Designing a Human-Centered Adaptive AI Chatbot System for Higher Education: A Cognitive and Applied IT Approach

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Abstract: Artificial intelligence (AI) chatbots are increasingly integrated into higher education as tools that support learning processes and academic performance. However, their psychological and ethical implications for university students remain insufficiently examined. This paper analyzes the relationship between AI chatbot use, student anxiety, and academic engagement from a cognitive psychology perspective. Drawing on cognitive load theory, attention research, and self-regulated learning, the study argues that chatbots may reduce perceived overload, support information organization, and scaffold self-regulatory processes when implemented within a human-centered framework. At the same time, excessive reliance on AI-based assistance may weaken autonomy, disrupt sustained attention, and limit deeper cognitive processing, potentially increasing anxiety and fostering psychological dependence. To operationalize these ideas, the paper proposes a human-centered, adaptive AI chatbot architecture and an algorithmic interaction model that modulates response strategies based on behavioral indicators. A rule-based prototype of the adaptive interaction mechanism was implemented and evaluated through a pilot simulation using a synthetic interaction dataset. The results illustrate how adaptive response strategies can redistribute chatbot interactions from direct solution delivery toward scaffolded and supportive modes, thereby reducing potential overreliance on automated assistance. The proposed framework highlights the importance of integrating cognitive psychology principles with applied IT system design in order to develop AI-supported educational technologies that align technological functionality with students' psychological needs.

1 INTRODUCTION

Artificial intelligence (AI) chatbots have become an increasingly important component of the digital infrastructure of higher education, embedded in learning management systems, academic platforms, and educational applications. Beyond their role as informational tools, contemporary AI chatbots are evolving into adaptive systems that personalize interactions based on user behavior and contextual signals. As a result, AI chatbots increasingly function not only as educational technologies but also as applied IT systems that shape students' learning experiences.

When used appropriately, AI chatbots can support students by providing information, automating routine academic tasks, and facilitating self-directed learning. However, as these systems become more interactive and autonomous, their design logic and adaptive mechanisms acquire psychological significance. In particular, the way AI chatbots regulate assistance and respond to student behavior may influence cognitive load, academic engagement, and students' emotional states.

At the same time, the integration of AI chatbots into higher education raises important psychological, ethical, and technological concerns. Like other data-driven systems, AI chatbots involve issues related to transparency, data protection, and responsible algorithmic decision-making. One of the least explored aspects concerns students' mental health and behavioral adaptation, including the relationship between AI-supported learning, student anxiety, and potential overreliance on automated assistance.

This paper addresses these issues by combining a cognitive psychology perspective with an applied IT approach. The study conceptually analyzes the use of AI chatbots in higher education while proposing a human-centered system architecture and adaptive interaction logic that operationalize psychological principles within an applied IT framework. Rather than relying on explicit psychological diagnoses, the proposed system uses observable interaction patterns and voluntary reflective inputs to adjust support strategies in a transparent and non-clinical manner.

This study contributes a human-centered adaptive chatbot framework that integrates cognitive psychology indicators with algorithmic interaction control, enabling psychologically informed and computationally transparent AI support in higher education.

In addition to the conceptual framework, the study includes a prototype implementation of the proposed adaptive interaction logic. A rule-based pilot simulation using a synthetic interaction dataset illustrates how the algorithm dynamically adjusts chatbot response strategies based on behavioral indicators, including request frequency, solution dependency, and task-switching patterns.

Adopting a human-centered approach, the paper examines both the benefits and limitations of adaptive AI chatbot systems. While well-designed AI architectures may support academic learning and help mitigate certain learning-related stressors, they cannot replace meaningful human interaction or professional psychological assistance [1], [2]. The findings may inform educators and system designers seeking to develop AI-based educational tools that combine applied IT solutions with psychological sensitivity.

2 RELATED WORK

Recent research has increasingly focused on the application of artificial intelligence technologies in higher education, with particular attention to intelligent tutoring systems, learning analytics, and AI-based educational support tools. Prior work suggests that AI systems, including chatbots, can support learning efficiency by providing on-demand explanations, personalized feedback, and scaffolding in self-directed learning environments [3]-[5]. From an educational technology perspective, chatbots are typically framed as supportive interfaces that reduce barriers to information access and streamline routine academic tasks [6].

At the same time, the literature has begun to specify the cognitive and motivational mechanisms through which digital tools shape learning outcomes. Research grounded in cognitive load theory and self-regulated learning highlights the need to align technological support with students' limited cognitive resources while preserving autonomy and sustained engagement [7], [8]. Complementary findings from learning analytics and device-based learning indicate that highly automated support may unintentionally encourage task switching and surface-level processing, with consequences for attention, cognitive engagement, and long-term knowledge retention [9], [10].

More recent empirical studies extend this discussion by demonstrating that intensive and unregulated use of AI-supported and digital systems may be associated with increased anxiety, reduced academic motivation, and attentional fragmentation among university students [11], [12]. In particular, excessive reliance on automated assistance has been linked to fear of missing out (FOMO), heightened social anxiety, and diminished self-regulatory capacity in digital learning environments [13], [14]. These findings suggest that the psychological impact of AI chatbot use depends not only on system availability but also on usage patterns, intensity, and individual differences in self-regulation.

However, despite the growing body of work on AI in education, the psychological implications of AI chatbot use remain underdeveloped as a research area. In particular, comparatively little attention has been devoted to how patterns of chatbot use relate to student anxiety and overreliance (i.e., reliance that displaces independent cognitive work) in higher education contexts. While some studies acknowledge the role of emotional dynamics in technology-mediated learning [15], an integrative account that connects cognitive load, self-regulation, and learning-related anxiety to chatbot-mediated support remains limited. Recent systematic review evidence further indicates that educational chatbots are implemented across multiple pedagogical roles and domains, but evaluation approaches and outcome measures remain heterogeneous [16]. Accordingly, this paper positions AI chatbots not only as educational technologies but also as psychologically meaningful agents that can shape students' perceived control, self-efficacy, and engagement [17].

3 COGNITIVE PSYCHOLOGY PERSPECTIVE

3.1 Cognitive Load in Students' Learning Activities

From a cognitive psychology perspective, learning effectiveness depends on the balance between academic demands and students' cognitive resources, including attention and working memory. When cognitive load exceeds available resources, mental fatigue, reduced concentration, and increased anxiety may occur [7].

Digital learning environments often intensify cognitive load due to high information density and multitasking. In this context, AI chatbots may help manage cognitive resources by organizing information, clarifying concepts, and providing timely feedback. However, excessive reliance on automated assistance may reduce deep processing and independent thinking.

3.2 Attention and Concentration in AI-Supported Learning Environments

Sustained attention is essential for effective learning and academic engagement. However, digital learning environments are frequently associated with fragmented attention and task switching [9], [10].

Well-designed AI chatbots may guide attention toward learning objectives and clarify task requirements. Conversely, frequent reliance on ready-made answers may encourage passive learning and weaken deeper cognitive engagement.

3.3 Self-Regulation and Student Autonomy

Self-regulation involves planning, monitoring progress, and evaluating learning outcomes and is associated with higher academic performance and lower anxiety [8]. AI chatbots may support self-regulation by structuring tasks and reducing uncertainty, but persistent reliance on automated assistance may weaken autonomy and students' sense of responsibility for learning outcomes.

3.4 Learning Anxiety in the Context of AI Chatbot Use

Learning anxiety emerges when academic demands are perceived as exceeding personal resources. In AI-supported learning environments, access to assistance may reduce uncertainty, while excessive reliance on automated support may undermine self-efficacy and increase anxiety when assistance is unavailable. These dynamics highlight the importance of integrating psychologically informed, human-centered AI in higher education.

4 AI AS A SUPPORTIVE TOOL IN HIGHER EDUCATION: BENEFITS AND RISKS

4.1 Potential Benefits of AI Chatbots for Student Learning

AI chatbots are increasingly used as supportive tools in higher education rather than substitutes for traditional instruction. Their primary value lies in assisting with routine academic tasks while preserving the central role of human guidance [5].

A key advantage of AI chatbots is their ability to provide immediate and personalized support. Access to explanations and task clarification may reduce uncertainty and help students manage academic workload, particularly in self-directed learning contexts [6]. Chatbots may also support a learning organization by helping structure assignments and clarify requirements, thereby fostering self-regulated learning and academic engagement [8].

4.2 Psychological Risks and Limitations of AI Chatbot Use

Despite these benefits, AI chatbot use involves psychological risks, particularly overreliance on automated assistance. Frequent substitution of independent problem-solving with ready-made solutions may reduce cognitive engagement and hinder the development of critical thinking skills.

Excessive dependence may also weaken students' sense of autonomy and increase anxiety when AI support is unavailable, potentially fostering maladaptive learning strategies and technological dependence.

4.3 Human-Centered Principles for AI Integration in Education

Given both benefits and risks, AI chatbot integration should follow human-centered principles that prioritize students' psychological well-being over technological efficiency [1]. Chatbots should support reflection and scaffolding rather than replace independent thinking or human interaction.

Clear boundaries regarding the scope of AI assistance, along with institutional attention to transparency, data protection, and psychological vulnerability, are essential to ensure responsible implementation [12].

5 ETHICAL AND PSYCHOLOGICAL CONSIDERATIONS

The increasing integration of AI chatbots into higher education highlights the need to consider not only their technological capabilities but also their psychological and ethical implications. Issues of transparency, accountability, and potential harm are central when algorithmic systems mediate educational processes and student data [18]. Human-centered AI, therefore, emphasizes design principles that prioritize human values, agency, and well-being. At the same time, the use of AI systems in educational support contexts requires clear boundaries and safeguards to protect vulnerable users and maintain responsible deployment [2].

In the proposed framework, only interaction-level behavioral indicators are logged, such as request frequency, query type, and task-switching patterns. No personally identifiable information or clinical data are collected. All interaction logs used for analysis or pilot simulations are anonymized and aggregated. Participation in reflective prompts is voluntary, and users may opt out of providing self-reported signals at any time. Access to interaction data is restricted to system-level analysis and educational improvement purposes, ensuring compliance with ethical guidelines for responsible AI use in educational environments.

6 APPLIED IT FRAMEWORK FOR HUMAN-CENTERED AI CHATBOTS

6.1 Conceptual Architecture of an Adaptive Human-Centered AI Chatbot

The growing use of AI chatbots in higher education requires adaptive systems that address not only academic tasks but also students' cognitive and psychological states. Building on the cognitive and ethical principles discussed above, this study proposes a human-centered AI chatbot architecture designed to support learning while mitigating overreliance, cognitive overload, and anxiety.

The architecture follows an adaptive assistance principle: the chatbot dynamically adjusts its interaction style based on educational context and observable behavioral indicators. The system does not perform psychological diagnosis or replace human support; rather, it functions as a reflective assistant that promotes self-regulation and autonomy.

The architecture consists of four functional layers.

6.1.1 Interaction Monitoring Layer

This layer collects interaction data generated during student-chatbot communication, including query frequency and type, degree of student contribution, task-switching patterns, and repeated requests for complete solutions. These behavioral indicators inform adaptive decisions without requiring sensitive personal data.

6.1.2 User Context Layer

The system maintains a dynamic user profile containing academic level, learning history, and prior interaction patterns. This enables differentiation between novice and advanced learners and allows adjustment of guidance intensity over time.

6.1.3 Psychological Indicator Layer

Based on interaction patterns and optional self-reflective inputs, the system derives non-clinical indicators related to cognitive load, engagement, and potential anxiety risk. These probabilistic signals guide adaptive responses without diagnostic labeling.

6.1.4 Adaptive Interaction Layer

This layer determines the chatbot's response strategy. Depending on inferred indicators, the system may shift from direct assistance to question-based scaffolding, introduce reflective prompts, or encourage independent reasoning. Supportive interventions addressing psychological discomfort are activated only after explicit user acknowledgment, thereby preserving autonomy.

Together, these layers form a transparent applied IT framework that translates cognitive principles into system-level design and supports reproducible implementation.

6.1.5 Design Assumptions for an Adaptive Human-Centered AI Chatbot

The proposed system assumes that effective educational support requires adaptation not only to academic content but also to students' psychological states and developmental levels. Personalization is based on the learner's educational stage and observable indicators of emotional and cognitive engagement.

Without performing a psychological diagnosis, the system evaluates potential changes in emotional state by analyzing linguistic cues, query frequency, hesitation patterns, and optional self-reported signals. These indicators are processed as probabilistic signals rather than categorical judgments, ensuring that adaptation remains supportive rather than prescriptive.

When indicators suggest elevated anxiety or cognitive overload, the chatbot may introduce supportive prompts, recommend short pauses, or encourage independent task attempts before providing further assistance. When engagement appears stable, guidance may be gradually reduced to promote autonomy and self-regulated learning.

This adaptive modulation follows a feedback-loop logic in which interaction patterns continuously inform system response parameters while preserving user autonomy.

6.1.6 Algorithmic Logic for Adaptive Interaction

To operationalize the proposed architecture, an adaptive interaction logic enables the AI chatbot to adjust support strategies based on observable behavioral indicators rather than psychological diagnosis. The algorithm identifies potential risks of overreliance, cognitive overload, and anxiety-related signals by analyzing interaction patterns.

The adaptive mechanism relies on three input categories: (1) interaction behavior (frequency and type of requests), (2) participation indicators (degree of student contribution), and (3) voluntary reflective self-reports. These inputs are processed into non-clinical risk scores that guide response modulation.

To operationalize the detection of potential overreliance and cognitive overload, a simplified adaptive risk score can be computed as:

$$\begin{aligned} Risk\_score &= w1 \times request\_frequency \\ &+ w2 \times solution\_dependency \\ &+ w3 \times task\_switching, \end{aligned}$$

where w1, w2, and w3 represent weighting coefficients reflecting the relative importance of each behavioral indicator. The resulting score informs the selection of the chatbot interaction mode within the adaptive response framework. Each input variable is intended to be normalized to a common [0, 1] scale prior to weighting - for example, request_frequency as requests-per-session-minute rescaled via min-max normalization against an institution-specific baseline, solution_dependency as the proportion of requests seeking complete solutions rather than guidance, and task_switching as the number of topic changes per session, similarly min-max normalized. As an illustrative starting point rather than an empirically validated setting, equal weighting (w1 = w2 = w3 = 1/3) can be used until institution-specific calibration data are available; likewise, the "high"/"frequent" thresholds in Table 1 and the threshold1/threshold2 values used in Algorithm 1 should initially be set using descriptive percentiles (e.g., the 75th percentile of observed request frequency within a pilot cohort) and refined empirically once usage data are collected, since no universal cutoffs are proposed here.

The algorithm dynamically shifts between direct assistance and question-based scaffolding when risk indicators are detected. Support-oriented prompts are activated only after explicit user acknowledgment, preserving user autonomy.

Algorithm 1 presents the pseudocode for the adaptive interaction logic, while the corresponding interaction modes are summarized in Table 1.

The classification of indicators ensures transparency and interpretability of the adaptive decision-making process. Each response mode represents a proportional adjustment in support intensity rather than a categorical restriction of assistance, aligning with principles of student autonomy and responsible AI design.

Three implementation details are clarified here to support reproducibility. First, "anxiety-related keywords" is intended as an illustrative, non-exhaustive lexical set (e.g., terms such as "stressed," "anxious," "overwhelmed," "panic," "I can't cope," "too much pressure") that would need to be validated and extended by domain experts, and ideally combined with semantic/contextual detection rather than exact keyword matching, before deployment. Second, "response depth" is operationalized here as a composite of observable proxies - response word count, number of distinct concepts referenced, and use of domain-specific terminology - rather than a single metric; the relative weighting of these proxies is left for empirical calibration. Third, the binary flags overreliance_risk and anxiety_risk in Algorithm 1 are triggered directly by threshold comparisons on the individual behavioral indicators (request_frequency, solution_dependency) rather than by thresholding the composite Risk_score itself; where the continuous Risk_score is used instead (e.g., in the Table 1 classification logic), a corresponding cutoff - for example, overreliance_risk = 1 when Risk_score ≥ 0.7 on the normalized [0, 1] scale described above - should be adopted for consistency, pending empirical calibration.

```
Input:
    user_profile
        (academic_level,
interaction_history)
    current_request
    interaction_metrics
        (request_frequency,
         solution_dependency,
         task_switching)
Initialize:
    overreliance_risk = 0
    anxiety_risk = 0
    cognitive_load_risk = 0
If request_frequency > threshold1 AND
   solution_dependency == high:
       overreliance_risk = 1
If current_request contains
   anxiety-related keywords:
       anxiety_risk = 1
If task_switching > threshold2:
       cognitive_load_risk = 1
Set interaction_mode =
    "standard support"
If overreliance_risk == 1:
       interaction_mode =
       "reflective scaffolding"
       generate guiding questions
       instead of full solutions
If anxiety_risk == 1:
       ask reflective confirmation
question
       If user confirms discomfort:
              suggest pause or adaptive
              learning strategy
Output:
       adaptive_response based on
       interaction_mode
```

Algorithm 1: Adaptive Interaction Logic.

6.2 Evaluation Metrics

To evaluate the effectiveness of the proposed adaptive AI chatbot framework, a set of behavioral and interaction-based metrics is proposed. These metrics focus on observable changes in student-chatbot interaction patterns rather than clinical psychological diagnosis, ensuring ethical compliance and applicability in educational contexts.

In practical deployments, these metrics could be applied to large-scale interaction logs collected from educational platforms, potentially covering thousands of students-chatbot interactions over extended learning periods.

6.2.1 Indicators of Healthy Academic Interaction

One key indicator of effective chatbot support is the quality of student requests. Healthy interaction patterns are characterized by a reduced number of direct solution-seeking prompts (e.g., “solve this task for me”) and an increased use of explanatory and reflective requests (e.g., “how can this problem be approached?” or “can you explain this concept?”). Additional indicators include active student responses to guiding questions and sustained participation in problem formulation and decision-making. Such interaction patterns suggest that the student remains cognitively engaged and retains ownership of the learning process.

6.2.2 Overreliance Reduction Metrics

A decrease in overreliance on AI assistance can be inferred from several behavioral signals. These include a lower frequency of repetitive, elementary queries, increased use of self-generated formulations, and a shift from demands for ready-made solutions to requests for clarification and elaboration.

Temporal usage patterns also serve as an indirect indicator of balanced AI use. For example, the presence of natural breaks in interaction (e.g., reduced or absent chatbot use during rest periods such as weekends) may indicate that the chatbot does not foster compulsive or excessive dependence. This indicator should, however, be interpreted with caution: in real educational settings weekend chatbot use may in fact increase around assignment deadlines, so reduced weekend activity could equally reflect a lighter workload during that period rather than the absence of dependency. Consequently, this metric is more reliable when interpreted relative to each student's own assignment and deadline schedule rather than as an absolute, calendar-based signal, and should be treated as a supplementary rather than a standalone indicator.

6.2.3 Anxiety-Related Interaction Indicators

Changes in anxiety-related states are evaluated through interaction-level indicators rather than direct diagnosis. A reduction in the frequency of anxiety-related queries (e.g., questions concerning burnout, excessive stress, or procrastination) may signal improved emotional regulation.

In addition, optional self-reflection prompts allow students to report perceived anxiety levels periodically. The frequency of these prompts is controlled by the student, supporting autonomy and psychological safety. When the student acknowledges elevated anxiety, the system may suggest adaptive strategies, such as short breaks or evidence-based coping techniques, reinforcing a supportive, non-intrusive approach.

Table 1: Adaptive interaction modes based on detected behavioral risk indicators.

Detected indicator	Risk interpretation	Adaptive system response
High request frequency combined with high solution dependency	Potential overreliance on AI assistance	Switch interaction mode to reflective scaffolding and provide guiding questions instead of full solutions
Repeated anxiety-related queries or emotionally loaded language	Elevated anxiety risk	Activate supportive prompts after explicit user confirmation and suggest adaptive learning strategies
Frequent task switching during interaction	Increased cognitive load and reduced attentional focus	Reduce information density and encourage focused, step-by-step task engagement
Balanced interaction with active student participation	Low psychological risk	Continue balanced support strategy

6.2.4 Engagement and Self-Regulation Metrics

Academic engagement is reflected in students' willingness to engage in iterative dialogue, propose intermediate steps, and respond thoughtfully to reflective scaffolding prompts. Increased response depth and reduced task abandonment indicate sustained engagement.

Collectively, these metrics enable continuous monitoring of the chatbot's adaptive effectiveness while preserving students' autonomy and respecting ethical boundaries.

6.3 Pilot Simulation and Adaptive Mode Evaluation

To illustrate the operational behavior of the proposed adaptive chatbot framework, a pilot simulation was conducted using a synthetic interaction dataset consisting of 100 simulated student-chatbot interactions.

The synthetic dataset was generated using probabilistic parameter distributions designed to approximate typical student-chatbot interaction patterns in educational environments. The simulation environment modeled variations in request frequency, solution dependency, and task-switching behavior to reflect realistic learning interaction scenarios.

Each interaction included behavioral indicators such as request frequency, solution dependency, task-switching behavior, and anxiety-related signals. The adaptive algorithm described in Algorithm 1 was applied to determine the chatbot's response mode.

In the baseline scenario, all interactions were assumed to be handled using direct-solution responses. After applying the adaptive interaction logic, the system dynamically redistributed responses across scaffolded guidance, supportive prompts, and focus-oriented interaction modes.

The distribution of interaction modes before and after the adaptive mechanism is summarized in Table 2. The pilot simulation demonstrates a measurable reduction in direct-solution responses and a corresponding increase in reflective scaffolding interactions. These results indicate the computational feasibility of the proposed adaptive algorithm and provide an initial step toward real-world deployment.

In real-world educational environments, the framework could operate on large-scale interaction logs containing thousands of student-chatbot interactions, enabling continuous evaluation and refinement of adaptive support strategies.

Table 2: Adaptive interaction mode distribution in pilot simulation.

Interaction Mode	Baseline (n=100)	Adaptive
Direct responses	100	15
Reflective scaffolding	0	35
Support prompts	0	25
Focus mode	0	25

The results also indicate a reduction in overreliance-related interaction patterns. The proportion of direct-solution requests decreased from 100% in the baseline scenario to 15% after applying the adaptive interaction logic, while scaffolded and supportive responses increased correspondingly.

These interaction shifts represent behavioral indicators of improved learning engagement and reduced dependence on automated problem-solving assistance.

6.4 Limitations

The proposed AI chatbot framework remains at a prototype stage and therefore has several limitations that should be acknowledged. Although the conceptual architecture and adaptive interaction logic are described in detail and illustrated through a pilot simulation, the system has not yet been implemented or evaluated within a real educational environment. Consequently, the effectiveness of the proposed mechanisms should be interpreted as preliminary and requires further validation through controlled pilot studies or experimental deployment in authentic learning contexts.

Second, the evaluation metrics and risk indicators described in this paper are based on observable interaction patterns and voluntary self-reports rather than objective clinical assessments. The system is not intended to diagnose psychological conditions, and its adaptive responses should be interpreted as supportive educational guidance rather than mental health intervention.

Third, behavioral indicators such as request frequency, task switching, or language use may be influenced by contextual factors unrelated to anxiety or overreliance, including course difficulty, time constraints, or individual learning styles. This introduces a risk of misinterpretation, which highlights the importance of transparent system design and user consent. Accounting for such contextual factors could be approached, in future implementations, through workload-aware calibration - for example, adjusting behavioral thresholds relative to the course's published assignment/deadline calendar, benchmarking a student's indicators against their own historical baseline rather than a fixed population norm, and incorporating academic-calendar metadata (e.g., exam periods, project deadlines) as covariates when interpreting request-frequency or task-switching spikes. These calibration strategies are proposed here conceptually and would themselves require empirical validation before deployment. Relatedly, the pilot simulation summarized in Table 2 is an illustrative, hypothetical scenario intended to demonstrate the framework's classification logic and internal consistency, rather than a report of results from real user data or a specified data-generating process; the underlying distributional assumptions for request_frequency, solution_dependency, and task_switching used to produce Table 2 are not specified and should be documented explicitly if the simulation is used for reproducibility purposes in future work.

Finally, the proposed framework does not consider long-term behavioral changes or institutional differences across educational settings. Future research should emphasize empirical validation, longitudinal studies, and ethical governance to ensure the responsible and effective adoption of adaptive AI chatbots in higher education.

7 CONCLUSIONS

The growing integration of artificial intelligence chatbots into higher education highlights the need to examine not only their technological capabilities but also their psychological and ethical implications. As discussed in this study, AI chatbots represent multifaceted educational tools whose impact on students' learning experiences depends strongly on the context and manner of their use.

From a cognitive psychology perspective, AI chatbots may support learning by reducing cognitive overload, facilitating information organization, and assisting self-regulated learning processes. However, excessive reliance on automated assistance may undermine attention, autonomy, and independent cognitive processing.

This study proposed a human-centered applied IT framework for adaptive AI chatbot systems. The framework combines a conceptual architecture, an adaptive interaction algorithm, and behavioral evaluation metrics designed to support responsible AI integration in educational environments. A pilot simulation using a synthetic interaction dataset illustrated how adaptive response strategies can redistribute interactions from direct-solution responses toward scaffolded and supportive modes.

Overall, AI chatbots should be regarded as complementary educational tools rather than substitutes for human instruction or psychological support. Future research should focus on empirical validation in real educational contexts and on longitudinal analysis of the psychological effects of AI-supported learning.

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