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ChatGPT as Learning Support among Mechatronics Engineering Technology Students: A Descriptive Survey

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ABSTRACT

Generative artificial intelligence is increasingly used in higher education, yet evidence from applied engineering programs remains limited. This descriptive survey examined self-reported ChatGPT use across six academic dimensions among 51 first- and third-semester students enrolled in an Applied Bachelor program in Mechatronics Engineering Technology who had previously used ChatGPT. A 30-item, five-point Likert questionnaire assessed frequency of use, theory, report writing, coding, design, and usage behavior. Descriptive statistics and Cronbach's alpha were calculated. Overall use was moderate (M = 3.270). Theory had the highest mean (M = 3.490), followed by design (M = 3.290), frequency of use (M = 3.255), coding (M = 3.243), reports (M = 3.180), and usage behavior (M = 3.161). The full instrument yielded alpha = 0.923, whereas Reports (alpha = 0.581) and Usage Behavior (alpha = 0.450) showed weak internal consistency. The findings indicate that ChatGPT primarily supported conceptual learning; broader interpretation requires caution.

Keywords
ChatGPT; generative artificial intelligence; engineering education; mechatronics education; vocational higher education

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INTRODUCTION

Generative artificial intelligence (AI) systems can provide conversational explanations, worked examples, feedback, text drafting, and code-related assistance. In higher education, these capabilities offer timely and individualized learning support, but they also introduce risks related to inaccurate outputs, opaque reasoning, bias, academic misconduct, and overreliance [1]–[3]. These concerns are especially consequential in engineering education, where a fluent response is not equivalent to a solution verified against mathematical, computational, and physical constraints [4], [5].

Responsible integration therefore requires more than access to an AI tool. Students must be able to formulate purposeful queries, inspect assumptions, compare outputs with authoritative sources, and test technical claims. Institutions likewise need explicit expectations for permitted use, disclosure, data protection, and assessment. International guidance and higher-education policy frameworks favor a human-centered approach in which generative AI supplements learning while students remain accountable for their reasoning and submitted work [6]–[8].

Student use is nevertheless heterogeneous across disciplines and academic tasks. University students report benefits for explanation, brainstorming, writing, and research support while also expressing concerns about accuracy and ethics [9]. Engineering students have used ChatGPT to initiate and reorganize problem-solving processes [10], whereas students in physics have valued rapid tutoring support but still required explicit guidance on verification and AI literacy [11]. Such differences make discipline-specific mapping necessary because aggregate measures of adoption can obscure how students use AI for conceptual, written, computational, and design activities.

The need for contextual evidence is particularly strong in vocational and applied engineering education, where learning outcomes combine conceptual knowledge with demonstrable practical competence. A review of AI in vocational education identified growing opportunities for learning support alongside persistent challenges in infrastructure, educator preparation, ethics, and practical training [12]. Vocational education research has also examined both digitally mediated learning environments [13] and physical trainers designed to develop applied technical skills [14], [15]. These complementary strands of evidence position generative AI as a preparatory and reflective resource, while technical outputs still require verification through authoritative references, calculation, simulation, compilation, measurement, or laboratory testing.

Mechatronics Engineering Technology integrates mechanics, electronics, control, programming, and system design. However, limited evidence is available on how students in this applied discipline distribute their ChatGPT use across distinct academic functions. This study therefore aimed to describe self-reported ChatGPT usage patterns among students enrolled in an Applied Bachelor program in Mechatronics Engineering Technology across six study-specific dimensions: frequency of use, theory, report writing, coding, design, and usage behavior. It also identified the highest- and lowest-scoring items and examined the internal consistency of the questionnaire. The study was descriptive and did not test causal effects on learning outcomes or practical competence.

METHOD

Research Design

A cross-sectional descriptive quantitative survey was used to characterize self-reported ChatGPT use at one point in time. The design was appropriate because the objective was to summarize patterns within the participating group rather than estimate a treatment effect or test causal relationships [16].

Participants

The eligible population comprised active first- and third-semester students enrolled in an Applied Bachelor program in Mechatronics Engineering Technology. All eligible students were invited through class communication channels, and participation was voluntary. The final analytic sample consisted of 51 students who submitted complete questionnaires. Prior academic use of ChatGPT was also required for eligibility. The sample therefore represents participating ChatGPT users rather than all students or non-users in the program.

Research Instrument

The study used a structured questionnaire developed from the research objective and relevant literature and adapted to the program's academic activities. It contained 30 statements (P1–P30) rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Five items were assigned to each of six study-specific dimensions: Frequency of Use (P1–P5), Theory (P6–P10), Reports (P11–P15), Coding (P16–P20), Design (P21–P25), and Usage Behavior (P26–P30). Because no separate construct-validation procedure was reported for the present questionnaire, the six dimensions were treated as descriptive subscales for this sample rather than established latent constructs.

Data Collection and Analysis

The questionnaire was administered online through Google Forms. Before responding, students received information about the study purpose, voluntary participation, and confidentiality. No personal identifiers were included in the analytic dataset, and only complete responses were retained.

For each participant, the five item scores assigned to a dimension were averaged to obtain a dimension score. Means, standard deviations (SD), minimum values, and maximum values were then calculated for each dimension, and an overall score was summarized across all 30 items. For descriptive interpretation, the possible five-point range was divided into five equal intervals: 1.00–1.80 (very low), 1.81–2.60 (low), 2.61–3.40 (moderate), 3.41–4.20 (high), and 4.21–5.00 (very high). Internal consistency was evaluated using Cronbach's alpha for each dimension and the complete instrument. Alpha was interpreted as an index of item interrelatedness rather than evidence of unidimensionality or construct validity [17], [18]. Scale-development research on academic ChatGPT use has combined expert review with factor-analytic and reliability evidence [19]. No inferential statistical tests were applied because the study objective was descriptive.

Ethical Considerations

Participation was voluntary and based on informed consent. Respondent identities were not collected, and the data were used only for academic research purposes.

RESULTS AND DISCUSSION

Results

Internal Consistency

Table 1 summarizes the internal consistency coefficients. The complete 30-item instrument yielded alpha = 0.923. At the subscale level, Coding also yielded 0.923, followed by Design (0.805), Theory (0.796), and Frequency of Use (0.740). Reports (0.581) and Usage Behavior (0.450) had the lowest coefficients.

Table 1. Internal consistency of the questionnaire dimensions (n = 51)

Dimension	Item range	No. of items	Cronbach's alpha
Frequency of Use	P1–P5	5	0.740
Theory	P6–P10	5	0.796
Reports	P11–P15	5	0.581
Coding	P16–P20	5	0.923
Design	P21–P25	5	0.805
Usage Behavior	P26–P30	5	0.450
Overall instrument	P1–P30	30	0.923

Note: Alpha coefficients describe internal consistency in this sample and do not, by themselves, establish unidimensionality or construct validity.

The contrast between the full-instrument coefficient and the two lowest subscale coefficients is analytically important. The overall value does not demonstrate that all 30 items measure a single construct, and the Reports and Usage Behavior means should not be interpreted as precise measurements of internally coherent subscales. Their results are therefore retained as descriptive summaries but require caution.

Indicator-Level Usage Patterns

Table 2 presents the descriptive statistics for the six dimensions. The overall mean across all 30 items was 3.270, which fell within the moderate category. Theory was the only dimension categorized as high (M = 3.490, SD = 0.600). The remaining dimensions were moderate: Design (M = 3.290), Frequency of Use (M = 3.255), Coding (M = 3.243), Reports (M = 3.180), and Usage Behavior (M = 3.161).

Table 2. Descriptive statistics for ChatGPT use by dimension (n = 51)

Dimension	Items	Mean	SD	Min	Max	Category
Frequency of Use	5	3.255	0.569	1.8	4.6	Moderate
Theory	5	3.490	0.600	1.6	4.8	High
Reports	5	3.180	0.457	2.2	4.2	Moderate
Coding	5	3.243	0.729	1.2	5.0	Moderate
Design	5	3.290	0.573	2.0	4.8	Moderate
Usage Behavior	5	3.161	0.503	1.6	4.2	Moderate

Note: Category intervals: 1.00-1.80 very low; 1.81-2.60 low; 2.61-3.40 moderate; 3.41-4.20 high; 4.21-5.00 very high.

The difference between the highest and lowest dimension means was 0.329 points on the five-point scale. Theory exceeded the next-highest dimension, Design, by 0.200 points. These values indicate a relative concentration of use in conceptual and theoretical activities, but the differences were not tested inferentially and should not be interpreted as statistically significant.

Figure 1 compares the six means with their participant-level standard deviations. The error bars represent dispersion among respondents rather than confidence intervals; accordingly, their overlap is descriptive and does not test whether the population means differ.

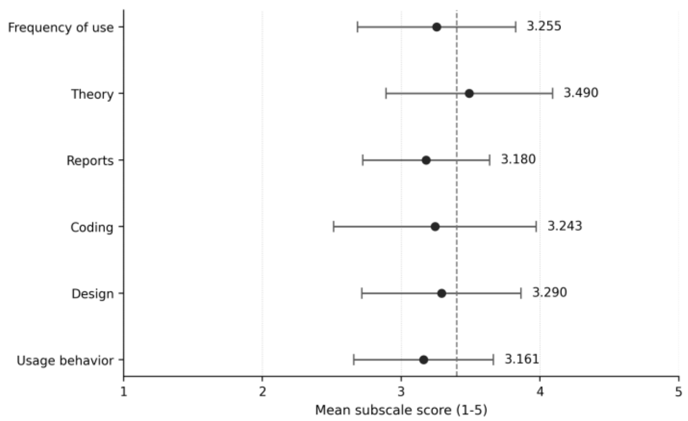

Figure 1. Mean dimension scores with standard deviations (n = 51). The dashed line at 3.40 marks the study's boundary between the moderate and high descriptive categories.

Item-Level Highlights

Table 3 summarizes the highest- and lowest-scoring items. The two highest means occurred within the Theory dimension. P6, "I use ChatGPT to help me understand course materials," had M = 3.902 (SD = 0.855), and P7, "I use ChatGPT to understand theory more clearly," had M = 3.686 (SD = 0.883). These items reinforce the dimension-level pattern that conceptual clarification was the most strongly reported use.

Table 3. Highest- and lowest-scoring questionnaire items (n = 51)

Group	Item	Statement	Mean	SD
Highest	P6	I use ChatGPT to help me understand course materials	3.902	0.855
Highest	P7	I use ChatGPT to understand theory more clearly	3.686	0.883
Lowest	P29	I trust ChatGPT outputs more than other academic resources	2.431	0.900
Lowest	P3	I use ChatGPT almost every time I work on academic assignments	2.725	0.750

The lowest item was P29, "I trust ChatGPT outputs more than other academic resources" (M = 2.431, SD = 0.900), followed by P3, "I use ChatGPT almost every time I work on academic assignments" (M = 2.725, SD = 0.750). Both means were below the neutral midpoint of 3.0. Respondents therefore tended not to endorse greater trust in ChatGPT than in other academic resources or its use for nearly every assignment. This pattern is compatible with selective use, but it does not establish responsible behavior, particularly because the Usage Behavior subscale had weak internal consistency.

Discussion

The distribution in Table 2, reinforced by the item-level results in Table 3, indicates that ChatGPT was used most strongly for theoretical understanding. This pattern is consistent with research describing generative AI as a conversational scaffold for initiating explanations, reorganizing difficult material, and asking follow-up questions [1], [3], [9]–[11]. In a multidisciplinary field such as mechatronics, this function is plausible because students must move between concepts from mechanics, electronics, control, and programming. ChatGPT may lower the initial barrier to engaging with an unfamiliar concept, although its explanations still require verification. Figure 1 also shows that the dimension means were relatively close and accompanied by overlapping participant-level dispersion, so their ordering should be read as a descriptive tendency rather than evidence of distinct population-level differences.

Coding and Design were moderate despite the technical orientation of the program. The present data cannot determine why these means were lower than Theory, but applied engineering tasks impose constraints that conversational explanations alone cannot satisfy. Code must compile and operate as intended, while a design must meet requirements, interfaces, safety constraints, and test conditions. Engineering education research has emphasized both the learning opportunities and assessment risks associated with generative AI [4], [5]. Task-dependent adoption has also been observed in undergraduate engineering design, where students' use or non-use was shaped by perceived task fit, output limitations, and prompting capability [20]. ChatGPT may therefore assist with an initial algorithm, error interpretation, or design alternatives, but competent performance still depends on simulation, code review, physical testing, and documented reasoning.

Reports also remained moderate. Generative AI can assist with outlining and language revision, yet technical report writing is closely tied to source accuracy, authorship, and academic integrity. The low mean for P29 is encouraging only at the level of that individual statement because respondents did not generally place ChatGPT above other academic resources. It should not be expanded into a broad conclusion that students used AI responsibly. Moreover, the Usage Behavior coefficient of 0.450 indicates that its five items did not function consistently enough to support a strong composite interpretation. The subscale may combine different behaviors, or its wording may not have been sufficiently coherent for this sample.

These findings support structured use of ChatGPT as cognitive assistance rather than as an unrestricted answer generator or a substitute for practical learning. Students can be required to compare conceptual explanations with textbooks or peer-reviewed sources, identify unverifiable statements, and document how an AI response was checked. Programming and design submissions should include evidence of compilation, simulation, test cases, measurements, and design decisions, while written assignments should require transparent disclosure and citation verification. Such measures are consistent with human-centered guidance and recommendations to redesign assessment around observable reasoning and accountability [5]–[8]. Survey evidence from engineering education further indicates that students and instructors may differ in familiarity, usage patterns, and concerns, strengthening the case for course-specific guidance developed through dialogue rather than unilateral assumptions [21].

This approach is particularly relevant to vocational engineering. AI-supported innovation must remain aligned with practical competence, educator readiness, and ethical safeguards [12]. Digitally mediated learning environments can broaden access to instructional resources [13], whereas physical engineering trainers provide direct opportunities to develop and demonstrate applied skills [14], [15]. ChatGPT can complement these modes by preparing students for practice, supporting reflection after practice, and helping them articulate technical reasoning. It cannot, however, provide the physical evidence needed to show that a mechatronic system has been assembled, programmed, calibrated, and tested correctly.

Several limitations constrain interpretation. The study involved 51 voluntary respondents from one program and included only first- and third-semester students who had previously used ChatGPT for academic activities. The findings therefore do not estimate adoption among all students, and voluntary-response bias is possible. The cross-sectional self-report design cannot establish actual usage frequency, learning gains, practical competence, or causal effects. The category thresholds were descriptive conventions rather than empirically validated cut points. In addition, the instrument was not supported by independent content validation, pilot testing, or factor-analytic evidence, and two subscales had weak internal consistency. Future work should recruit a larger multi-institutional sample, include users and non-users, refine items through expert review and cognitive interviews, evaluate dimensionality, report additional reliability evidence, and relate self-reports to usage logs or performance-based outcomes. Established ChatGPT scale-development research illustrates the value of combining content review, factor analysis, and reliability assessment before interpreting subscale scores as stable constructs [19].

CONCLUSION

Among 51 participating students in an Applied Bachelor program in Mechatronics Engineering Technology, overall self-reported ChatGPT use was moderate, and Theory was the highest-scoring dimension. The highest individual items concerned understanding course material and theory, whereas respondents tended not to endorse trusting ChatGPT more than other academic resources or using it for nearly every assignment. Within this sample, ChatGPT therefore functioned primarily as a conceptual and preparatory learning aid rather than evidence of improved learning outcomes or a replacement for practice-based competence. Instructional use should emphasize transparency, source verification, and technical validation through calculation, simulation, compilation, measurement, and laboratory testing. Because the Reports and Usage Behavior subscales had weak internal consistency and the sample was limited to voluntary respondents from one program, broader conclusions require a refined instrument and a larger, more diverse study.

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