Chatbots on Emotional and Social Skills; Are they really improving Student`s Learning?

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Abstract

This study investigates the interplay between chatbot utility (CU), emotional and social skills (ESS), and teacher support (TS) in influencing students' academic performance in higher education. As artificial intelligence becomes increasingly embedded in educational settings, chatbots have emerged as personalized tools for learning assistance. However, their effectiveness is contingent upon students' emotional intelligence and the presence of supportive teacher engagement. Drawing on the SAC (Student-AI-Content) model, this research examines how CU and ESS jointly impact academic outcomes and how TS mediates this relationship. A quantitative methodology was employed using a structured equation modeling (SEM) approach. Data were collected from 236 computer science students in Karachi, Pakistan, who are considered adept in using AI tools. The findings confirm that CU and ESS significantly predict perceived teacher support, which in turn strongly influences academic performance. The study concludes that while chatbot integration in education holds promise, its effectiveness is optimized through the cultivation of emotional competencies and consistent teacher support. The research offers critical implications for AI integration in educational practices, emphasizing the need for holistic learning environments that blend technology with human relational elements.

Keywords: Chatbot Utility, Emotional and Social Skills (ESS), Teacher Support, Artificial Intelligence in Education, Academic Performance, Student-AI-Content (SAC) Model, Higher Education, Structural Equation Modeling (SEM), Digital Learning, Educational Technology

1. INTRODUCTION

In the age of educational transformation, educational institutions are increasingly integrating artificial intelligence into their teaching (Harry, A.2023). Among many AI tools, chatbots; an AI conversation tool has gained among the most personalized tools that provide timely feedback and continuous support. Literature shows that with the rapid integration and usage of chatbots, students emotional and social skills are affected, which in turn might affect students` development. Students with high emotional skills can manage their emotions as well as others (Zhai etal.,2021). They understand and respond well to different people as per their needs. They also tend to get higher GPAs compared to other students. Students with low levels of emotional intelligence and skills may find difficulty in managing their own emotions and also face problems in coordination with other people (Mosleh et al., 2024). Studies also proved that in combination of chatbot utility and emotional and social skills academic development progresses dominantly. Teachers` support plays a major role as in many places' teachers are rigid are reluctant to allow them to use chatbots. But despite students using them but didn't get the positive outcomes as compared to places where teachers support is present for chatbot.

Researchers found a significant gap in integrating chatbot utility (CU) and emotional and social skills (ESS) and how they combinedly produce a positive effect on student's academic achievement(Campbell & von Stauffenberg, 2008). Current study employs an adapted scale of chatbot utility and emotional and social intelligence and utilized it to find out its effectiveness on student`s academic scores. Teacher support plays a detrimental role, as the guidance and mentoring of a teacher is important to make proper utilization of technology especially AI. Study was conducted on university students of computer science departments in context of Karachi, Pakistan as they know well about usage of technology and digitization.

The study thus aimed at:

- to measure the combined effect of chatbot utility and emotional and social skills on student academic performance
- to explore the role of teachers' support in enhancing the effectiveness of chatbot utility and students 'academic outcomes

It is guided by the following research questions:

Q.1 To what extent do chatbot utility and social and emotional intelligence interact to improve student`s academic performances?

Q.2 Does teachers 'support moderate the relationship between chatbot utility and academic performances?

This research holds significance in bridging a gap between finding out the collecting relationship of chat bot utility and emotional and social skills (ESS) as compared to individual correlation between chatbot utility and academic scores. Also provides empirical evidence of how teachers' support can make it more applicable for students' learning. As AI continues to shape landscape in future, the study provides useful direction that how it can be made fruitful for students learning.

2. LITERATURE REVIEW

2.1 AI in Education

As AI is increasing rapidly in all fields, especially in the field of education. It is gaining popularity and studies showed that it proved to be effectives in upgrading student learning outcomes (Wu & Yu, 2023).AI now a days are working as a partner , as an assistant and more effectively as a mentor towards the learning (Fidan & Gencel, 2022; Wollny et al., 2021).They even help learners to practice languages using artificial partners (Lee et al., 2022; Liu, Liao et al., 2022).Literature suggests due to potential use AI is used largely in Mathematics (Yin et al., 2021), Language (Kim, 2019),medicine (Lee et al., 2022) and psychology (Lin & Chang, 2020). An increasing amount of research has examined the potential impact of AI chatbots within educational settings (Jeon, 2022). Findings suggest that these tools can enhance students' academic outcomes (Kim, 2018a; Vázquez-Cano et al., 2021), foster interest in learning (Wambsganss et al., 2021), and improve motivation (Chien et al., 2022; Kim, 2018b), engagement (Ruan et al., 2021), and self-efficacy in learning (Yin et al., 2021). Additionally, AI chatbots have been associated with reductions in students' learning-related stress and anxiety (Klos et al., 2021; Terblanche et al., 2022). On the other hand, more recent investigations have shown no notable differences between students who used chatbots and those who did not in terms of engagement (Liu, Liao et al., 2022), confidence (Han et al., 2022), motivation (Kumar, 2021), and academic performance (Yin et al., 2021). These mixed findings highlight the nuanced and potentially complex nature of chatbot effects in education.

The use of chatbots in education is increasingly supported by theoretical frameworks that explain how users come to accept and rely on new technologies (Davis, Bagozzi, and Warshaw 1989; Moussawi, Koufaris, and Benbunan-Fich 2020). One widely recognized framework is the Technology Acceptance Model (TAM), initially proposed by Davis and further refined by subsequent researchers. At its core, this model suggests that users are more likely to adopt a technology when they find it beneficial to their goals and easy to interact with. Applying this perspective to educational chatbots, when students perceive these tools as helpful for their learning (Liu, Liao, and Pratt 2009)offering timely information, answering questions, or clarifying doubt they are more likely to engage with them. This interaction doesn't happen in isolation. As students become more engaged and supported by the chatbot, their perception of teacher responsiveness and availability can also improve (Park 2010). The chatbot, in this sense, acts as an extension of the teacher's support, enhancing the learning environment. Therefore, students who view chatbots as useful may feel that their teachers are more supportive, approachable, and invested in their success.

Because the TAM has been used across a wide range of technologies and settings, it offers a flexible structure for understanding how perceptions of chatbot utility might shape broader educational experiences, such as the level of teacher support a student perceives (Venkatesh 2000).

Hypothesis thus developed based on the literature is:

H:1 There exists a positive relationship between CU and TS

2.2 Emotional and Social Skills

Social skills and competencies include a set of skills that facilitates social interactions. (Denham & Brown,2010). During early childhood a child develops under two domains; interpersonal skills that guide him to deal with the environment and emotional stability that makes him train to stabilize his emotions during stress and excitement (Fabes, Gaertner, & Popp, 2006). During early ages children are exposed to less number of people but as they grow their circle enlarges that necessitates them develop social skills(Campbell & von Stauffenberg, 2008; Ladd, Herald, & Kochel,2006) . Teachers consider social skills as one of the most important variables in achieving good academic scores (Lin, Lawrence, & Gorrell, 2003) but literature finds some mixed evidences. It is reported that social skills are not strong predators of academic achievements (Claessens et al., 2009; Duncan et al., 2007) while other studies showed a positive relationship (Trentacosta & Fine,2010).

Academic performance is frequently assessed through students' grades. However, research suggests that these grades do not solely represent subject-specific knowledge; they are also shaped by additional elements such as students' social competencies (Lekholm & Cliffordson, 2008; Malecki & Elliot, 2002). Even when variables like IQ, ethnicity, classroom behaviour, and teacher preferences are accounted for, prosocial behaviours continue to serve as significant predictors of academic grades (Teo, Carlson, Mathieu, Egeland, & Sroufe, 1996). Classroom conduct appears to have a notable impact on learning outcomes and achievement (Wentzel, 1991), indicating that social skills play a crucial role in how teachers evaluate student performance (Cornwell, Mustard, & Parys, 2013). Additionally, teacher evaluations tend to be more closely related to students' social behaviours than standardized test results (DiPrete & Jennings, 2012). Researchers have also found that gender disparities are more pronounced in teacher-assigned grades than in standardized assessments (Cornwell et al., 2013; Lekholm & Cliffordson, 2008).

Students with higher emotional and social skills may be better at communicating their needs, interacting positively with peers and teachers, and participating actively in class. These behaviors likely elicit more responsive, supportive, and positive interactions from teachers((Curby et al., 2013). Social and emotional skills are foundational for building supportive relationships with peers and adults, including teachers. Students who exhibit strong emotional regulation and empathy are often better able to engage positively with teachers, which may lead to greater teacher support. Teacher support, in turn, plays a crucial mediating role in students' school success. Teachers view social-emotional competence as a key factor for positive classroom behavior and engagement (Lin, Lawrence, & Gorrell, 2003), though empirical findings are mixed. Some studies report that social skills do not strongly predict academic achievement (Claessens et al., 2009; Duncan et al., 2007), while others suggest a significant positive relationship (Trentacosta & Fine, 2010).

In particular, emotional competencies such as emotion recognition, self-regulation, and empathy have been shown to enhance student-teacher relationships (Denham et al., 2012), which is reflected in increased perceived teacher support. This aligns with evidence from the structural model indicating that students' essential social skills (ESS) positively predict teacher support (TS). Therefore, integrating emotional skills as part of the broader framework of social competencies provides a deeper understanding of how students' interpersonal behaviors influence their academic environments through teacher relationships.

Therefore, Hypothesis developed is:

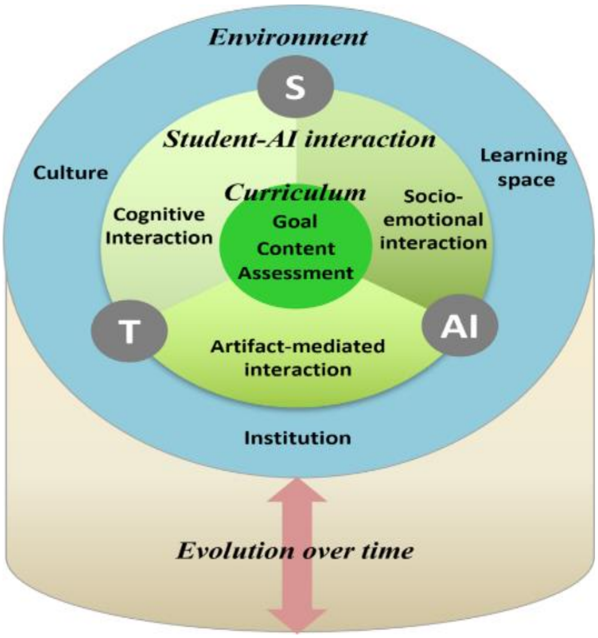
H2: *Students' essential social and emotional skills significantly and positively predict perceived teacher support, which may subsequently influence academic performance.*

2.3 Teacher`s Support

Speculations that artificial intelligence might entirely take over the role of educators (Nazaretsky et al., 2022) are frequently met with doubt and ongoing discourse among education professionals (Chiu, 2021).

Figure 1

SAC Model



Although AI has progressed considerably across various educational domains (Zhai et al., 2021), such assertions require careful scrutiny, especially given the complex and multidimensional nature of teaching. While AI can support educational settings by streamlining administrative duties and offering tailored learning pathways, it remains incapable of replicating the full range of human attributes that educators contribute to classrooms (Bertolin & Da Rin, 2020). Teaching goes beyond simply conveying content—it entails fostering analytical thinking, nurturing emotional intelligence, facilitating social engagement, and adapting to a wide range of learner differences. These vital components of education depend heavily on human teachers, who play a central role in inspiring, guiding, and connecting with students on a personal level (Guan et al., 2020). As AI is increasing the permeation, entire system of education is increasing the collaboration and interaction and building the social skills to maintain social relationships and enhance personalize learning(Lee & Kim, 2020; Kim et al., 2020). The study is based on the SAC model that requires the participation of students, AI and teachers to follow curriculum. The model suggests AI working as a collaborator for student learning, in which teacher`s support plays an important role. One of the studies revealed that learners with higher perceived teacher support have higher levels of affective learning, cognitive learning, and academic self-confidence, as well as less procrastination and a higher willingness to make changes to it (Duan et al., 2024).As teacher`s support and motivation helps learners to grow, it is also found that teachers support can also help students to learn AI effectively(Chiu et al., 2023).The above studies support the development of the hypothesis:

H:3 Teachers` support mediates the relationship between CU, ESS and Academic Scores

Chapter: 3 Methodology

Study utilized quantitative methodology, Structure Equation Modeling (SEM) is done using SPSS version:23 and AMOS version :22. Study is conducted among private university students of Karachi, Pakistan. Students are selected randomly from 5 universities from the CS (Computer Science) Department as it is believed that students of computer science know well to use Chatbots more effectively than other students. For the sample size, online calculator was used to determine a priori sample size for structure equation models (Soper, 2016). Based on the calculations, the minimum sample size of 119 proved sufficient enough to detect the effect. However, SEM is a large technique, so we distributed approximately 400 questionnaires out of which 261 responses were collected. During the data screening 25 outliers were detected which were eliminated and hence a sample size of 236 responses were left for the analysis technique.

Demographic Characteristics of the Respondents:

The demographic profile of the respondents reveals that a majority were under the age of 18, accounting for 58.9% (n = 139) of the total sample. This was followed by those aged 18–19 years, comprising 30.5% (n = 72), while smaller proportions were observed in the older age groups: 3.8% (n = 9) were between 20–22 years, 2.5% (n = 6) between 23–25 years, and 2.1% (n = 5) each for the 25–28 and 28+ age categories. This indicates that the sample was predominantly composed of younger individuals, likely reflecting the target population of early-year university students. In terms of gender distribution, the data shows a significantly higher number of female participants (71.2%, n = 168) compared to male participants (28.8%, n = 68). This suggests a gender imbalance in the sample, possibly due to the higher enrollment of females in the particular program or institution from which the sample was drawn.Regarding educational level, more than half of the respondents (51.7%, n = 122) were enrolled in the first year of their academic program. This was followed by students in the fourth year (33.1%, n = 78), while smaller proportions were observed in the third year (10.6%, n = 25), MS level (3.4%, n = 8), and second year (1.3%, n = 3). These figures suggest that the data is largely representative of early-stage undergraduate students, with limited representation from postgraduate or more senior undergraduate students.

Table 1

Demographic table

Age in Years	Frequency	Percent
18-19	139	58.9
20-22	72	30.5
23-25	9	3.8
25-28	6	2.5
28+	5	2.1
Under 18	5	2.1
Gender		
Male	68	28.8
Female	168	71.2
Educational Level		
First Year	122	51.7
2nd Year	3	1.3
3rd Year	25	10.6
4th Year	78	33.1
MS	8	3.4

Measures

The study includes three constructs: Chatbot usability (CU), Emotional Intelligence and Social Skills (ESS) and Teachers' Support (TS) in which chatbot usability is the independent variable whereas ESS and TS are the mediating variables through which effect of CU can be measured on Student`s Academic Scores which is a continuous variable. The self-administered questionnaire comprises 26 items that were measured on a 5-point Likert scale (1-5) from strongly disagree to strongly agree.

Table 2

Data tools

Constructs and Indicators	Sources
Chatbot Usability	(Borsci et al., 2022)
Chatbot understood me very well Chatbot is very easy to use' The chatbot coped well with any errors or mistakes The chatbot's personality is realistic and engaging Chatbot responses are useful, appropriate and informative	

The chatbot is welcoming during initial setup	
Social and Emotional Intelligence	Perez, R. (2023)
I realize immediately when I lose my temper I am able to always motivate myself to do difficult tasks I know when I am happy I am an excellent listener I usually recognize when I am stressed I can always motivate myself even when I feel low I can tell if someone has upset or annoyed me I can suppress my emotions when I need to I generally build solid relationships with those I work with I am good at reconciling differences with other people I need a variety of work colleagues to make my job interesting Difficult people do not annoy me I can sometimes see things from others' point of view I see working with difficult people as simply a challenge to win them over	
Teacher`s Support	(Chiu et al., 2023)
My teacher provides clear guidelines on how to use ChatGPT effectively for learning. My teacher discusses both the benefits and limitations of using ChatGPT. My teacher helps me understand when and how to use ChatGPT appropriately in my academic work. My teacher encourages me to reflect on the accuracy and relevance of ChatGPT-generated responses.	

Analysis and Result

Exploratory Factor Analysis

This study utilizes 26 Likert scale items to measure three constructs. Exploratory Factor Analysis. (EFA) is a data reduction technique, in order to extract three variables by measuring convergent, construct and discriminant validity. Principal Component Analysis was used in order to extract the component (Foster, Barkus, & Yavorsky, 2006; Leech, Barrett, & Morgan, 2005). Kaiser- Meyer-Olkin (KMO) measure of sample adequacy came out to be 0.918 which is greater than the threshold of 0.7 which indicates sample was adequate to run the EFA. Bartlett's Test of Sphericity having chi square value of 3544.859 and p value significant depicts that correlation matrix is not an identity matrix (Leech et al., 2005; Tabachnick &Fidell, 2007).

Table 3 below depicts factor loadings with varimax rotation being 22 items being retained each aligned with its designated factors. Items having factor loading below 0.4 were excluded to maintain clarity. It should be acknowledged that SPSS does not provide p-values or tests for the statistical significance of loadings (Field, 2005). Nonetheless, the adequacy of the sample size can serve as an indirect indicator of their significance (Stevens, 2012). Scholars such as Gaskin (2016) recommend that each item's loading should exceed 0.50 and an average loading should exceed 0.7. As in the table it is observed that the lowest factor loadings were of 6.62 which exceeds the recommended threshold. These results collectively support the convergent validity.

Table 3

Exploratory Factor Analysis (n=236)

	Component		
	1	2	3
CU1	.741		
CU2	.750		
CU3	.694		
CU4	.779		
CU5	.800		
CU6	.727		
CU7	.789		
CU8	.589		
CU9	.477		
CU10	.662		
ESS4		.490	
ESS5		.547	
ESS7		.762	
ESS8		.840	
ESS9		.871	
ESS10		.878	
ESS11		.790	
ESS12		.732	
TS1			.823
TS2			.907
TS3			.868
TS4			.677

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Confirmatory Factor Analysis (Measurement Model)

Confirmatory Factor Analysis was conducted by AMOS to validate the hypothesized model. Composite reliability was measured that serves as the measure of internal consistency reliability Hair et al. (2011, p. 145). Table 4 below shows composite reliability, convergent and discriminant validity.

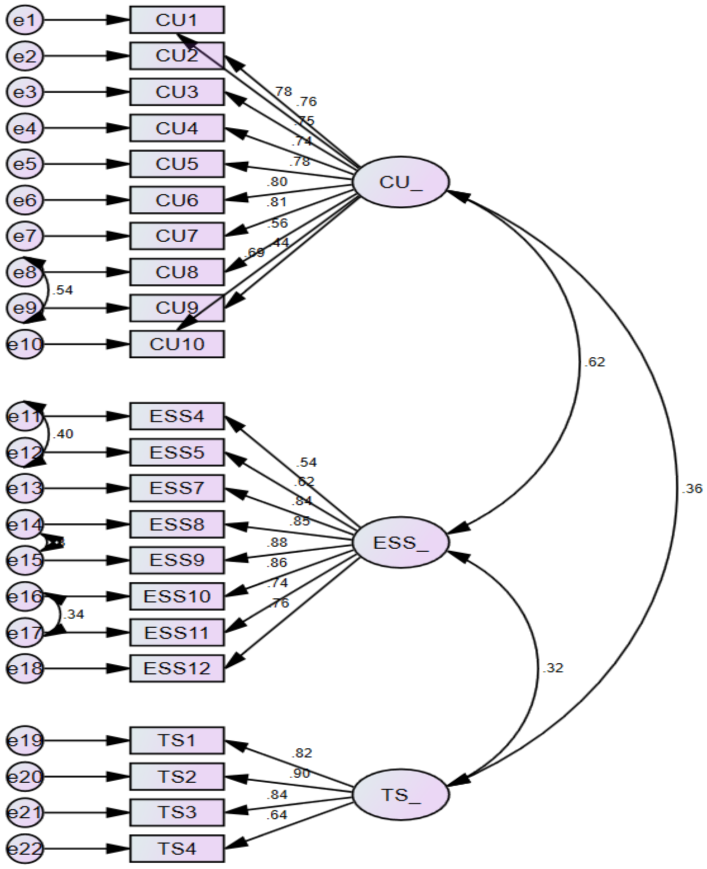


Table 4

Reliability Measures

	CR	AVE	MSV	MaxR(H)	ESS_	CU_	TS_
ESS_	0.922	0.603	0.375	0.942	**0.776**		
CU_	0.914	0.520	0.375	0.924	0.612	**0.721**	
TS_	0.879	0.649	0.134	0.905	0.317	0.366	**0.805**

The result presented in the table below represents strong convergent and discriminant validity among three constructs. Composite reliability for all three constricts exceeds the threshold of 0.7, indicating strong internal consistency (Hair, Black, Babin, & Anderson, 2010; Hair et al., 2011, 2012). Average Variance Extracted is above 0.5 which is acceptable confirming that a substantial portion of variance is captured by the constructions rather than error (Hair et al., 2011, 2012). For each construct AVE is greater than maximum shared variance (MSV) fulfilling one condition for discriminant validity (Byrne, 2010; Hair et al., 2010). Additionally, Fornell Larcker Criterion is satisfied as the square root of AVE is greater than the inter-construct correlations. These findings suggest that the measurement model is reliable and valid (Byrne, 2010; Fornell & Larcker, 1981; Hair et al., 2010).

Table 5
Measures of Model Fit

Goodness of Fit Measures	CMIN/DF	RMSEA	SRMR	CFI	TLI
Recommended Value	<3[a] - <5	<0.08[b]	<0.08[c]	≥0.95[c]	≥0.95[d]
CFA Measurement Model	2.2	0.07	0.057	0.9	0.9

Notes: CMIN = Minimum Discrepancy (Chi-Square); DF = Degree of Freedom TLI = Tucker-Lewis Index RMSEA = Root Mean Square Error of Approximation SRMR = Standardized Root Mean Squared Residual ,CFI =Comparative Fit Index
a = Byrne (2010); b = Browne and Cudeck (1993)c= *SEM: Fit (Menny,2024))*, n.d ; c = Bagozzi and Yi (1988); d = Bentler and Bonett (1980)

The Confirmatory Factor Analysis (CFA) results indicate an acceptable model fit. The chi-square divided by degrees of freedom (CMIN/DF) is 2.2, which falls within the generally accepted threshold of less than 3 to 5(Bryne,2010), suggesting a reasonable fit between the proposed model and the observed data. The Root Mean Square Error of Approximation (RMSEA) is 0.07, remaining below the recommended maximum of 0.08, thereby indicating an adequate approximation of the model to the population data(Browne and Cudeeck,1993). The Standardized Root Mean Square Residual (SRMR) is 0.057, also under the 0.08 guideline, further supporting a good fit(Kenny, 2024). However, both the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are at 0.90, which is slightly below the commonly preferred threshold of 0.95(Bagozzi and Yi,1988 : Bentler and Bonett ,1980). While these values suggest that the model fits reasonably well, they also point to some room for improvement, particularly in comparative and incremental fit measures.

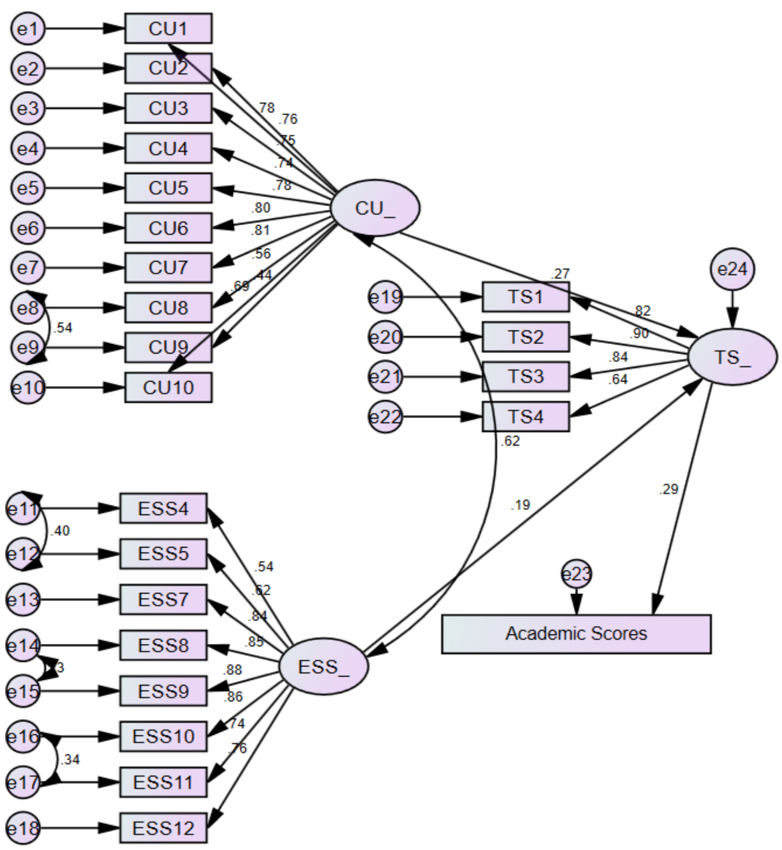
Hypothesis Testing using SEM Analysis

Based on CFA, a structural model was constructed using SEM analysis to illustrate the relationship between three variables. Based on the results all relationships are positively established and hypotheses proved to be accepted as shown in the table below:

Table :6
Hypothesis Testing

SEM Regression path			Estimate	S.E.	C.R.	P	Remarks
TS_	<---	ESS_	0.295	0.144	2.051	0.04*	Supported
TS_	<---	CU_	0.328	0.112	2.934	0.003*	Supported
AcademicScores	<---	TS_	0.196	0.046	4.28	0.000***	Supported

S.E (Standard Error), C.R (Critical Ratio) P (Probability level)
*P<0.05
***P<0.001



The structural equation modeling (SEM) analysis revealed several statistically significant relationships among the studied variables. Emotional and Social Skills (ESS) exhibited a positive and statistically significant influence on Teacher Support (TS), with a standardized estimate of 0.295 (p = 0.04). This indicates that as levels of emotional and social skills increase, perceived teacher support also tends to rise. Additionally, Chat bot utility (CU) demonstrated a significant positive effect on Teacher Support, with a standardized estimate of 0.328 and a p-value of 0.003, highlighting its meaningful role in enhancing teacher support. Lastly, Teacher Support was found to significantly predict Academic Scores, as evidenced by a standardized estimate of 0.196 and a highly significant p-value ($p < 0.001$), suggesting that greater teacher support is associated with improved academic outcomes.

Conclusion and Recommendations

This study set out to investigate how the use of chatbots in higher education, when combined with emotional and social skills, contributes to students' academic performance, and how the support of teachers further shapes these outcomes. Conducted among computer science students in Karachi, the research offers timely insight into the evolving dynamics of digital learning environments in a rapidly digitizing world.

The results reveal that chatbot utility alone is not sufficient to guarantee academic improvement. Instead, when students possess strong emotional and social skills, their engagement with technology becomes more meaningful. These students tend to regulate their learning, seek guidance effectively, and engage in deeper interactions—both with digital tools and with peers or mentors. Furthermore, teacher support significantly strengthens the relationship between technology use and learning outcomes, confirming that the human dimension of education remains irreplaceable.

The study also shows that teacher support mediates the impact of both chatbot usage and emotional intelligence on academic performance. Students who feel guided, encouraged, and mentored by their teachers derive more benefit from chatbot use and are more likely to demonstrate improved academic outcomes. This reinforces the view that effective learning with AI tools depends not only on the tools themselves but also on the ecosystem in which they are embedded—particularly the relational dynamics between students and teachers.

Collectively, the study highlights that integrating AI tools like chatbots in education requires more than access to technology. It requires cultivating emotional readiness in learners, promoting social engagement, and ensuring continuous support from educators. Without these conditions, even the most sophisticated digital tools may fall short of their promise.

Recommendations

Based on the findings, several practical recommendations can be drawn for educational institutions, policymakers, and practitioners:

1. **Embed Emotional and Social Skills Training in the Curriculum**
   Institutions should recognize emotional and social competencies as fundamental to academic success in digitally mediated environments. Regular workshops and integrated curriculum modules should aim to enhance students' self-awareness, emotional regulation, empathy, and interpersonal skills.
2. **Position Teachers as Technology Mentors, Not Replacers**
   Teacher professional development programs must include training on how to guide students in effectively using AI tools. Teachers should be encouraged to co-navigate these technologies with students rather than view them as threats or replacements.
3. **Develop a Supportive Learning Ecosystem**
   Universities should foster environments that combine digital resources with strong human support systems. This includes creating spaces for dialogue between students and teachers about technology use, its ethical implications, and its limits.
4. **Focus on Integration, Not Just Implementation**
   Rather than introducing chatbots as stand-alone tools, institutions should

aim to integrate them within well-structured learning models—such as the SAC model (Student-AI-Content)—that emphasize interaction and reflection.

5. **Contextualize Digital Innovations for Local Needs**
   AI tools should be adapted to fit local learning cultures. In the context of Pakistani universities, especially where access to resources and teacher guidance varies, customization is key to ensuring equitable benefits from chatbot use.
6. **Future Research and Monitoring**
   Further studies should examine long-term impacts of AI-supported learning and explore how variables such as student motivation, teacher digital literacy, and institutional readiness influence outcomes. Continuous monitoring and feedback loops can ensure that AI implementation remains responsive to student needs.

In conclusion, the future of AI in education, particularly through tools like chatbots, is promising but highly dependent on human relationships, emotional competence, and pedagogical support. The findings of this study advocate for a blended approach where technology enhances—rather than replaces—the essential human elements of teaching and learning.

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