Exploring Students' Adoption of ChatGPT as a Mentor for Undergraduate Computing Projects: PLS-SEM Analysis

Swapna GOTTIPATI*, Kyong Jin SHIM, Venky SHANKARARAMAN
School of Computing and Information Systems, Singapore Management University, Singapore
Swapnag,kjshim,venks@smu.edu.sg

Abstract: As computing projects increasingly become a core component of undergraduate courses, effective mentorship is crucial for supporting students' learning and development. Our study examines the adoption of ChatGPT as a mentor for undergraduate computing projects. It explores the impact of ChatGPT mentorship, specifically, skills development, and mentor responsiveness, i.e., ChatGPT's responsiveness to students' needs and requests. We utilize PLS-SEM to investigate the interrelationships between different factors and develop a model that captures their contribution to the effectiveness of ChatGPT as a mentor. The findings suggest that mentor responsiveness and technical/design support are key factors for the adoption of AI tools like ChatGPT. The study provides practical implications for educators seeking to incorporate AI as a mentor to support students doing computing projects and contributes to the broader understanding of the use of AI in education.

Keywords: Artificial Intelligence, ChatGPT, mentorship, computing projects, PLS-SEM analysis

1. Introduction

Recently, chatbots and virtual assistants gained popularity in education, providing personalized support to students (Mhlanga, 2023). ChatGPT, an AI language model by OpenAI, has been used in education (Sok et al., 2023) but not extensively as a mentor for computing projects. This study investigates the impact of ChatGPT mentorship, skills development, and responsiveness on its adoption as a mentor for undergraduate computing projects. Mentorship is crucial in student learning, especially in computing (Kuhail et al., 2023; Gottipati et al., 2023). However, traditional human mentors face limitations in availability and expertise (Eller et al., 2014). Chatbots like ChatGPT offer on-demand support, trained on vast data for tailored responses, making them attractive mentors. Still, their effectiveness in computing projects is unclear. Previous research focused on chatbots in education but not as mentors in computing (Kuhail et al., 2023). Variables like ChatGPT mentorship, skills development, and responsiveness in the context of computing projects need further exploration.

This paper examines the relationship between ChatGPT mentorship and its adoption in computing projects. Using the Partial Least Squares Structural Equation Modeling (PLS-SEM) statistical analysis method, we investigate the connections between various factors related to ChatGPT's use as a mentor (Hair et al., 2021. It explores how factors like ChatGPT's effectiveness as a mentor, its usage in mentoring, and student skills development are interconnected. Ultimately, a comprehensive model is developed to understand how these factors contribute to ChatGPT's effectiveness as a mentor in computing projects. This study's implications are significant. It highlights chatbots' potential as mentors for computing projects, guides the design of effective mentorship programs, and contributes to the understanding of AI in education's benefits and limitations.

2. Related Work

Artificial Intelligence in Education (AIED) can enrich teaching and learning in higher education by personalizing student learning, automating assessment tasks, and even providing around-the-clock access to learning resources In education, chatbots can be integrated into e-learning platforms that use Natural Language Processing (NLP) to interact with students by interpreting their questions and retrieving relevant information from the knowledge base module to assist students with revision (Clarizia et al., 2018). Interfacing with such conversational chatbots can provide students with the benefits of one-on-one mentoring, Active and frequent interaction between the student and the instructor impacts the student’s academic performance (Kuhail et al., 2023). Using chatbot software applications, institutions can scale one-on-one mentoring so that students have continuous support and can receive feedback 24/7 Benefits of chatbots for undergraduate students’ academic performance are demonstrated by Essel et al. (2022). In our work, we adopt the approaches from recent studies and apply them to analyze the use of ChatGPT to mentor students while doing their computing projects.

3. Hypothesis Development

In this section, we present the hypothesis of the study by identifying the factors of mentorship.

Technical mentorship: ChatGPT provides technical guidance to the student, covering data engineering, analysis, software architecture, coding standards, and best practices in software development (Castro et al., 2018). We assess the quality of advice provided by ChatGPT for completing technical tasks as a measure of technical mentorship.

Design mentorship: This construct involves ChatGPT's guidance in design-related areas (Castro et al., 2018). It includes advising on software modules, analytical techniques, data sources, and data processing methods to achieve project objectives (Iacob & Faily, 2020). We evaluate ChatGPT's effectiveness in helping students complete design-related tasks as a measure of design mentorship.

Mentor responsiveness: This construct focuses on ChatGPT's prompt and effective response to the student's needs and requests. Effective communication and understanding are crucial for successful problem-solving (Yin & Qiu, 2021). To assess mentor responsiveness, we measure the speed and quality of ChatGPT's responses to the student's questions.

Skills development: This construct focuses on the specific skills and knowledge gained by the student through ChatGPT's mentorship. A mentor enhances the student's professional and personal development by transferring technical and soft skills. We assess skills development by measuring the student's perception of acquired skills after the mentorship.

Future adoption: This construct relates to students' likelihood of using AI tools in future computing projects. Positive experiences increase the likelihood of future use, while challenges may discourage it. To assess future adoption, we measure student satisfaction and their intention to use ChatGPT in subsequent tasks.

We formulate below statistical hypothesis and test it with SMART-PLS 4 (Khoi & Van, 2018).

H1: ChatGPT technical mentorship has a positive impact on student technical skills development

H2: ChatGPT design mentorship has a positive impact on student soft skills development

H3: ChatGPT responsiveness has a positive impact on the future adoption of ChatGPT as mentor

H4: Technical skills development has a positive impact on the future adoption of ChatGPT as mentor

H5: Soft skills development has a positive impact on the future adoption of ChatGPT as mentor

4. Methodology

4.1 Participants

Participants in this study were undergraduate students from a "Text Mining and Language Processing" course at a university. The course lasted for 14 weeks, with a 12-week project component starting from week 3 and ending in week 14. The students worked in teams, applying skills in designing a text analytics application using Python and Java libraries. They were also required to demonstrate test cases during project presentations and complete a technical report. A total of 64 students were recruited for the survey questionnaire, with 58 fully completed surveys used for the PLS-SEM study.

4.2 Data Collection and Analysis

The survey instrument comprises several sections, each targeting different aspects of ChatGPT's mentorship. The technical mentorship section focuses on code-related solutions, while the design mentorship section examines project design approaches. The responsiveness section gauges student satisfaction with ChatGPT's guidance, and the skills development section assesses its impact on both technical and soft skills. Additionally, the survey explores students' future intentions regarding ChatGPT's use as a mentor. Finally, an open-ended question aids the qualitative analysis of the research question. We use the statistical software package SmartPLS 4 (Khoi & Van, 2018) for data analysis. The significance of relationships among variables is tested using regression coefficients, T-statistics, and P-values. The reliability and validity of the scale are tested by Cronbach's Alpha, Average Variance Extracted (AVE), and Composite Reliability (rho_c). A Cronbach's alpha coefficient greater than 0.6 ensures scale reliability (Hajjar, 2018). Rho_c should be better than 0.6 and AVE must be greater than 0.5 (Hair et al., 2021).

5. PLS-SEM Model Results and Analysis

5.1 Model Construction

Table 1 presents the variables used in the study and their descriptions.

Table 1. Construction of the variables.

Construct Variable	Description
TUSE_1	ChatGPT provided code without logical errors for my project.
TUSE_2	ChatGPT provided code without missing steps for my project.
TUSE_3	ChatGPT provided clear solutions to my questions.
DUSE_1	ChatGPT supported me to find additional resources to support my project.
DUSE_2	ChatGPT supported me to generate new ideas or approaches for my project.
MSUP_1	ChatGPT responded to my questions and concerns during the project.
MSUP_2	ChatGPT provided sufficient support and guidance for my project.
MSUP_3	The feedback and suggestions provided by ChatGPT were helpful for my project.
TSKILL_1	ChatGPT increased my confidence in coding.
TSKILL_2	ChatGPT increased my confidence in technical report writing skills.
TSKILL_3	ChatGPT increased my levels of problem-solving skills.
TSKILL_4	ChatGPT made me less dependent on faculty/peers for coding help.
SSKILL_1	ChatGPT increased my levels of participation in team discussions.
SSKILL_2	ChatGPT increased my levels of quality in work submission.
SSKILL_3	ChatGPT increased my levels of time management in work submission.
FUT_1	ChatGPT is helpful as a mentor for my computing project.
FUT_2	I would use ChatGPT as a mentor for a future computing project.

5.2 Model Validity Checks, Results, and Analysis

5.2.1 Convergent validity

Table 2 shows that composite reliability varies from 0.762 to 0.894, which is above the preferred value of 0.5, demonstrating that the model is internally consistent. From Table 2, it can be observed that all the factors are reliable (Cronbach's alpha > 0.64, AVE > 0.5) and have composite reliability (rho_c, rho_a) greater than 0.65. Therefore, all the factors are supported, and we can proceed with the model analysis in the next steps.

Table 2: Consistency and reliability results

Variable	Cronbach's alpha	Composite reliability	Composite reliability	AVE	Findings
DUSE	0.674	0.869	0.848	0.738	Supported
FUT	0.644	0.67	0.847	0.735	Supported
MFB	0.69	0.716	0.829	0.62	Supported
SSKILL	0.666	0.96	0.84	0.728	Supported
TSKILL	0.707	0.727	0.812	0.526	Supported
TUSE	0.822	0.825	0.894	0.738	Supported

According to Chin, 2009, the variables that have path coefficients less than or equal to 0.5 should be excluded. Therefore, we removed SSkill_3 (path coefficient of 0.410) from the model. The final measurement model is depicted in Figure 1 (convergent validity is confirmed).

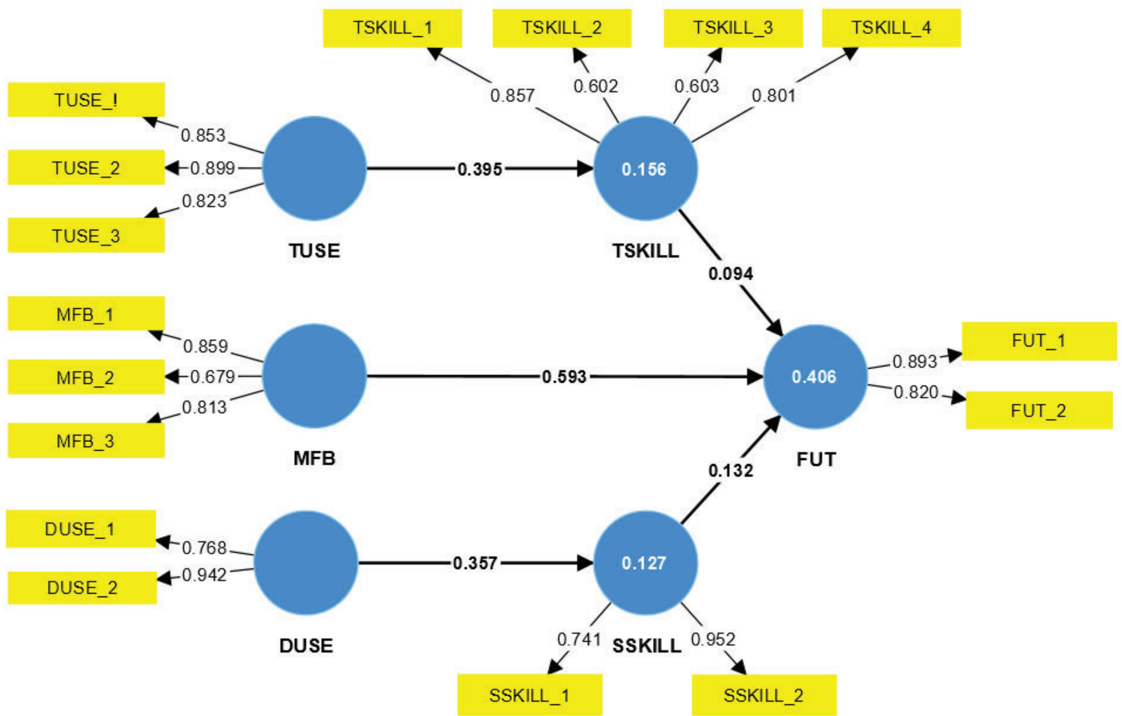

Figure 1. Measurement Model with variables whose path coefficient >0.5

5.2.2 Discriminant Validity

The AVE can be used to verify the discriminant validity (Fornell & Larcker, 1981). If the squared correlation coefficients among the latent variables are less than the AVE values of the respective latent variables, then the discriminant validity is confirmed. Table 3 presents the data, and we observe that the correlation coefficients are less than the AVE indicating that variables are distinct and unrelated to each other, providing evidence for discriminant validity.

Table 3. Correlation coefficients among the variables.

Variable	DUSE	FUT	MFB	SSKILL	TSKILL	TUSE	AVE
DUSE	1						0.738
FUT	0.576	1					0.735
MFB	0.536	0.605	1				0.62
SSKILL	0.357	0.239	0.091	1			0.728
TSKILL	0.133	0.162	-0.01	0.558	1		0.526
TUSE	0.301	0.273	0.189	0.123	0.395	1	0.738

By comparing correlation coefficients among the latent variables squared with the AVE indicators, we confirm the discriminant validity of the model.

5.2.3 Discussion and Analysis of Results

Table 4 displays the results of the research hypotheses after a bootstrap test is performed. We conclude that H1, H2, and H3 are valid hypotheses, while H4 and H5 are not.

Table 4: Hypotheses testing results

Hypothesis	Constructs	Path	Standard deviation	T-stats	P-value	Validated
(H1)	TUSE -> TSKILL	0.395	0.11	3.573	**0.000**	**Yes**
(H2)	DUSE -> SSKILL	0.357	0.112	3.172	**0.002**	**Yes**
(H3)	MFB -> FUT	0.593	0.096	6.172	**0.000**	**Yes**
(H4)	TSKILL -> FUT	0.094	0.165	0.571	0.568	No
(H5)	SSKILL -> FUT	0.132	0.143	0.927	0.354	No

The results indicate that both design mentorship and technical mentorship have positive impacts on the development of soft skills and technical skills, respectively. Additionally, mentor responsiveness has a significant positive impact on the effectiveness of ChatGPT adoption as a mentor for future computing projects.

5.2.4 Qualitative Analysis

The open-ended question reveals insights into why H4 and H5 hypotheses are not validated. Student feedback on ChatGPT shows two key observations. First, many students find ChatGPT helpful for the technical and design aspects of their projects. Some even compare it favorably to existing resources, citing more accurate answers. ChatGPT aids with brainstorming and analysis options, positively impacting work quality. Second, some students express caution about using ChatGPT. They mention unreliability in coding and faulty code returns. Students emphasize the need to cross-reference ChatGPT's responses to ensure reliability. Despite skill improvement, code errors affect technical mentorship quality. The comments demonstrate that ChatGPT has helped students to progress in their work and improve their work quality. However, caution needs to be exercised while using ChatGPT as some students have pointed out its limitations, particularly in areas such as coding, where it can be highly inaccurate and return faulty code. Future research will explore other factors such as ease of use, trust, and ethics to better understand ChatGPT's impact on various computing activities. Expanding the sample size to include multiple computing courses would offer a more comprehensive understanding of ChatGPT adoption in diverse contexts. Techniques like focus group interviews and longitudinal studies could further enhance data collection.

6. Conclusion

Our research studies ChatGPT's impact as a mentor in undergraduate computing projects. Mentor responsiveness emerges as a crucial factor influencing the future adoption of AI tools. Providing responsive mentorship with technical and design support is key to AI tool adoption.

Our study offers valuable insights into factors influencing ChatGPT's adoption as a mentor and provides practical implications for educators integrating AI into computing projects.

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