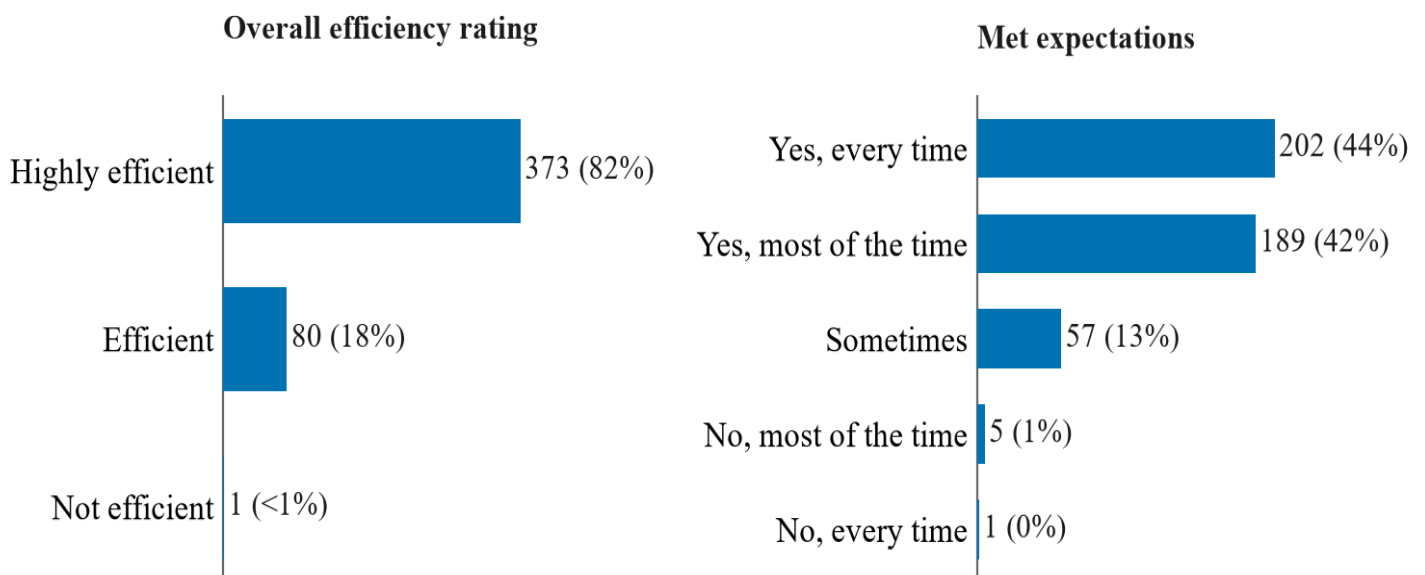


Figure 6: Overall efficiency rating (left) and whether AskEPTbot met users' expectations (right)

Figure 6 shows an overall efficiency rating across three categories, namely not efficient, efficient and highly efficient, from the 454 respondents to the satisfaction survey. In total, 373 respondents (82%) rated AskEPTbot as highly efficient, 80 (18%) as efficient, and 1 (<1%) as not efficient. Most respondents therefore placed the chatbot at the top of the efficiency scale.

The remaining charts describe users' satisfaction across five further aspects: whether the application met their expectations, how easy the responses were to understand, the speed of the replies, the appropriateness of the interaction pace, and the appropriateness of the responses. As the right-hand panel of Figure 6 shows, 202 respondents (44%) felt that AskEPTbot met their expectations every time, and 189 (42%) felt it did so most of the time. Together these two categories account for 391 respondents (86%) who agreed that AskEPTbot gave responses that met their expectations. The two most positive categories thus accounted for the large majority of responses.

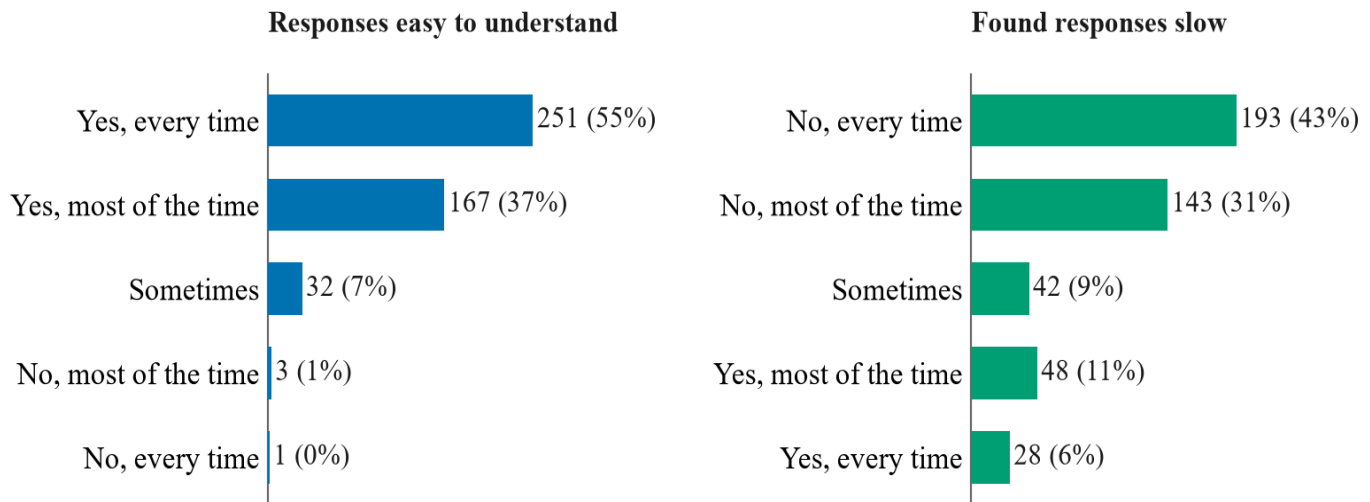


Figure 7: Ease of understanding the responses (left) and perceived speed of the responses (right)

Figure 7 reports two further aspects. For ease of understanding, 251 respondents (55%) found the responses easy to understand every time, and 167 (37%) most of the time, giving a combined 418 (92%). For response speed, 193 respondents (43%) did not find the responses slow at any time, and 143 (31%) did not find them slow most of the time, giving a combined 336 (74%) who agreed that AskEPTbot did not respond slowly. In both aspects, the two most positive categories together accounted for the large majority of responses.

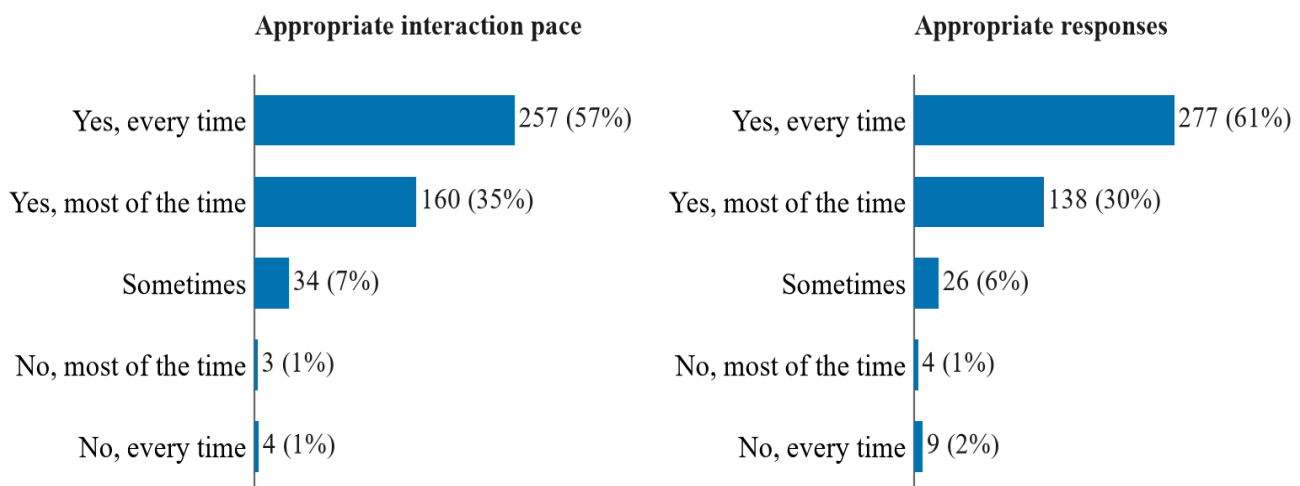


Figure 8: Appropriateness of the interaction pace (left) and appropriateness of the responses (right)

Figure 8 reports the final two aspects. For the interaction pace, 257 respondents (56%) found it appropriate every time, and 160 (35%) most of the time, giving a combined 417 (91%). For the appropriateness of the responses, 277 respondents (61%) found the responses appropriate every time, and 138 (30%) most of the time, giving a

combined 415 (91%). In both aspects, the two most positive categories together accounted for the large majority of responses.

DISCUSSION

The results speak to both research questions. On the first, the analytics show that students returned to AskEPTbot repeatedly, generating many short sessions to gather information about the EPT. The low number of interactions per session, at about 1.14, suggests that these were brief, targeted look-ups rather than extended exchanges, a pattern consistent with the role of an information hub rather than with deep conversational engagement. This repeated, low-friction use is nonetheless in keeping with Richardson et al. (2017), who found that students favoured chatbots because they could ask many questions without fear of reprimand or of causing emotional harm. Users were also more inclined to raise enquiries about specific announced events than general questions, which suggests that the chatbot was most valued at the points in the EPT cycle where timely information mattered most. This pattern aligns with Hew et al. (2023), who showed that a chatbot can provide students with valuable, well-timed assistance and thereby encourage a positive response.

On satisfaction, AskEPTbot consistently returned accurate and precise responses, with an accuracy rate of 94.61% over the sampled week. Accuracy of this kind has been linked to user satisfaction in other service settings; the Your.MD healthcare chatbot, for instance, achieved high satisfaction by supplying accurate health information (Your.MD, n.d.). Most respondents also reported strong satisfaction with their overall experience, judged by whether the application met their expectations, how easily they understood the responses, the speed of the replies, and the appropriateness of the interaction. These findings align with recent evidence that perceived usefulness is among the strongest drivers of satisfaction with educational chatbots (Yu et al., 2024), and that students particularly value the immediacy of a chatbot's responses (Sáiz-Manzanares et al., 2023), which mirrors the high ratings AskEPTbot received for response speed. Read through the lens of the technology acceptance model, the aspects rated here correspond to its central constructs: the usefulness and expectation-meeting items reflect perceived usefulness, while the ease-of-understanding and interaction items reflect perceived ease of use (Yahaya et al., 2024). The present study describes these perceptions rather than testing the model's causal structure. Taken together, the results point to a positive user experience with AskEPTbot. These findings should, however, be read as descriptive: the satisfaction figures come from a voluntary, in-application survey completed by 454 of the 5,067 users, about 9%, and this self-selected group is likely to over-represent satisfied and persistent users.

CONCLUSION

This study set out to coordinate the communication system surrounding the EPT and to ease the workload of the lecturers in charge across UiTM's branch campuses. The evidence indicates that AskEPTbot served the first aim well. Usage was high, with users generating many short sessions and interactions and gravitating towards event-based enquiries at the moments when timely information was most needed, and the chatbot answered accurately in the large majority of sampled cases. Respondents also rated their experience positively across the efficiency, expectation-meeting, clarity, speed and appropriateness of the responses. By acting as a single, accessible hub, AskEPTbot may have reduced the need for lecturers to answer repeated enquiries individually or through group chats; its direct effect on the workload of the lecturers in charge was not measured and remains an inference to be tested. The study is limited by its convenience-sampling design, the voluntary nature of the satisfaction survey (about 9% of users), its reliance on descriptive statistics, and its focus on a single assessment at one university, so the findings should be read as indicative rather than generalisable. As reviews of university support chatbots note, such tools are increasingly moving beyond answering frequently asked questions towards more personalised, proactive support (Peyton et al., 2025), a direction that AskEPTbot's machine-learning feature is well placed to pursue. Future work could test the chatbot across other assessments and campuses, compare it with alternative platforms, and examine how its machine-learning feature improves accuracy over longer periods.

ACKNOWLEDGEMENTS

The authors thank the EPT team and Akademi Pengajian Bahasa, Universiti Teknologi MARA, for their support in developing and deploying AskePTbot.

Declarations

Ethics approval and informed consent

Participation in the user satisfaction survey was voluntary, and responses were collected anonymously without any personally identifiable information.

Conflict of interest

The authors declare that they have no conflict of interest.

Funding

This study is funded by APB Incentive Grant or “Geran Insentif APB” from Akademi Pengajian Bahasa, Univesiti Teknologi MARA Shah Alam

Data availability

The datasets generated and analysed during the study are available from the corresponding author on reasonable request.

REFERENCES

1. Ait-Mlouk, A., & Jiang, L. (2020). KBot: A knowledge graph based chatbot for natural language understanding over linked data. *IEEE Access*, 8, 149220–149230. <https://doi.org/10.1109/ACCESS.2020.3016142>
2. Ariastuti, M. D., & Wahyudin, A. Y. (2022). Exploring academic performance and learning style of undergraduate students in English education program. *Journal of English Language Teaching and Learning*, 3(1), 67–73.
3. Avisyah, G. F., Putra, I. J., & Hidayat, S. S. (2023). Open artificial intelligence analysis using ChatGPT integrated with Telegram bot. *Jurnal ELTIKOM*, 7(1), 60–66. <https://doi.org/10.31961/eltikom.v7i1.724>
4. Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4.
5. Følstad, A., & Taylor, C. (2020). Conversational repair in chatbots for customer service: The effect of expressing uncertainty and suggesting alternatives. In A. Følstad et al. (Eds.), *Chatbot research and design (CONVERSATIONS 2019)*. Lecture Notes in Computer Science (Vol. 11970, pp. 201–214). Springer. https://doi.org/10.1007/978-3-030-39540-7_14
6. Gehlbach, H., & Brinkworth, M. E. (2011). Measure twice, cut down error: A process for enhancing the validity of survey scales. *Review of General Psychology*, 15(4), 380–387.
7. Gultom, S., & Oktaviani, L. (2022). The correlation between students' self-esteem and their English proficiency test result. *Journal of English Language Teaching and Learning*, 3(2), 52–57.
8. Gustanti, Y., & Ayu, M. (2021). The correlation between cognitive reading strategies and students' English proficiency test. *Journal of English Language Teaching and Learning*, 2(2), 95–100.
9. Ha, S., Monadjemi, S., Garnett, R., & Ottley, A. (2022). A unified comparison of user modeling techniques for predicting data interaction and detecting exploration bias. *IEEE Transactions on Visualization and Computer Graphics*, 29(1), 483–492.

10. Hew, K. F., Huang, W., Du, J., & Jia, C. (2023). Using chatbots to support student goal setting and social presence in fully online activities: Learner engagement and perceptions. *Journal of Computing in Higher Education*, 35(1), 40–68.
11. Khalil, M., & Rambech, M. (2022). Eduino: A Telegram learning-based platform and chatbot in higher education. In *Learning and collaboration technologies: Novel technological environments* (pp. 188–204). Springer. https://doi.org/10.1007/978-3-031-05675-8_15
12. Koç, F. Ş., & Savaş, P. (2025). The use of artificially intelligent chatbots in English language learning: A systematic meta-synthesis study of articles published between 2010 and 2024. *ReCALL*, 37(1), 4–21. <https://doi.org/10.1017/S0958344024000168>
13. Kuhail, M. A., Alturki, N., Alramlawi, S., & Alhejori, K. (2023). Interacting with educational chatbots: A systematic review. *Education and Information Technologies*, 28(1), 973–1018. <https://doi.org/10.1007/s10639-022-11177-3>
14. Lo, C. K., Hew, K. F., & Jong, M. S.-Y. (2024). The influence of ChatGPT on student engagement: A systematic review and future research agenda. *Computers & Education*, 219, Article 105100. <https://doi.org/10.1016/j.compedu.2024.105100>
15. Manullang, E. B., Hartati, R., & Nasution, R. D. (2023). Utilization of chatbot Telegram AI to promote students' creative and innovative entrepreneurship in learning context. *Southeast Asia Language Teaching and Learning (SALTel) Journal*, 6(2), 27–35. <https://doi.org/10.35307/saltel.v6i2.111>
16. Neuman, W. L. (2014). *Social research methods: Qualitative and quantitative approaches* (7th ed.). Pearson.
17. Peyton, K., Unnikrishnan, S., & Mulligan, B. (2025). A review of university chatbots for student support: FAQs and beyond. *Discover Education*, 4(1), Article 21. <https://doi.org/10.1007/s44217-025-00397-7>
18. Pramata, K., & Theotokis, A. (2009). Consumer acceptance of RFID-enabled services: A model of multiple attitudes, perceived system characteristics and individual traits. *European Journal of Information Systems*, 18(6), 541–552.
19. Rea, L. M., & Parker, R. A. (2014). *Designing and conducting survey research: A comprehensive guide*. John Wiley & Sons.
20. Richardson, J. C., Maeda, Y., Lv, J., & Caskurlu, S. (2017). Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior*, 71, 402–417.
21. Rieke, T. D. (2018). *The relationship between motives for using a chatbot and satisfaction with chatbot characteristics in the Portuguese Millennial population: An exploratory study* [Doctoral dissertation, University of Porto].
22. Sáiz-Manzanares, M. C., Marticorena-Sánchez, R., Martín-Antón, L. J., González-Díez, I., & Almeida, L. (2023). Perceived satisfaction of university students with the use of chatbots as a tool for self-regulated learning. *Heliyon*, 9(1), Article e12843. <https://doi.org/10.1016/j.heliyon.2023.e12843>
23. Sanny, L., Susastra, A., Roberts, C., & Yusramdaleni, R. (2020). The analysis of customer satisfaction factors which influence chatbot acceptance in Indonesia. *Management Science Letters*, 10(6), 1225–1232.
24. Sauro, J., & Lewis, J. R. (2016). *Quantifying the user experience: Practical statistics for user research* (2nd ed.). Morgan Kaufmann.
25. Segura, C., Palau, À., Luque, J., Costa-Jussà, M. R., & Banchs, R. E. (2019). Chatbol, a chatbot for the Spanish "La Liga". In *9th International Workshop on Spoken Dialogue System Technology* (pp. 319–330). Springer.
26. Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). John Wiley & Sons.
27. Singh, J., Joseph, M. H., & Jabbar, K. B. A. (2019). Rule-based chatbot for student enquiries. *Journal of Physics: Conference Series*, 1228(1), Article 012060.
28. Tezcan, T., & Zhang, J. (2014). Routing and staffing in customer service chat systems with impatient customers. *Operations Research*, 62(4), 943–956.

29. Weston, S. J., Ritchie, S. J., Rohrer, J. M., & Przybylski, A. K. (2019). Recommendations for increasing the transparency of analysis of preexisting data sets. *Advances in Methods and Practices in Psychological Science*, 2(3), 214–227.
30. Yahaya, S. N., Bakar, M. H., Jabar, J., Abdullah, M. M., & Segaran, Y. (2024). Evaluating students acceptance of AI chatbot to enhance virtual collaborative learning in Malaysia. *International Journal of Sustainable Development and Planning*, 19(1), 209–219. <https://doi.org/10.18280/ijstdp.190119>
31. Your.MD. (n.d.). Our mission is simple: To help you find your health. Retrieved October 14, 2019, from <https://www.your.md/about/>
32. Yu, C., Yan, J., & Cai, N. (2024). ChatGPT in higher education: Factors influencing ChatGPT user satisfaction and continued use intention. *Frontiers in Education*, 9, Article 1354929. <https://doi.org/10.3389/feduc.2024.1354929>
33. Zheng, K., Padman, R., Johnson, M. P., & Diamond, H. S. (2009). An interface-driven analysis of user interactions with an electronic health records system. *Journal of the American Medical Informatics Association*, 16(2), 228–237.