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EDUHELPER as A Smart Educational Service: An Empirical Study of AI Chatbots, Student Acceptance, and Economic Value Creation in Higher Education

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Abstract: *Higher education institutions increasingly deploy artificial intelligence (AI)–based chatbots to enhance student services, reduce administrative workload, and improve institutional efficiency. This study presents an empirical investigation of EduHelper, an AI-powered educational chatbot implemented in a higher education institution in Goa. Moving beyond a purely technical evaluation, the research integrates perspectives from education technology, service marketing, and economics. Using a mixed-method design, system performance data are combined with a structured student survey analyzed through Structural Equation Modeling (SEM). The results indicate that perceived usefulness and perceived service value significantly influence students' behavioral intention to use the chatbot, which in turn affects willingness to pay for AI-enabled educational services. From a commercial standpoint, the findings demonstrate substantial cost savings through automation of routine inquiries and scalable service delivery. The study contributes to interdisciplinary literature by positioning educational chatbots as marketable smart services that generate measurable economic and societal value.*

Keywords: Educational chatbots, artificial intelligence, technology acceptance, perceived value, SEM, higher education, service marketing

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI) and natural language processing (NLP) has significantly transformed service delivery across sectors, including higher education. Universities and colleges face increasing pressure to provide timely, personalized, and efficient services to students while operating under constrained budgets and limited administrative capacity. Routine academic and administrative inquiries—such as questions related to attendance, timetables, examination schedules, and institutional procedures—consume substantial staff time and often result in delayed responses.

AI-powered chatbots have emerged as a promising solution to these challenges. By simulating human conversation and leveraging institutional databases, chatbots can provide round-the-clock support, reduce response times, and enhance the overall student experience. While prior studies largely emphasize the technical feasibility and functional performance of educational chatbots, limited empirical research examines their acceptance by students, their perceived value as a service innovation, and their broader commercial and economic implications.

This study addresses this gap by examining the implementation of *EduHelper*, an AI-enabled chatbot deployed in a higher education institution in Goa. The research adopts an interdisciplinary approach that integrates information systems theory, service marketing concepts, and economic analysis. Specifically, the study evaluates system effectiveness, student technology acceptance, perceived service value, and willingness to pay, thereby positioning the chatbot as both an educational support tool and a commercially viable smart service.

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II. REVIEW OF LITERATURE

The evolution of chatbots and conversational agents can be traced back to foundational work in artificial intelligence and human–computer interaction. Turing's (1950) seminal paper introduced the concept of machine intelligence through the imitation game, establishing a theoretical basis for evaluating intelligent behavior in machines. Building on this idea, Weizenbaum (1966) developed ELIZA, one of the earliest conversational programs, demonstrating that rule-based natural language interaction could simulate human-like conversation. These early efforts laid the groundwork for contemporary chatbot systems used across domains, including education.

With advances in natural language processing (NLP) and web technologies, chatbots have increasingly been adopted in higher education to address administrative and academic communication challenges. Dahiya (2017) described chatbots as effective conversational tools capable of delivering rapid responses and reducing dependency on human operators. Early educational implementations primarily relied on rule-based architectures, focusing on accuracy and response speed for predefined queries.

Recent studies have explored chatbot deployment specifically within college and university environments. Turkar et al. (2019) demonstrated that a Google Actions–based college chatbot significantly improved accessibility to institutional information, enabling students to obtain responses to common queries at any time. Similarly, Jain (2019) proposed an iterative model for a college enquiry chatbot, highlighting the importance of continuous training and refinement to enhance response accuracy and system reliability.

Several researchers have focused on the architectural and technological design of educational chatbots. Magnale et al. (2021) presented the RUBAN College Enquiry Chatbot, emphasizing the effectiveness of rule-based logic in resolving routine student inquiries with minimal computational overhead. Shingte et al. (2019) examined chatbot development for educational institutions, reporting improved responsiveness and reduced administrative workload. Sharma (2020) further demonstrated that Python-based chatbot frameworks offer scalability and ease of integration with institutional databases, making them suitable for real-world academic environments.

Beyond functional performance, recent literature has evaluated educational chatbots from a pedagogical and service-quality perspective. Gonda et al. (2018) assessed educational chatbots using the seven principles for good teaching and found that chatbots can positively influence student engagement and learning support when aligned with instructional goals. Sarma and Gayatri (2021) reinforced these findings by showing that college enquiry chatbots enhance student satisfaction through faster query resolution and consistent information delivery.

Collectively, the literature indicates that educational chatbots have progressed from simple rule-based conversational tools to strategically important digital services within higher education. However, most existing studies remain focused on technical design, functional evaluation, or pedagogical support. Limited empirical research integrates student acceptance, perceived service value, and economic implications of chatbot adoption. This study addresses this gap by examining educational chatbots as smart service innovations, combining artificial intelligence, marketing perspectives, and economic value creation within a unified empirical framework.

III. CONCEPTUAL FRAMEWORK AND HYPOTHESES

3.1 Conceptual Model

The conceptual framework integrates the Technology Acceptance Model with perceived value and commercial outcomes. System effectiveness is proposed to influence perceived usefulness and perceived value. These perceptions shape students' behavioral intention to use the chatbot, which subsequently affects their willingness to pay for AI-enabled educational services.

3.2 Hypotheses

H1: System effectiveness positively influences perceived usefulness of the educational chatbot.
H2: System effectiveness positively influences perceived service value of the educational chatbot.
H3: Perceived usefulness positively influences behavioral intention to use the chatbot.
H4: Perceived service value positively influences behavioral intention to use the chatbot.
H5: Behavioral intention positively influences willingness to pay for chatbot-based educational services.
H6: Perceived service value positively influences willingness to pay for chatbot-based educational services.

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IV. RESEARCH METHODOLOGY

4.1 Research Design

The study adopts a mixed-method research design combining system performance evaluation with a cross-sectional survey of students who interacted with the EduHelper chatbot during a pilot deployment.

4.2 System Description

EduHelper is a web-based chatbot developed using Python and Flask, incorporating a hybrid rule-based and probabilistic response mechanism. The system integrates with a relational database to retrieve academic and administrative information and provides instant responses through a browser-based interface.

4.3 Survey Instrument and Measurement Scales

A structured questionnaire was administered to students (N = 220). All items were measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Measurement Scales:

System Effectiveness (SEF): Accuracy, response speed, reliability
Perceived Usefulness (PU): Usefulness in resolving queries, improving efficiency
Perceived Value (PV): Overall value, time savings, convenience
Behavioral Intention (BI): Intention to continue using the chatbot
Willingness to Pay (WTP): Willingness to pay for AI-enabled support services

4.4 Data Analysis Technique

Structural Equation Modeling (SEM) was employed to test the hypothesized relationships. Reliability, convergent validity, discriminant validity, and model fit were assessed prior to hypothesis testing.

V. RESULTS

5.1 Descriptive and System Performance Results

System logs indicated that approximately 80% of routine student and administrative queries were resolved automatically without human intervention. Average response time was under two seconds, demonstrating high operational efficiency.

5.2 Measurement Model Assessment

All constructs demonstrated satisfactory reliability and validity.

Table 1. Measurement Model Results

Construct	CR	AVE
System Effectiveness	0.88	0.64
Perceived Usefulness	0.91	0.68
Perceived Value	0.89	0.66
Behavioral Intention	0.92	0.70
Willingness to Pay	0.87	0.62

5.3 Structural Model Results

Table 2. Structural Equation Model Results

Hypothesis	Path	β	t-value	p-value	Result
H1	SEF → PU	0.56	7.84	<0.001	Supported
H2	SEF → PV	0.49	6.91	<0.001	Supported
H3	PU → BI	0.41	5.63	<0.001	Supported

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H4	PV → BI	0.38	5.12	<0.001	Supported
H5	BI → WTP	0.46	6.02	<0.001	Supported
H6	PV → WTP	0.29	4.08	<0.001	Supported

5.4 Model Fit Indices

Table 3. Model Fit Statistics

Fit Index	Recommended	Observed
χ^2/df	< 3.00	2.14
CFI	> 0.90	0.94
TLI	> 0.90	0.93
RMSEA	< 0.08	0.056
SRMR	< 0.08	0.048

VI. DISCUSSION

The results confirm that system effectiveness significantly enhances perceived usefulness and perceived value, which in turn drive students' intention to use educational chatbots. Perceived value and behavioral intention also play a critical role in shaping willingness to pay, highlighting the commercial potential of AI-enabled educational services. These findings extend technology acceptance theory by incorporating monetization outcomes in an educational context.

VII. COMMERCIAL AND ECONOMIC IMPLICATIONS

From a commercial perspective, educational chatbots can be marketed as Software-as-a-Service (SaaS) solutions to higher education institutions. Automation of routine queries can reduce administrative workload by 30–50%, translating into estimated annual cost savings of INR 8–15 lakhs for medium-sized institutions. At a macro-economic level, widespread adoption of AI-enabled student support systems can enhance institutional efficiency, reduce operational costs, and support national digital education initiatives.

VIII. CONTRIBUTIONS OF THE STUDY

8.1 Theoretical Contributions

The study extends TAM by integrating perceived value and willingness to pay in the context of AI-enabled educational services. It also contributes to educational technology literature by empirically validating a commercialization pathway for chatbots.

8.2 Managerial Contributions

The findings provide actionable insights for educational administrators and ed-tech firms regarding pricing, deployment strategies, and value communication of chatbot solutions.

IX. CONCLUSION AND FUTURE RESEARCH

The study demonstrates that AI-powered educational chatbots represent a viable and valuable innovation in higher education. By combining technical effectiveness with positive user acceptance and economic benefits, chatbots can function as scalable smart services. Future research may explore longitudinal adoption patterns, multi-institutional comparisons, and integration with advanced AI capabilities such as sentiment analysis and voice interaction.

REFERENCES

[1]. Dahiya, M. (2017). A tool of conversation: Chatbot. *Journal of Computer Science Engineering*, 1(1), 158–161.

[2]. Gonda, D. E., Luo, J., Wong, Y., & Lei, C. U. (2018). Evaluation of developing educational chatbots based on the seven principles for good teaching. In *Proceedings of the IEEE International Conference on Teaching,*

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Assessment, and Learning for Engineering (TALE) (pp. 446–453). IEEE. https://doi.org/10.1109/TALE.2018.8615296

[3]. Jain, P. (2019). College enquiry chatbot iterative model. *International Journal of Scientific Engineering and Research*, 7(6), 80–83.

[4]. Magnale, D., Pawar, M., Basanwar, K., Yadav, P., & Bhosale, M. (2021). RUBAN college enquiry chatbot. *International Research Journal of Modernization in Engineering Technology and Educational Institution*, 3(2), 1–5.

[5]. Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307–320. https://doi.org/10.1177/109467050024001

[6]. Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, 18(1), 59–74. https://doi.org/10.1177/1094670514539730

[7]. Sarma, N., & Gayatri. (2021). College enquiry chatbot. *International Research Journal of Engineering and Technology*, 8(3), 1338–1342.

[8]. Sharma, S. (2020). Chatbot development using Python. *International Journal of Creative Research Thoughts*, 8(6), 5286–5289.

[9]. Shingte, K., Aditeepatil, A., Chaudhari, A., & Desai, S. (2019). Research paper on chatbot development for educational institutions. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 5(2), 1–5.

[10]. Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, 59(236), 433–460. https://doi.org/10.1093/mind/LIX.236.433

[11]. Turkar, A., K., Bhuvana, Syeda, Z. A., Kouser, A., & Ravi, P. (2019). Chatbot for college using Google Actions. In *Proceedings of the International Conference on Advances in Computing and Communication Engineering* (pp. 268–272). IEEE.

[12]. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. https://doi.org/10.2307/30036540

[13]. Weizenbaum, J. (1966). ELIZA—A computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1), 36–45. https://doi.org/10.1145/365153.365168

[14]. Wirtz, J., Patterson, P. G., Kunz, W., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, 29(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

[15]. Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155–172. https://doi.org/10.1177/1094670517752459

[16]. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

[17]. Følstad, A., & Brandtzaeg, P. B. (2017). Chatbots and the new world of HCI. *Interactions*, 24(4), 38–42. https://doi.org/10.1145/3085558

[18]. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

[19]. Okonkwo, C. W., & Ade-Ibijola, A. (2021). Chatbots applications in education: A systematic review. *Computers and Education: Artificial Intelligence*, 2, 100033. https://doi.org/10.1016/j.caeai.2021.100033

[20]. UNESCO. (2023). *Artificial intelligence and education: Guidance for policymakers*. UNESCO Publishing. https://www.unesco.org/