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Research article

**ME AND MY AI BOT: AN SEM–MEREC–VIKOR ANALYSIS
OF THE “AIHOLIC” PHENOMENON AND UNIVERSITY
STUDENTS’ DEPENDENCE ON GENERATIVE AI
CHATBOTS**

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Abstract: “Alholic” refers to the excessive reliance on artificial intelligence (AI) systems, where users depend on these systems not only for practical support, such as information searching, problem-solving, and task completion, but also for reassurance, validation, and emotional comfort. In higher education, Generative AI chatbots have become widely used in universities because they provide students with instant, personalized, and continuous academic support, not only practical support such as information searching, problem-solving, and task completion but also emotional support such as reassurance and validation. However, this rapid use has also raised concerns about students’ growing dependence on these tools. Based on self-determination theory and compulsive behavior theory, this study examines how situational triggers and psychological needs, namely, competence, relatedness, and autonomy, are associated with students’ actual dependency level on generative AI chatbots and their inability to reduce use. The study also examines the moderating role of risk perception in these relationships. Data collected from 787 university students in Iraq and Oman were analyzed using structural equation modeling. In addition, the MEREC method was used to determine the objective weights of the main criteria, while the VIKOR method was applied to compare the weighted determinants across the two national contexts. The findings indicate that psychological needs, especially competence and autonomy, and contextual triggers are important factors in explaining chatbot dependency. Students use chatbots not only for academic support but also for reassurance, connection, and self-directed learning. Furthermore, the results from using the multi-criteria decision-making approaches reveal contextual differences between the two countries. Risk perception received the highest weight in Oman, whereas triggers received the highest weight in Iraq. This study explains AI dependency as a psychological and behavioral phenomenon and provides practical insights for the responsible use of generative AI tools in higher education.

Keywords: Chatbots, dependency, digital interactions, generative AI, multi-criteria decision-making, MEREC, VIKOR.

MSC: 90B50

1. INTRODUCTION

As artificial intelligence (AI) reshapes numerous sectors, its transformative impact on education is particularly profound. Generative AI chatbots have permeated academic environments, offering uninterrupted support, personalized learning, and enhanced student engagement [1,2]. AI platforms mitigate knowledge gaps through instant, prompt-driven assistance and help improve academic outcomes. However, the rapid adoption of AI in education has led to significant challenges, especially an escalating dependence on chatbots. Students increasingly rely on these digital tools not only for academic assistance but also to satisfy deeper psychological needs such as competence, relatedness, and autonomy [3,4].

In contrast to previous research that has predominantly examined AI's technological capabilities and performance outcomes, our study examines the psychological underpinnings of this dependency. We introduce the term "AIholic" to describe the phenomenon whereby generative AI chatbots evolve from functional aids into central mechanisms for emotional coping and academic support. In this study, "AIholic" is used as a conceptual label rather than as a clinical diagnosis. It is related to dependency, overreliance, problematic technology use, and compulsive digital behavior; however, it differs from these concepts. Dependency mainly refers to reliance on a tool for support, while overreliance refers to excessive use that may replace independent effort. Problematic technology use usually refers to use that produces negative academic, social, or psychological consequences, whereas compulsive digital behavior focuses on repeated engagement that becomes difficult to reduce [5,6,7]. However, AIholic is more specific to generative AI chatbots because it reflects the combination of academic reliance, emotional reassurance, perceived social connection, and self-directed decision support. Therefore, students may not only use chatbots to complete academic tasks; they may also depend on them to feel competent, supported, less anxious, and more in control of their learning. Thus, the AIholic phenomenon captures a broader pattern in which generative AI chatbots gradually move from being supportive learning tools to becoming central psychological resources in students' academic and personal routines. This trend raises significant concerns about academic integrity, the erosion of self-regulation, and potential disruptions to the broader learning ecosystem [8].

While previous studies have explored the various educational benefits and shortcomings of AI [9,10], most have narrowly focused on technological effectiveness, student performance, and isolated ethical issues. By contrast, our research is novel in that it emphasizes the intrinsic psychological drivers, specifically the roles of competence, relatedness, and autonomy, in fueling students' growing dependence on generative AI chatbots [11,12]. Additionally, our study examines the moderating effect of risk perception, that is, how students' awareness of potential harm such as diminished critical thinking and overdependence may mitigate this dependency, a factor largely overlooked by previous studies. Addressing this gap is crucial to understanding how overreliance on AI can undermine learning outcomes, compromise academic integrity, and distort ethical practices [13]. To systematically evaluate the relative importance of these psychological determinants, this study also adopts multi-criteria decision-making (MCDM) approaches. The MEREC (Method based on the Removal Effects of Criteria) method is employed to determine the objective weights of the study criteria, while the VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje) method is applied to rank the influencing factors

and identify the most critical determinants of chatbot dependency across the examined contexts [14,15].

Thus, this study's novelty lies in its investigation of the psychological drivers underlying chatbot dependency by integrating self-determination theory (SDT) and compulsive behavior theory (CBT). This dual-theoretical framework enables us to examine the interplay between psychological triggers and intrinsic motivational needs while also considering how risk perception moderates these relationships. Specifically, this research aims to:

- Examine the psychological triggers that drive students to engage with AI chatbots.
- Identify how the intrinsic needs of competence, relatedness, and autonomy influence chatbot dependency.
- Assess how risk perception moderates the relationship between these needs and chatbot overuse.
- Apply MCDM techniques (MEREC and VIKOR) to determine the relative importance and ranking of the factors influencing AI chatbot dependency.

This study makes valuable practical and theoretical contributions by offering educators, policymakers, and AI developers strategic insights into harnessing AI's advantages, including enhanced personalization and efficiency, while ensuring its responsible integration to foster genuine learning. Theoretically, our work augments knowledge on AI's psychological ramifications by addressing gaps in the research and laying a foundational framework for future studies on AI dependency in education.

2. LITERATURE REVIEW

2.1. The Rise of AI in Education and Evolution of Chatbots

Integrating AI into higher education has rapidly transformed the educational landscape by changing how students access information, receive feedback, and complete learning tasks. Generative AI chatbots such as ChatGPT and Google Gemini are now widely used in academic environments because they provide personalized support, instant responses, and continuous assistance beyond the limits of traditional classroom interaction [1,2,16]. Unlike earlier rule-based chatbots, which were mainly designed to answer fixed questions and provide basic administrative support, current generative AI chatbots can produce human-like responses, adapt to students' prompts, and offer support in a more conversational and personalized form [17,18]. This shift has changed the role of chatbots from simple digital assistants into interactive learning companions that students may consult repeatedly during their academic work.

AI chatbots offer several significant benefits for students. They can support personalized learning, improve access to academic materials, assist with writing and problem-solving, and provide immediate clarification when students face difficulty [9], [11]. They may also strengthen students' confidence by giving quick feedback, reducing uncertainty, and allowing learners to study at their own pace. Therefore, these tools can make learning more flexible, accessible, and responsive to students' needs. At the same time, the same features that make generative AI useful may also increase the possibility of dependency. When students become used to instant answers, continuous availability, and personalized guidance, they may begin to depend on chatbots as their first and main source of explanation, feedback, and decision-making.

The development of educational chatbots shows this shift clearly. Early chatbot systems were limited in function and mostly used for frequently asked questions, administrative services, and simple learning support [17]. Later developments in machine learning and natural language processing made these systems more interactive and adaptive [18,19]. With the rise of generative AI, chatbots can now produce extended explanations, simulate dialogue, generate academic content, and respond to students' emotional and cognitive needs. Although this development has created new opportunities for teaching and learning, it has also raised new concerns about overreliance, academic integrity, reduced independent thinking, and weak self-regulation [12,20].

Thus, the educational value of generative AI should be examined together with its psychological and behavioral consequences. In higher education, chatbot use is no longer only a matter of access to technology; it is also connected to how students manage pressure, uncertainty, and academic workload as well as their need for support. For this reason, the present study examines chatbot dependency through two outcomes: actual dependency level and inability to reduce chatbot use. This focus allows the study to move beyond the general discussion of AI's benefits and examine how generative AI chatbots may become embedded in students' learning routines and psychological coping practices.

2.2. Challenges and Concerns

Despite its benefits, the rapid integration of AI in educational contexts raises concerns about our overreliance on technology. Excessive use of AI tools can foster a "Google-it mentality" in which students rely on AI for immediate answers rather than engaging in deep, critical analysis, undermining independent thinking and problem-solving abilities [19]. This may adversely impact students' cognitive abilities, motivation, and learning effort [20]. Ethical concerns about academic integrity also arise, as students may use AI to complete assignments without sufficiently understanding the material, which may increase the risk of academic dishonesty [21]. In addition, overdependence on AI chatbots may reduce face-to-face academic interaction, weaken peer learning, and encourage students to avoid more demanding forms of reflection and independent inquiry [22].

Recent research has begun to focus more directly on students' dependence on AI. This shows that AI dependency is no longer only a general concern but has become a measurable student-related phenomenon. The psychological impacts of AI use are also multifaceted. While AI can enhance engagement, cognitive achievement, and self-efficacy, it may also induce anxiety, stress, digital fatigue, and technostress when use becomes excessive or poorly regulated [23,24,25]. Therefore, the problem is not the use of AI itself but the movement from balanced academic support to repeated and uncontrolled reliance.

CBT explains how repeated behavior can become habit-forming when it provides immediate relief from stress, pressure, or emotional discomfort [26,27]. In the context of generative AI, students may turn to chatbots when they face tight deadlines, academic anxiety, uncertainty, loneliness, or fear of failure. These situational and emotional conditions can work as triggers that push students toward immediate chatbot use. When the chatbot provides quick answers, reassurance, or emotional comfort, the behavior may be reinforced. Over time, students may begin to regard chatbots as necessary for academic progress and psychological support [11,26]. Accordingly, chatbot dependency can develop through a repeated cycle. First, students experience triggers such as workload, stress, and uncertainty. Second, they use the chatbot to obtain immediate academic or emotional relief. Third, relief strengthens the likelihood of reusing the chatbot in similar situations. This

cycle may gradually weaken self-regulation and make it difficult for students to reduce chatbot use. Therefore, in this study, triggers are not treated as general background factors but as important psychological and situational conditions that may increase both actual dependency level and inability to reduce use.

Furthermore, excessive chatbot use may increase the risks of misinformation, plagiarism, superficial learning, and technostress, which can compromise trust and educational outcomes [8,12,27]. To address these concerns, educational institutions need to promote digital literacy, clear usage policies, stronger academic mentoring, and balanced learning practices [2,28]. Such measures can help students use AI chatbots as supportive learning tools rather than as replacements for independent thinking, instructor feedback, and peer interaction. Thus, a CBT-informed understanding of chatbot dependency could explain not only why students use AI chatbots but also why some may struggle to reduce their use even when they recognize the academic or psychological risks.

2.3. SDT and Psychological Needs

SDT explains that three basic psychological needs, namely, competence, relatedness, and autonomy, are essential drivers of human motivation and behavior [4]. In educational settings, SDT suggests that students are more likely to flourish when they feel capable, connected, and able to make their own learning choices. However, students' increasing reliance on external digital tools such as generative AI chatbots to satisfy these needs may also create a risk of dependency [11]. Therefore, SDT provides a useful theoretical lens for explaining why chatbot dependency is related not only to technology availability but also to students' internal psychological needs.

Competence refers to students' need to feel capable, effective, and able to achieve academic goals. Generative AI chatbots may support competence by providing rapid feedback, simplified explanations, examples, and direct answers to learning problems [22]. These functions can increase students' confidence and reduce uncertainty during academic tasks. However, this instant reinforcement has a potential downside. When students repeatedly depend on chatbot feedback to understand concepts, solve problems, and complete tasks, the chatbot may gradually replace self-directed problem-solving and critical reflection. Students may begin to view chatbots as necessary for academic success. Thus, competence satisfaction through chatbots may increase both actual dependency level and inability to reduce chatbot use.

Relatedness refers to the need to feel understood, supported, and connected. Generative AI chatbots may partially satisfy this need because they provide continuous, non-judgmental, and conversational interaction. This can be especially important for students who are hesitant to ask instructors or peers for help or for those who experience isolation in remote or hybrid learning environments [23,24]. However, overreliance on chatbot interaction may reduce genuine interpersonal communication. When students repeatedly use chatbots for reassurance, emotional comfort, and support, these tools may begin to weaken peer interaction, instructor engagement, and students' sense of belonging within the learning environment. Therefore, relatedness may contribute to chatbot dependency when students begin to use generative AI not only for information but also for connection and reassurance.

Autonomy refers to students' need to feel independent and self-directed in their learning. Generative AI chatbots may strengthen autonomy because they allow students to ask questions freely, learn at their own pace, and receive immediate guidance without

waiting for instructors or classmates [2,25]. Nevertheless, this flexibility may also produce an autonomy–dependency paradox. Although chatbots appear to increase students' control over their learning, repeated reliance on automated guidance may reduce their ability to make independent academic judgments. In this case, the chatbot supports autonomy in the short term but may weaken independent inquiry and deeper cognitive engagement in the long term. Thus, autonomy may become a driver of dependency when students depend on AI chatbots to guide their decisions, structure their thinking, and reduce uncertainty.

Based on this theoretical view, AIholic should be understood as an AI-specific dependency pattern rather than a simple increase in chatbot use. A student may use generative AI frequently without being AIholic if the use remains intentional, limited, and balanced with independent thinking, peer discussion, and instructor guidance. By contrast, AIholic tendencies appear when the chatbot becomes a repeated source of academic reassurance, emotional comfort, perceived connection, and decision support. Therefore, the concept extends previous discussions of problematic internet use, smartphone addiction, and compulsive technology use by focusing on the distinctive affordances of generative AI chatbots such as instant response, conversational interaction, perceived empathy, personalization, and continuous availability [5,6,7,11]. In this sense, AIholic not only describes how much students use chatbots but also why they use them and what psychological functions these tools serve in their learning lives.

In higher education, AIholic tendencies can significantly influence students' success and psychological well-being. Students who are overloaded with coursework, uncertain about academic expectations, and socially isolated may become more dependent on generative AI tools for immediate answers and pseudo-social engagement [11,26]. While these tools can improve efficiency, customization, and immediate problem-solving, their constant availability may also weaken important formative learning experiences such as instructor-led feedback, peer collaboration, iterative problem-solving, and deep reflection [27]. Thus, prolonged reliance on chatbots may reduce students' autonomy, self-efficacy, critical thinking, and opportunities to form authentic academic relationships.

Addressing the AIholic phenomenon requires digital literacy initiatives and intentional curricular design that preserve human-centered learning. Structured reflective activities, collaborative projects, face-to-face interaction, and clear guidance on responsible chatbot use can help reduce compulsive usage patterns [28]. Ultimately, educators must integrate AI into pedagogy in a balanced way, where chatbots supplement rather than replace critical thinking, interpersonal skills, and authentic learning experiences [2].

2.4. Moderating Role of Risk Perception

Risk perception plays an important role in explaining how students respond to psychological triggers, intrinsic needs, and the use of generative AI chatbots. In general, risk perception refers to students' evaluation of the possible negative consequences of using AI tools, including weakened critical thinking, academic misconduct, misinformation, privacy concerns, technostress, and overdependence [12,29]. University students may not evaluate these risks in the same way. Some may recognize the possible academic and psychological costs of excessive chatbot use, while others may focus on immediate benefits such as speed, convenience, reassurance, and easy access to answers.

Students' risk perceptions may be influenced by their experience of and trust in technology, cultural attitudes toward AI, and awareness of digital risks [30]. Students with higher risk awareness may use chatbots more carefully, compare chatbot responses with

other sources, and maintain stronger interaction with instructors and peers. Conversely, students with lower perceived risk may rely on chatbots more freely and repeatedly because they do not recognize the possible costs of overuse. Therefore, risk perception may not only directly shape students' attitudes toward chatbot use but also change the strength of the relationships among psychological needs, situational triggers, and dependency-related outcomes.

Risk perception also intersects with the three psychological needs proposed by SDT. Students who use chatbots to feel competent may become dependent on instant feedback if they do not perceive strong risks in such reliance. Students who use chatbots for relatedness may depend more on their conversational and non-judgmental nature if they do not view this interaction as a possible substitute for human support. Similarly, students who use chatbots to feel autonomous may depend more on automated guidance if they do not recognize that this form of autonomy may gradually reduce independent academic judgment. Thus, risk perception may alter how competence, relatedness, and autonomy are translated into actual dependency level and inability to reduce chatbot use.

However, the role of risk perception should be interpreted carefully. Risk perception does not necessarily weaken all relationships in the same way. In moderation analysis, the meaning of the interaction depends on the size, direction, and slope pattern of the interaction effect. Therefore, a significant positive interaction coefficient does not automatically mean that risk perception increases harmful dependency in all cases. Rather, it indicates that the relationship between the independent variable and dependency outcome changes at different levels of risk perception. For this reason, the present study interprets the findings on the moderating effects together with interaction plots and not only through the sign of the coefficient. This point is important because students with higher risk perception may become more cautious in some situations, but risk awareness may also make them more conscious of their own dependency when they already rely heavily on chatbots.

By integrating CBT, SDT, and risk perception, this study offers a more complete understanding of chatbot dependency. CBT explains how repeated use may be reinforced by triggers such as academic pressure, uncertainty, and emotional discomfort. SDT explains how competence, relatedness, and autonomy may motivate chatbot use. Risk perception explains why the strength of these relationships may differ among students. Therefore, this study treats risk perception as a moderating factor that conditions the relationships among triggers, psychological needs, and the two dependency-related outcomes: inability to reduce chatbot use and actual dependency level.

Based on the literature review, this study hypothesizes the following:

Direct Effects

- H1: Triggers positively influence students' inability to reduce chatbot use.
- H2: Triggers positively influence students' actual dependency level.
- H3: Competence positively influences students' inability to reduce chatbot use.
- H4: Competence positively influences students' actual dependency level.
- H5: Relatedness positively influences students' inability to reduce chatbot use.
- H6: Relatedness positively influences students' actual dependency level.
- H7: Autonomy positively influences students' inability to reduce chatbot use.
- H8: Autonomy positively influences students' actual dependency level.

Moderating Effects of Risk Perception

H9: Risk perception moderates the relationship between triggers and students' inability to reduce chatbot use.

H10: Risk perception moderates the relationship between triggers and students' actual dependency level.

H11: Risk perception moderates the relationship between competence and students' inability to reduce chatbot use.

H12: Risk perception moderates the relationship between competence and students' actual dependency level.

H13: Risk perception moderates the relationship between relatedness and students' inability to reduce chatbot use.

H14: Risk perception moderates the relationship between relatedness and students' actual dependency level.

H15: Risk perception moderates the relationship between autonomy and students' inability to reduce chatbot use.

H16: Risk perception moderates the relationship between autonomy and students' actual dependency level.

Figure 1 presents the flowchart of the study. The model shows how the theoretical foundations, namely, SDT, CBT, and risk perception, are linked to the main variables. It also shows the direct relationships among psychological triggers, competence, relatedness, autonomy, and the two dependency-related outcomes. In addition, the figure illustrates the moderating role of risk perception and complementary MCDM layer, where MEREC is used to determine the criteria weights and VIKOR is used to rank and compare student cases.

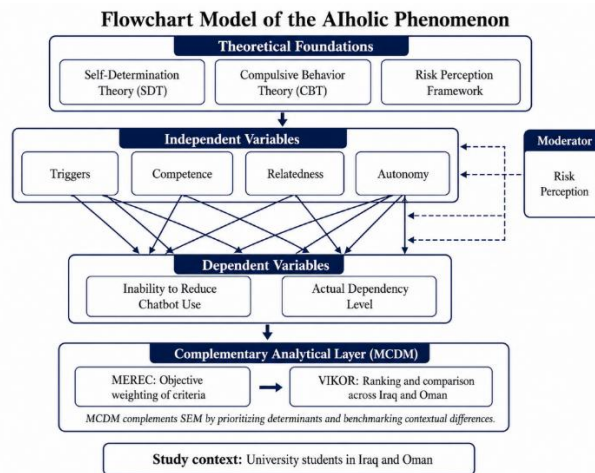


Figure 1: Flowchart of the Alholic phenomenon and complementary SEM–MCDM analytical structure

3. METHODS

This study employs a quantitative, cross-sectional research design to systematically investigate the growing dependency of university students on generative AI chatbots. A cross-sectional design was considered appropriate because the study aims to examine

students' perceptions, psychological needs, risk perception, and dependency-related behaviors at a point in time. To analyze the complex interplay among psychological triggers, intrinsic needs, risk perception, and chatbot dependency, structural equation modeling (SEM) using SmartPLS 4 software was applied. The theoretical model was grounded in CBT, SDT, and risk perception, which together provide a comprehensive lens for examining the psychological and behavioral factors influencing chatbot use. SEM was chosen because of its capability to assess multiple interdependent relationships simultaneously, control for measurement error, and validate theoretical models involving several latent constructs [31].

Data were collected through an online survey designed for university students who actively use generative AI chatbots. The survey assessed students' triggers influencing chatbot usage, psychological needs (competence, relatedness, and autonomy), actual dependency behaviors, inability to reduce chatbot use, and perceived risks associated with chatbot use. The study employed adapted versions of established and validated instruments. All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree, while selected frequency-based items ranged from "not often" to "very often." Three subject matter experts reviewed the instruments to ensure conceptual alignment, clarity, and contextual relevance for assessing the use of generative AI chatbots in education. The adapted items remained consistent with the original constructs while also fitting the context of generative AI use among university students. The scale is presented in Appendix.

The survey was translated into Arabic using a back-translation procedure [32]. A bilingual expert reviewed the translated version to confirm the accuracy, cultural appropriateness, and semantic equivalence of all items. This step was important because the data were collected from students in Iraq and Oman, where Arabic is the main language of communication. Table 1 presents the adapted measurement scales.

Participants included full- or part-time university students enrolled in undergraduate or postgraduate programs, aged 18 or older, who interacted with generative AI chatbots at least once per week for academic or educational purposes. Individuals with limited or no familiarity with generative AI chatbots, defined as less than weekly use, were excluded. An online survey was administered to a diverse sample of 787 respondents from several universities in Iraq and Oman. This included 366 students from several Iraqi universities and 421 students from the National University of Science and Technology and the Modern College of Business and Science in Oman.

To enhance representativeness and external validity, participants were recruited using diverse and widely accessible communication platforms commonly used by student populations, including WhatsApp and Telegram. Multiple reminders were distributed during the data collection period to reduce non-response and selection bias and encourage participation across different demographics, including gender, academic discipline, and academic level. Data were collected from May 4, 2023 to May 27, 2024. Although this was an extended data collection period, the study treats the dataset as a single cross-sectional snapshot because the aim was not to examine changes over time but to capture students' perceptions, psychological needs, risk perception, and dependency-related behaviors at the time of response. During this period, the generative AI environment developed rapidly and students' exposure to these tools may also have changed. Therefore, this issue is acknowledged as an important contextual consideration. However, the extended data collection window also allowed the study to include students across different academic

periods, including normal coursework, assignment periods, and examination-related pressure. This helped capture a broader range of student experiences with generative AI chatbots.

Table 1: Measurement scales

Scale	Source Instrument	Adaptations	Sample Item
Triggers of Chatbot Use	Young's Internet Addiction Test [33]	Items were adapted by replacing references to "Internet" or "online use" with "chatbots" or "generative AI." Some social and academic examples were adjusted to fit the student and educational context.	"How often do you find that you stay on chatbots/generative AI longer than you intended?"
Inability to Reduce Chatbot Use	Compulsive Internet Use Scale [6]	Items were adapted to reflect difficulty controlling, reducing, or stopping chatbot/generative AI interaction. Several items were contextualized to reflect chatbot-specific engagement and interference with daily functioning.	"How often do you have trouble controlling the amount of time you spend interacting with chatbots/generative AI?"
Actual Dependency Level	Smartphone Addiction Scale--Short Version [7]	Items were tailored to measure cognitive, behavioral, and emotional dependence on generative AI chatbots by replacing smartphone use references with chatbot/generative AI use.	"Do you often think about chatbots/generative AI even when you are not interacting with them?"
Psychological Needs	Basic Psychological Needs Scale [4]	Items were adapted based on the three SDT needs: competence, relatedness, and autonomy. The wording was contextualized to reflect students' educational interaction with generative AI chatbots.	Competence: "Using chatbots/generative AI allows me to achieve the goals I set for myself." Relatedness: "I feel cared for when interacting with chatbots/generative AI." Autonomy: "I feel independent when making choices in my interactions with chatbots/generative AI."
Risk Perception	Prior risk perception measures [29]	Items were adapted to reflect students' perceived academic, personal, and practical risks of relying on chatbots/generative AI.	"If I use chatbots and generative AI without caution, I will likely face negative consequences."

4. DATA ANALYSIS

4.1. Symmetric Analysis

We first evaluated item reliability, internal consistency reliability, convergent validity, and discriminant validity. Regarding item reliability, most items either exceeded the recommended loading threshold of 0.707 or had loadings above 0.50, indicating moderate-to-strong associations with their respective latent constructs [31]. Consistent with PLS-SEM guidelines, two items, namely TRG11 and IBRU1, were retained despite having loadings below 0.70 because their loadings were still above the minimum acceptable level of 0.50 and their removal did not improve the overall measurement quality of the constructs [31], [34]. In addition, these items were theoretically relevant to their constructs; therefore, deleting them only on statistical grounds could reduce the conceptual coverage of the measurement model.

We calculated the composite reliability for each construct to assess internal consistency reliability. The composite reliability values ranged from 0.751 to 0.926, which exceeded the recommended benchmark of 0.70 [31]. We further examined convergent validity and found that the average variance extracted values ranged from 0.533 to 0.767, which were above the recommended cutoff value of 0.50 [31]. This indicates that each latent construct explained more than half of the variance in its observed indicators, supporting convergent validity. Table 2 presents the results.

Table 2: Convergent and discriminant validity

Construct	Item	Loading (> 0.5)	CA (> 0.7)	CR (> 0.7)	AVE (> 0.5)
Triggers	TRG1	0.787	0.814	0.860	0.666
	TRG2	0.856			
	TRG3	0.880			
	TRG4	0.878			
	TRG5	0.815			
	TRG6	0.788			
	TRG7	0.789			
	TRG8	0.798			
	TRG9	0.776			
	TRG10	0.856			
	TRG11	0.640			
	TRG12	0.788			
	TRG13	0.768			
	TRG14	0.856			
	TRG15	0.790			
	TRG16	0.778			
	TRG17	0.758			
	TRG18	0.856			
	TRG19	0.781			
	TRG20	0.746			
Competence	COM1	0.793	0.822	0.882	0.665
	COM2	0.853			
	COM3	0.723			
	COM4	0.772			
	COM5	0.829			
	COM6	0.790			
	COM7	0.753			

Table 2: (continued)[illegible]

Discriminant validity was also established. First, the square root of the average variance extracted value for each construct was greater than its correlations with the other latent constructs, which supports the Fornell–Larcker criterion [31]. Additionally, we employed the heterotrait–monotrait ratio of correlations (HTMT) to provide a more rigorous assessment of discriminant validity. All the HTMT values remained below the recommended threshold of 0.90, indicating acceptable discriminant validity among the constructs [31,35]. Furthermore, the confidence intervals for the HTMT values did not include 1, providing additional evidence that the constructs were empirically distinct. Therefore, the measurement model demonstrated adequate reliability, convergent validity, and discriminant validity. Following the assessment of the measurement model, the structural model was examined by testing the hypothesized direct effects (H1–H8), with the results summarized in Table 3.

Table 3: Structural path analysis: direct effects

Hypothesis	Relationship	Std Beta	t-value	p-value	Decision
H1	Triggers -> Inability to Reduce Use	0.386	6.467	0.000	Supported
H2	Triggers -> Actual Dependency Level	0.198	3.019	0.001	Supported
H3	Competence -> Inability to Reduce Use	0.28	3.99	0.000	Supported
H4	Competence -> Actual Dependency Level	0.301	4.881	0.000	Supported
H5	Relatedness-> Inability to Reduce Use	0.154	3.412	0.000	Supported
H6	Relatedness-> Actual Dependency Level	0.101	1.024	0.153	Not Supported
H7	Autonomy-> Inability to Reduce Use	0.128	2.583	0.005	Supported
H8	Autonomy-> Actual Dependency Level	0.242	4.672	0.000	Supported
H9	Triggers * Risk Perception-> Inability to Reduce Use	0.066	2.641	0.001	Supported
H10	Triggers * Risk Perception -> Actual Dependency Level	0.215	3.524	0.000	Supported
H11	Competence * Risk Perception -> Inability to Reduce Use	0.049	2.722	0.003	Supported
H12	Competence * Risk Perception -> Actual Dependency Level	0.106	1.139	0.126	Not Supported
H13	Relatedness * Risk Perception -> Inability to Reduce Use	0.099	2.166	0.001	supported
H14	Relatedness * Risk Perception -> Actual Dependency Level	0.131	4.640	0.000	Supported
H15	Autonomy * Risk Perception -> Inability to Reduce Use	0.149	2.988	0.001	Supported
H16	Autonomy * Risk Perception -> Actual Dependency Level	0.045	1.024	0.153	Not supported

The analysis of H1–H8 provides clear evidence direct effects. Triggers had a positive and significant effect on inability to reduce chatbot use ($\beta = 0.386$, $t = 6.467$, $p < 0.001$). Thus, H1 was supported. Triggers also had a positive and significant effect on actual

dependency level ($\beta = 0.198$, $t = 3.019$, $p < 0.001$). Thus, H2 was supported. Competence had a positive and significant effect on inability to reduce chatbot use ($\beta = 0.280$, $t = 3.990$, $p < 0.001$). Therefore, H3 was supported. Competence also had a positive and significant effect on actual dependency level ($\beta = 0.301$, $t = 4.881$, $p < 0.001$). Thus, H4 was supported.

Relatedness had a positive and significant effect on inability to reduce chatbot use ($\beta = 0.154$, $t = 3.412$, $p < 0.001$), supporting H5. However, relatedness did not have a significant effect on actual dependency level ($\beta = 0.101$, $t = 1.024$, $p = 0.153$). Therefore, H6 was not supported. Autonomy had a positive and significant effect on inability to reduce chatbot use ($\beta = 0.128$, $t = 2.583$, $p < 0.01$), supporting H7. Finally, autonomy had a positive and significant effect on actual dependency level ($\beta = 0.242$, $t = 4.672$, $p < 0.001$). Thus, H8 was supported. Overall, the results for the direct effects indicate that triggers, competence, and autonomy are important predictors of both dependency outcomes, while relatedness predicts inability to reduce use but not actual dependency level.

Figure 2 presents the structural model results generated using SmartPLS. The figure shows the direct relationships among the four predictor variables (triggers, competence, relatedness, and autonomy) and two dependency-related outcomes. It also presents the moderating role of risk perception in the proposed relationships. The path coefficients indicate that triggers, competence, and autonomy were significantly associated with both dependency outcomes, while relatedness was significantly associated with inability to reduce use but not with actual dependency level. The figure also shows that several interaction effects involving risk perception were significant, indicating that risk perception changed the strength of some relationships between the predictors and dependency outcomes.

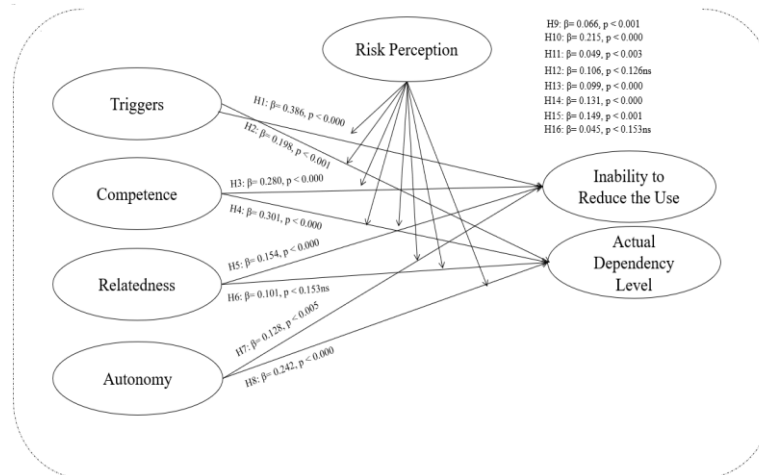


Figure 2: Structural model results with the moderating effects

We employed the PLS bootstrapping method with 5,000 re-samples to analyze the structural model and generate the t-values and significance levels. As bootstrapping does not require the assumption of a normal data distribution, it is widely recommended in PLS-SEM for testing direct and interaction effects [31]. For the moderation analysis, the interpretation of the interaction effect was not based only on the sign of the coefficient. This is because a moderation coefficient indicates whether the relationship between two

variables changes across different levels of the moderator but does not fully explain the form of this change. Therefore, the size and precise nature of the moderating effect may remain unclear if only the coefficient is reported [36]. Accordingly, interaction plots were examined to compare the slopes under high and low levels of risk perception to clarify whether risk perception strengthens, weakens, or changes the direction of the relationship between the independent variables and two dependency outcomes.

The coefficient of determination (R^2) the predictive power of the model is measured as the squared correlation between the actual and predicted values of an endogenous construct. In PLS-SEM, R^2 explains the proportion of variance in the endogenous construct that is accounted for by the exogenous constructs in the model [31]. The R^2 value ranges from 0 to 1, with higher values indicating greater predictive accuracy. Following commonly used guidelines, R^2 values of 0.75, 0.50, and 0.25 can be interpreted as substantial, moderate, and weak levels of explanatory power, respectively. The model yielded R^2 values of 0.532 for inability to reduce use and 0.530 for actual dependency level, indicating a moderate-to-substantial effect.

4.2. MCDM Approaches

MCDM techniques are useful when a research problem involves several criteria to be evaluated simultaneously. In this study, MCDM was used to complement the PLS-SEM analysis. The purpose of using MCDM was to extend the interpretation of the SEM results by adding a prioritization and benchmarking perspective. SEM explains the strength and significance of the relationships among constructs, while MCDM shows which criteria carry greater relative importance in each national context. The two approaches answer different but connected questions. SEM answers whether triggers, competence, relatedness, autonomy, and risk perception are statistically associated with chatbot dependency outcomes, whereas MCDM answers which of these criteria should be prioritized when comparing students' dependency profiles across Iraq and Oman.

This complementary logic is important because the study aims not only to test theoretical relationships but also to identify which determinants deserve more practical attention in each country. For example, SEM can show that triggers, competence, and autonomy are significant predictors of dependency outcomes. However, SEM alone does not rank these determinants according to their relative decision importance or show how student cases compare when all criteria are considered together. Thus, MCDM adds value by translating the psychological model into a criteria-weighting and ranking framework. This allows the analysis to move from relationship testing to contextual prioritization, which is useful for educators, policymakers, and university administrators who need to decide which factors should be addressed first in responsible AI use interventions.

MCDM methods can be divided into two main groups according to their decision-making function. The first group is related to criteria weighting, where the aim is to determine the relative importance of each criterion in the decision problem. In this study, the MEREC method was used for this purpose [37]. MEREC is an objective weighting method because it determines the importance of each criterion based on the effect of removing that criterion from the decision matrix. In other words, if removing a criterion causes a greater change in the overall performance of the alternatives, that criterion receives a higher weight. This makes MEREC suitable for the present study because it reduces reliance on subjective judgment and allows the empirical data to determine the

relative importance of triggers, competence, relatedness, autonomy, and risk perception [38], [39].

The second group of MCDM methods is related to ranking alternatives. In this study, the VIKOR method was used to rank the student cases based on the criteria weights obtained from MEREC. VIKOR is a compromise-ranking method originally developed to identify the alternative that is closest to the ideal solution when multiple and sometimes conflicting criteria are considered [40]. It balances two important decision perspectives: maximum group utility and minimum individual regret. This is relevant to the present study because students may not show the same dependency pattern across all criteria. Some students may report high triggers, while others may report stronger autonomy, relatedness, or risk perception. Therefore, VIKOR provides a balanced ranking procedure that identifies which student profiles are closest to the ideal weighted pattern rather than relying on one criterion alone.

Recent studies have shown the usefulness of MCDM methods in different decision-making contexts, including student-related prediction, logistics technology adoption, engineering benchmarking, and sustainability-oriented optimization [41-45]. However, the use of MCDM to examine psychological dependence on generative AI chatbots remains limited. Applying MEREC and VIKOR in this study provides a methodological contribution by connecting behavioral AI research with operations research-based prioritization methods. Specifically, PLS-SEM provides the explanatory model, MEREC identifies the objective weights of the dependency-related criteria, and VIKOR benchmarks student cases according to their closeness to the ideal weighted profile. Together, these methods provide a complete understanding of the AIholic phenomenon by combining statistical explanation with decision-based prioritization.

VIKOR was selected because the MCDM stage aimed to identify a compromise ranking rather than only a simple distance-based ranking. Student cases may not perform uniformly across all criteria. For example, one student may show high triggers but moderate risk perception, while another may show high autonomy but lower relatedness. Therefore, a method was needed that could balance overall group utility with the maximum individual regret. VIKOR is suitable for this purpose because it identifies alternatives that are closest to a compromise solution under multiple and potentially conflicting criteria. Although TOPSIS is also a widely used MCDM ranking method, it is mainly based on the relative distance from the positive and negative ideal solutions. By contrast, VIKOR is more appropriate for the present study because the aim was to identify balanced student dependency profiles across several psychological and contextual criteria rather than rank students only according to geometric closeness to an ideal point.

MEREC is based on the idea that the importance of each criterion can be measured by observing how much the overall performance changes when that criterion is removed. Unlike subjective methods that depend on expert judgment, MEREC relies directly on the decision matrix [46,47,48]. Thus, the weighting process is data-driven and less affected by researcher bias. In the present study, the five criteria were triggers, competence, relatedness, autonomy, and risk perception. The alternatives were the student cases in each country. Accordingly, the MCDM analysis complements the SEM findings by showing whether the relative importance of the determinants differs between Iraq and Oman and identifying how student cases are ranked when all weighted criteria are considered together [49]. The following steps describe the MEREC procedure used in this study [37].

Step 1: Normalize all five criteria using linear normalization.

Step 2: Apply equation (1) to determine the baseline of each of the alternatives.

$$S_i = \ln \left(1 + \frac{1}{n} \sum_{j=1}^n |\ln(r_{ij})| \right), i = 1, 2, \dots, m \quad (1)$$

Where m is the total number of attributes in the decision matrix, j represents the criterion index, and r_{ij} the value of the i^{th} alternative under the j^{th} criterion. This is a log transformation and criterion-by-criterion average.

Step 3: Compute performance point-by-point, omitting the criterion, using equation 2.

$$S'_{i(j)} = \ln \left(1 + \frac{1}{m} \sum_{\substack{k=1 \\ k \neq j}}^m |\ln(r_{ik})| \right) \quad (2)$$

Where k index representing the criteria included in the calculation and $k \neq j$ means criterion j is excluded from the summation. In every criterion j, recalculate leaving it out.

Step 4: Calculate the effect of removing D_j using equation (3).

$$D_j = \sum_{i=1}^m |S'_{i(j)} - S_i|, j = 1, 2, \dots, n \quad (3)$$

This is an improvement in how the performance assessment would change due to the criterion.

Step 5: Find the final weights of every criterion using equation (4).

$$W = \left(\frac{D_{tj}}{\sum_{j=1}^n (D_{tj})} \right) \quad (4)$$

Accordingly, each MEREC weight represents the relative importance of a criterion based on the effect of its removal. After obtaining the final criteria weights, the VIKOR method was applied to rank the alternatives and identify the compromise solution. The VIKOR procedure used in this study is presented below [40].

Stage 1: Identify the optimum f_i^* and minimum f_i^- of every criterion function as shown in equation (5).

$$f_i^* = \max_j f_{ij}, f_i^- = \min_j f_{ij} \quad (5)$$

Stage 2: Apply the weights of the criteria from the MEREC and incorporate the weights in the VIKOR method using equation (6).

$$\text{weighting matrix} = w_i * \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \quad (6)$$

The result of this stage produces the weighted matrix.

Stage 3: Obtain the values of S_j and R_j , $j=1,2,3,\dots,J, i=1,2,3,\dots,n$ by applying equations (7) and (8).

$$S_j = \sum_{i=1}^n w_i * \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \quad (7)$$

$$R_j = \max_i w_i * \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \quad (8)$$

where w_i characterizes the relative weights assigned to each criterion.

Stage 4: Compute the score Q_j , $j=(1, 2, \dots, J)$ using equation (9).

$$Q_j = \frac{v(S_j - S^*)}{S^- - S^*} + \frac{(1-v)(R_j - R^*)}{R^- - R^*} \quad (9)$$

Where

$$S^* = \min_j S_j, S^- = \max_j S_j$$

$$R^* = \min_j R_j, \quad R^- = \max_j R_j$$

In this case, $v = 0.5$ represents the “majority of criteria” approach (also known as “the largest group utility”).

Stage 5: Rank the students in ascending order of Q values. In VIKOR, the alternative with the lowest Q value is considered the closest to the compromise solution and is therefore ranked first. After completing the VIKOR ranking, the results of the MEREC-based criteria weighting and VIKOR-based ranking for Iraq and Oman are summarized. Table 4 presents the final weights of the five criteria.

Table 4: Final weights

Country	Triggers	Competence	Relatedness	Autonomy	Risk Perception
Oman	0.1699	0.1415	0.2269	0.2285	0.2332
Iraq	0.2134	0.1846	0.1873	0.2094	0.2053

As shown in Table 4, in Oman, risk perception received the highest weight (0.2332), followed by autonomy (0.2285) and relatedness (0.2269). This indicates that in the Omani context, students' awareness of AI-related risks and their need for self-directed learning were the most influential criteria in explaining chatbot dependency. In Iraq, triggers received the highest weight (0.2134), followed by autonomy (0.2094) and risk perception (0.2053). This suggests that situational pressures such as academic workload, urgency, and the need for immediate support played a stronger role in shaping students' dependency patterns in the Iraqi context. These differences indicate that the relative importance of the determinants of chatbot dependency differs across the two countries. While risk awareness appears more central in Oman, situational triggers appear more influential in Iraq. Therefore, the MEREC results provide useful evidence of contextual variation in the Alholic phenomenon.

Figure 3 presents the overall ranking of students in the Iraqi sample using the VIKOR method and MEREC-based criteria weights. The results show that S281, S285, S283, and S256 achieved the highest ranks, indicating that these cases were closest to the ideal compromise solution based on the prioritized criteria in the Iraqi context. By contrast, S111, S176, S184, and S342 obtained the lowest ranks, suggesting that their profiles showed greater deviation from the ideal weighted performance pattern. These results indicate that the higher relative importance of triggers and autonomy in Iraq influenced the final ranking of student cases. Specifically, students whose profiles were closer to the weighted pattern of situational pressure and self-directed chatbot use were ranked nearer to the ideal solution.

Figure 4 presents the final VIKOR ranking of students in the Omani sample based on the MEREC-based criteria weights. The results show that S357, S393, S349, and S362 achieved the first four ranks, indicating that these cases were closest to the ideal compromise solution in the Omani context. This suggests that their profiles were highly aligned with the most influential criteria in Oman, particularly risk perception and autonomy. By contrast, S69 and S41 obtained the lowest ranks, indicating greater deviation from the ideal weighted performance pattern. These findings show that risk awareness and self-directed chatbot use played a central role in shaping the VIKOR ranking in Oman. Therefore, the Omani results suggest that students' dependency patterns are strongly influenced by how they perceive the risks of AI use and how they use chatbots to support autonomous learning.

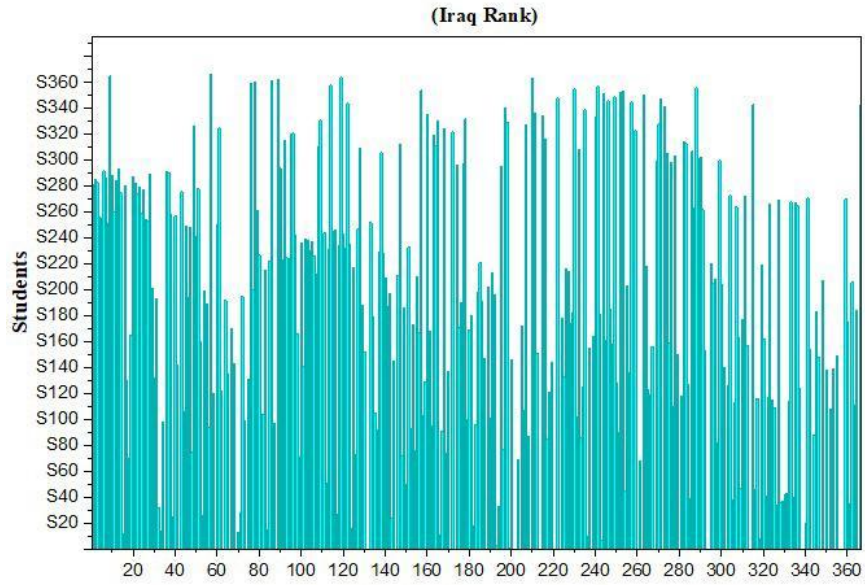


Figure 3: Rankings for Iraq

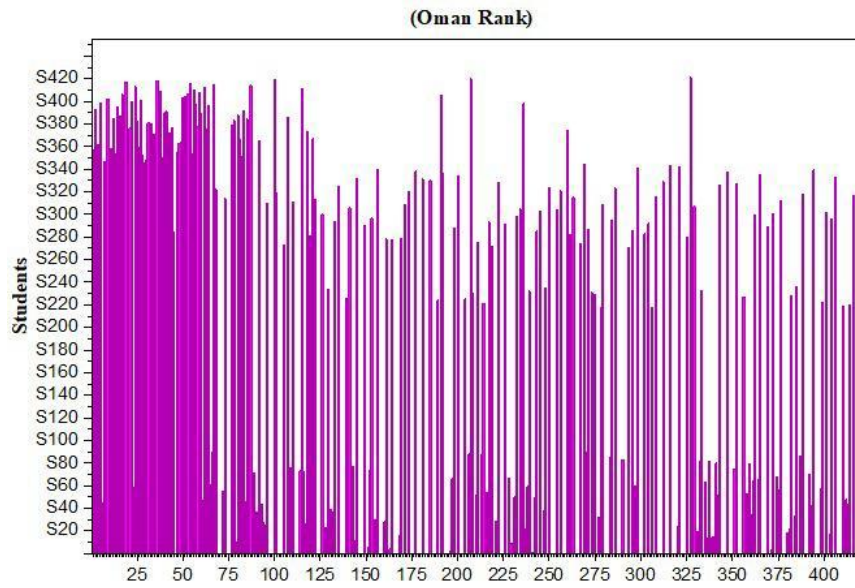


Figure 4: Rankings for Oman

In order to further validate the suitability and robustness of the proposed VIKOR based framework, the comparative analysis using Fuzzy Decision by Opinion Score Method (FDOSM) is performed. The aim of this comparison is to assess the performance of both methods on the problem of decision-making of this study and to verify the choice of VIKOR method as the main ranking method. FDOSM has been known as an effective

fuzzy decision-making method, but it is mostly based on linguistic evaluations and expert opinions, which restricts its applications to large-scale quantitative data. However, VIKOR offers a compromise ranking method which efficiently utilizes the actual decision matrix values and allows the analysis of multiple conflicting criteria. In the current study, as a relatively large decision matrix and statistically derived data from SEM analysis were used, the VIKOR method was found to be more suitable to get reliable and scalable ranking results. Hence, the comparative analysis is intended to show the merits and demerits of both methods and to highlight the merits of VIKOR in the proposed framework. Table 5 shows the comparative analysis.

Table 5: Comparative analysis

Comparison Aspect	VIKOR	FDOSM
Can be used for large decision matrices	Yes	No
Applies the values of a real quantitative data set	Yes	No
Works through a variety of options in an effective manner	Yes	No
Sensitive to expert bias	No	Yes
Adapts to ranking of compromise solutions	Yes	No
Well suited to solve complex MCDM problems	Yes	No
Can be scaled up to high-dimensional datasets	Yes	No
Carries out linguistic evaluations	No	Yes
primarily needs lots of professional support	No	Yes

The results of the structural review along 9 key aspects of the decision-making reveal that VIKOR is tremendously superior to FDOSM for doing empirical research for a large scale. In particular, VIKOR has been demonstrated to be able to process large, high dimensional quantitative datasets, which FDOSM cannot process because of computational complexity, across 4 data-handling aspects. Moreover, the amount of expert support required is quite high, and FDOSM is prone to cognitive bias on 3 qualitative parameters while VIKOR, due to its objective function based on mathematical distance measures, is free from expert bias. Finally, VIKOR's particular power of modelling multi-criteria trade-offs guarantees a stable and scalable compromise ranking, which is not possible for the hard-cutting of the FDOSM approach.

5. DISCUSSION

Our findings reveal a strong connection between situational triggers, including academic overload, social isolation, tight deadlines, and uncertainty, and students' increasing reliance on generative AI chatbots. Specifically, when students are exposed to these pressures, they may move from using chatbots as practical learning tools to relying on them as part of their academic and emotional coping mechanisms. This shift is reflected in their greater frequency and intensity of chatbot use, which is consistent with compulsive behavior patterns in which immediate relief reinforces repeated behavior [25,26,46]. The

continuous availability and predictability of chatbot responses may give students a sense of control and security, which gradually encourages them to prefer automated support over more demanding forms of help such as peer discussion, instructor feedback, and independent reflection [11]. Therefore, the results support the idea that the AIholic phenomenon is not only about frequent chatbot use but also about the psychological function that chatbots serve in students' learning routines.

Theoretically, the results are strongly aligned with SDT, which explains that competence, relatedness, and autonomy are key psychological needs that shape motivation and behavior [4]. In this study, generative AI chatbots appear to support students' need for competence by providing immediate feedback, direct explanations, and rapid academic reassurance. This may increase students' confidence and perceived academic capability [11]. However, this benefit can also produce a dependency risk. When students repeatedly receive instant validation from chatbots, they may become less willing to engage in slow, reflective, and independent problem-solving. Thus, the same mechanism that supports competence in the short term may weaken deeper learning and self-regulated academic effort in the long term [2].

The findings also provide useful insights into the role of relatedness. Chatbots may offer immediate, non-judgmental, and conversational interaction, which can partially satisfy students' need to feel understood and supported, especially in remote, hybrid, and socially isolating learning environments [23,24]. However, the results show that relatedness significantly predicted inability to reduce chatbot use but did not significantly predict actual dependency level. This suggests that although relatedness may make chatbot interaction emotionally attractive and difficult to reduce, it may not always develop into a broader dependency pattern. One possible explanation is that students may still obtain social and emotional support from other digital platforms, peers, family members, and instructors. Therefore, chatbot-related relatedness may increase attachment to chatbot use but may not always become the main source of dependency.

Autonomy also contributes to the interpretation of the findings. Generative AI chatbots provide flexible and on-demand support that allows students to learn at their own pace and ask questions without social pressure or time restrictions [2,25]. This can strengthen students' sense of independence. However, the results also show that autonomy positively influenced both inability to reduce use and actual dependency level. This supports the autonomy–dependency paradox: chatbots may appear to increase students' freedom and self-direction but repeated reliance on automated guidance may gradually reduce their independent academic judgment. Therefore, autonomy can become a driver of dependency when students depend on chatbots to structure their thinking, guide their choices, and reduce uncertainty during academic tasks.

The role of triggers is also central to the findings. Psychological and situational triggers such as anxiety, deadlines, workload, and uncertainty significantly predicted both inability to reduce chatbot use and actual dependency level. This finding is consistent with CBT, which suggests that behaviors can become repeated when they provide quick relief from pressure or discomfort [26,27]. In the context of generative AI, students may experience a trigger, use the chatbot to obtain immediate academic or emotional relief, and then repeat the same behavior when similar pressures appear again. Over time, this cycle may reduce students' tolerance for uncertainty and weaken their ability to complete academic tasks without chatbot support. The findings show that chatbot dependency is partly reinforced by repeated relationships among stress, immediate relief, and continued use.

Risk perception emerged as an important moderating factor, shaping the relationships among psychological needs, triggers, and the dependency outcomes. However, these findings should be interpreted carefully. A positive interaction coefficient does not automatically mean that risk perception increases dependency in a simple or direct way. Rather, it means that the strength of the relationship between the predictor and dependency outcome changes at different levels of risk perception. The findings suggest that students' awareness of AI-related risks may change how psychological needs and triggers are translated into dependency. Students with higher risk perception may be more aware of the possible academic and psychological costs of chatbot overuse such as reduced critical thinking, academic misconduct, misinformation, and weak self-regulation [12], [29]. However, risk awareness may also make some students more conscious of their reliance on chatbots when they already use them heavily. Therefore, risk perception should be understood as a condition that changes the dependency process rather than as a simple protective factor in all cases. This is important because students with high risk perception may still become dependent if their academic pressure, need for competence, or desire for autonomy is sufficiently strong. Thus, digital literacy programs should not only inform students about AI risks but also help them develop practical strategies for controlling chatbot use.

The MCDM findings add an important contextual layer to the PLS-SEM results. The MEREC results show that the relative importance of the determinants differed between Oman and Iraq. In Oman, risk perception received the highest weight, followed by autonomy and relatedness. This suggests that students' awareness of AI-related risks and their need for self-directed learning were especially important in shaping chatbot dependency in the Omani context. In Iraq, triggers received the highest weight, followed by autonomy and risk perception. This indicates that situational pressures such as workload, urgency, academic stress, and the need for immediate support were more central in shaping chatbot dependency in the Iraqi context. Thus, although the same theoretical model was applied in both countries, the dominant criteria differed. This finding supports the need to consider contextual differences when studying the Alholic phenomenon.

The VIKOR results further complement the MEREC weighting analysis by ranking student cases according to their closeness to the ideal weighted profile, providing further evidence that dependency-related profiles differ across contexts. In Iraq, the ranking was more strongly shaped by criteria such as triggers and autonomy, whereas the ranking was more strongly shaped by risk perception and autonomy in Oman. This means that educational interventions should not be designed uniformly. Institutions in Oman may need to pay more attention to risk-awareness training, responsible AI literacy, and reflective chatbot use. By contrast, institutions in Iraq may need to focus more on reducing situational triggers by improving academic support, workload management, mentoring, and stress-related interventions.

Overall, the findings show that generative AI chatbots play a dual role in higher education. On the one hand, they provide useful academic support, personalized learning, rapid feedback, and flexible access to information. On the other hand, they may increase dependency when students use them repeatedly to satisfy their psychological needs, manage academic pressure, and avoid uncertainty. Therefore, the Alholic phenomenon should be understood as a psychologically grounded pattern of chatbot reliance rather than a simple problem of technology use. Educational institutions should promote balanced AI integration by combining chatbot use with reflective assignments, peer collaboration,

instructor feedback, digital literacy, and clear guidance on responsible AI use to help students benefit from generative AI while protecting independent thinking, self-regulation, academic integrity, and authentic human interaction.

6. PRACTICAL AND THEORETICAL IMPLICATIONS

This study provides several practical implications for higher education institutions, educators, policymakers, and AI developers. Practically, educational institutions should view generative AI chatbots as supportive learning tools rather than replacements for human interaction, independent thinking, and instructor feedback. Integrating structured in-person discussions, collaborative projects, reflective assignments, and digital literacy programs can help balance the convenience of chatbots with the need for deeper cognitive engagement. This is important because the findings show that students may become dependent on chatbots not only for academic answers but also for reassurance, autonomy, and emotional support. Therefore, universities should not only provide access to AI tools but also guide students on how to use them responsibly.

The findings also suggest that risk awareness training should be embedded within AI literacy initiatives. Students must understand the possible risks of excessive chatbot reliance, including misinformation, weak critical thinking, academic misconduct, reduced self-regulation, and reduced human interaction [11,12]. However, risk awareness programs should not only warn students about AI use. They should also provide practical strategies for controlling use, checking chatbot outputs, combining AI support with peer and instructor feedback, and maintaining independent academic judgment. Tools such as usage dashboards, time reminders, reflective prompts, and task-based limits may also encourage more self-regulated chatbot use. Collaboration among policymakers, educators, and AI developers is therefore needed to create clear guidelines on the appropriate roles and limits of generative AI in learning.

The MCDM findings also provide practical implications for country-specific interventions. In Oman, interventions may benefit from a stronger emphasis on risk awareness, responsible AI literacy, and reflective evaluation of chatbot outputs. In Iraq, institutions may need to focus more on reducing academic pressure, improving mentoring, supporting students during deadlines, and strengthening stress management practices. Thus, universities should consider students' needs and the most influential determinants of dependency before tailoring intervention strategies.

Theoretically, this study contributes to the literature on human–AI interaction by framing chatbot dependency as a psychologically grounded phenomenon rather than only a technology-use behavior. It advances the “AIholic” concept by showing that generative AI dependency may involve academic reliance, emotional reassurance, perceived connection, and self-directed decision support. This extends previous discussions of overreliance and problematic technology use by showing that generative AI chatbots have distinctive affordances, including conversational interaction, instant feedback, continuous availability, and perceived personalization.

The study also extends SDT by showing that generative AI chatbots can both satisfy and undermine the psychological needs of competence, relatedness, and autonomy [4], [24]. Chatbots may support competence through quick feedback, relatedness through non-judgmental interaction, and autonomy through flexible self-directed learning. However, the findings show that the same psychological need satisfaction may also contribute to dependency when students begin to rely on chatbots as their main source of support. In

addition, this study extends CBT by explaining how situational triggers may reinforce repeated chatbot use when students use AI to reduce stress, uncertainty, and academic pressure [26], [27]. Finally, the integration of MEREC and VIKOR offers a methodological contribution by showing that MCDM techniques can complement SEM results and identify the relative importance of dependency-related criteria across contexts.

Future research could include more diverse educational settings beyond university education such as schools, vocational training institutions, and professional development programs. Longitudinal and mixed-method studies are also needed to examine how chatbot dependency develops over time and how students move from beneficial use to problematic reliance. Future studies could also examine specific chatbot features such as emotional tone, adaptive feedback, memory, personalization, and collaborative functions to determine which design elements increase or reduce dependency. In addition, comparative studies across disciplines and cultures may help explain how institutional policies, academic pressure, and digital literacy shape the AIholic phenomenon.

7. LIMITATIONS

This study has several limitations that should be considered. First, the study relied on self-reported data, which may introduce social desirability bias and recall bias. Participants may have over- or underestimated their chatbot use and psychological experiences, which may have influenced the observed relationships. Future studies could reduce this limitation by combining survey data with behavioral usage logs, learning analytics, and platform-based indicators of chatbot use.

Second, the study used a cross-sectional design, which limits the ability to make causal claims. Although the findings show significant associations among triggers, psychological needs, risk perception, and chatbot dependency, it remains difficult to determine whether these factors cause dependency or develop as a result of repeated chatbot use. Longitudinal and experimental designs are therefore needed to examine how chatbot dependency develops, increases, or decreases over time.

Third, the sample was drawn from university students in Iraq and Oman. Although this provides useful cross-national evidence, the findings may not be fully generalizable to other countries, educational systems, and student populations. Cultural, socioeconomic, institutional, and disciplinary differences may shape how students use and depend on generative AI chatbots. Future research could test the model in broader and more diverse contexts, including different regions, academic disciplines, and educational levels.

Finally, although this study used MEREC and VIKOR to provide additional prioritization evidence, other MCDM methods may produce different rankings and weights. Future research could compare MEREC and VIKOR with other approaches such as fuzzy MEREC, fuzzy VIKOR, TOPSIS, CRITIC, and DEMATEL to examine whether the prioritization of psychological determinants remains stable under different methodological assumptions. These limitations do not reduce the value of the findings but indicate useful directions for future research on generative AI dependency in higher education.

8. CONCLUSION

This study introduced and empirically examined the AIholic phenomenon, which refers to students' growing dependence on generative AI chatbots for academic support,

reassurance, emotional comfort, and self-directed decision-making. Using a cross-national sample from Iraq and Oman, the study examined how situational triggers and psychological needs, namely, competence, relatedness, and autonomy, influence two dependency-related outcomes: actual dependency level and inability to reduce chatbot use. The findings show that triggers, competence, and autonomy were significant predictors of both outcomes, while relatedness significantly predicted inability to reduce chatbot use but did not significantly predict actual dependency level.

The study also examined the moderating role of risk perception. The results show that risk perception changed several relationships between the predictors and dependency outcomes. However, risk perception should not be interpreted as a simple protective factor in all cases. Rather, its effect depends on the form of the interaction and slope patterns shown in the moderation analysis. Students' awareness of AI-related risks may shape how psychological needs and triggers are translated into dependency but it does not automatically prevent dependency when academic pressure or psychological reliance is strong.

In addition, the integration of MCDM techniques provided further insights into the relative importance of the determinants of chatbot dependency. The MEREC method was used to determine the objective weights of the study criteria, while the VIKOR method was applied to rank student cases across the examined contexts. The MEREC results showed that risk perception was the most influential criterion in Oman, whereas triggers were the most influential criterion in Iraq. This indicates that chatbot dependency is shaped by common psychological mechanisms but the most influential determinants may differ across national contexts.

The study contributes to the growing literature on human–AI interaction in education by framing chatbot dependency as a psychological and behavioral phenomenon rather than only a technological issue. The findings suggest that responsible AI integration should focus not only on access and efficiency but also on self-regulation, critical thinking, academic integrity, risk awareness, and human interaction. By combining psychological theory, PLS-SEM, and MCDM techniques, this study provides theoretical and practical insights for understanding and managing the Alholic phenomenon in higher education.

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APPENDIX

All items were measured using a five-point scale. Frequency-based items used response options ranging from 1 = Not often to 5 = Very often. Agreement-based items used response options ranging from 1 = Strongly disagree to 5 = Strongly agree.

A.1. Need for Competence (COM)

Item	Measurement item
COM1	When I interact with chatbots/generative AI, I feel competent.
COM2	Using chatbots/generative AI allows me to achieve the goals I set for myself.
COM3	I feel effective when navigating through tasks with chatbots/generative AI.
COM4	My ability to use chatbots/generative AI improves as I use them more.
COM5	I get a sense of satisfaction from overcoming challenges with chatbots/generative AI.
COM6	I feel like I can handle anything when I use chatbots/generative AI.
COM7	I am confident in my skills when I interact with chatbots/generative AI.

A.2. Triggers of Chatbot Use (TRG)

<i>Item</i>	<i>Measurement item</i>
TRG1	How often do you find that you stay on chatbots/generative AI longer than you intended?
TRG2	How often do you neglect household chores to spend more time on chatbots/generative AI?
TRG3	How often do you prefer the excitement of chatbot interaction over being with your friends?
TRG4	How often do others in your life complain to you about the amount of time you spend on chatbots/generative AI?
TRG5	How often do your grades or schoolwork suffer because of the amount of time you spend on chatbots/generative AI?
TRG6	How often do you check chatbots/generative AI before something else that you need to do?
TRG7	How often does your job performance or productivity suffer because of chatbot/generative AI usage?
TRG8	How often do you become defensive or secretive when anyone asks you what you do on chatbots/generative AI?
TRG9	How often do you block out disturbing thoughts about your life with calm thoughts of using chatbots/generative AI?
TRG10	How often do you find yourself anticipating when you will use chatbots/generative AI again?
TRG11	How often do you fear that life without chatbots/generative AI would be boring, empty, and joyless?
TRG12	How often do you snap, yell, or act annoyed if someone bothers you while you are using chatbots/generative AI?
TRG13	How often do you lose sleep due to late-night chatbot/generative AI sessions?
TRG14	How often do you feel preoccupied with chatbots/generative AI or fantasize about using them when offline?
TRG15	How often do you find yourself saying "just a few more minutes" when using chatbots/generative AI?
TRG16	How often do you try to cut down the amount of time you spend on chatbots/generative AI and fail?
TRG17	How often do you try to hide how long you have been using chatbots/generative AI?
TRG18	How often do you choose to spend more time on chatbots/generative AI over going out with others?
TRG19	How often do you feel depressed, moody, or nervous when you are not using chatbots/generative AI, which goes away once you are back using them?
TRG20	How often do you think you need to spend less time on chatbots/generative AI but continue to use them anyway?

A.3. Need for Relatedness (REL)

<i>Item</i>	<i>Measurement item</i>
REL1	I feel a sense of belonging when I use chatbots/generative AI.
REL2	My chatbot/generative AI interactions are satisfying at a personal level.
REL3	I feel cared for when interacting with chatbots/generative AI.
REL4	Using chatbots/generative AI gives me a comforting sense of not being alone.
REL5	I feel valued by the responses I get from chatbots/generative AI.
REL6	Chatbots/generative AI make me feel connected to something bigger.
REL7	I enjoy the sense of community that comes from the shared use of chatbots/generative AI with others.

A.4. Need for Autonomy (AUT)

<i>Item</i>	<i>Measurement item</i>
AUT1	Chatbots/generative AI provide me with the freedom to explore and learn on my own.
AUT2	I feel independent when making choices in my interactions with chatbots/generative AI.
AUT3	Using chatbots/generative AI allows me to take initiative in my learning.
AUT4	I feel that my decisions are respected when using chatbots/generative AI.
AUT5	I experience personal growth while using chatbots/generative AI.
AUT6	Chatbots/generative AI help me follow my own learning process.
AUT7	I feel autonomous in the choices I make with chatbot/generative AI guidance.

A.5. Risk Perception (RP)

<i>Item</i>	<i>Measurement item</i>
RP1	If I use chatbots and generative AI without caution, I will likely face negative consequences.
RP2	I feel I have little control over the outcomes of using chatbots and generative AI.
RP3	Using chatbots and generative AI could lead to serious issues for me.
RP4	If I rely heavily on chatbots and generative AI, my life could have major consequences.
RP5	Using chatbots and generative AI might lead to minor inconveniences for me.
RP6	Dependence on chatbots and generative AI could significantly impact my daily life.
RP7	Relying on chatbots and generative AI might have financial implications for me.
RP8	Using chatbots and generative AI could cause difficulties for people who are important to me.

A.6. Inability to Reduce Chatbot Use (IBRU)

<i>Item</i>	<i>Measurement item</i>
IBRU1	How often do you find yourself spending more time interacting with chatbots/generative AI than you originally intended?
IBRU2	How often do you prioritise chatting with chatbots/generative AI over other important tasks or responsibilities?
IBRU3	How often do you feel a sense of excitement or pleasure while interacting with chatbots/generative AI?
IBRU4	How often do you neglect spending time with friends or family in favour of chatting with chatbots/generative AI?
IBRU5	How often do you find yourself thinking about past interactions with chatbots/generative AI when you are not chatting with them?
IBRU6	How often do you have trouble controlling the amount of time you spend interacting with chatbots/generative AI?
IBRU7	How often do you feel anxious or upset when you are unable to chat with chatbots/generative AI?
IBRU8	How often do you feel a sense of satisfaction or accomplishment after a chatbot/generative AI interaction?
IBRU9	How often do you find yourself seeking out new chatbots to interact with?
IBRU10	How often do you feel that chatting with chatbots/generative AI is more enjoyable than interacting with real people?
IBRU11	How often do you feel that chatting with chatbots/generative AI helps you escape real-life problems or stressors?
IBRU12	How often do you experience negative consequences, such as loss of sleep or neglecting responsibilities, due to your interactions with chatbots/generative AI?
IBRU13	How often do you try to reduce the amount of time you spend interacting with chatbots/generative AI but find it difficult to do so?
IBRU14	How often do you feel that your interactions with chatbots/generative AI interfere with your daily functioning or productivity?

A.7. Actual Dependency Level (ADL)

<i>Item</i>	<i>Measurement item</i>
ADL1	Do you often neglect planned tasks or engagements because you spend too much time interacting with chatbots/generative AI?
ADL2	Do you find it hard to focus on important activities, such as work or study, because you are constantly engaged with chatbots/generative AI?
ADL3	Do you often experience physical discomfort, such as eye strain or headaches, after spending a lot of time interacting with chatbots/generative AI?
ADL4	Do you feel anxious or uneasy when you are unable to interact with chatbots/generative AI?
ADL5	Do you feel impatient or restless when you are not engaging with chatbots/generative AI?
ADL6	Do you often think about chatbots/generative AI even when you are not interacting with them?
ADL7	Are you unwilling to give up interacting with chatbots/generative AI even when it negatively affects your daily life?
ADL8	Do you constantly check chatbots/generative AI to ensure you do not miss any conversations or notifications?
ADL9	Do you often find yourself using chatbots/generative AI for longer periods than you had intended?
ADL10	Have you received feedback from others that you use chatbots/generative AI excessively?