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From Intention to Habit in ChatGPT Use: An Examination Through Person-Centered Profiles

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Abstract

This study examines the transition from intention to routine use in ChatGPT adoption in higher education from a person-centered perspective. A total of 351 valid responses from students and instructors were analyzed following data screening procedures. Although previous research on generative AI adoption has largely relied on variable-centered approaches such as UTAUT2 to explain average relationships among constructs, the present study argues that implementation challenges can be understood more effectively through user segments. Using k-means clustering on standardized UTAUT2 driver constructs, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, three adoption profiles were identified: Capability-Ready Explorers, Routine Adopters, and Skeptical/Detached Users. To interpret differences among these groups more precisely, the study introduces two conversion indicators: the Capability-to-Habit Discrepancy Index (CHDI) and the Intention-to-Use Residual (IUR). Findings show that the largest group, Capability-Ready Explorers, demonstrates relatively high perceived ease of use and support but low habit and only moderate use frequency, indicating a gap between readiness and routinized practice. Variation across faculties and school years further suggests that ChatGPT adoption is shaped by disciplinary and developmental context. The discussion integrates UTAUT2, habit formation theory, and self-regulated learning to argue that successful institutional adoption depends not only on promoting positive attitudes, but also on designing repeatable, legitimate, and accountable routines of use. The study concludes that person-centered profiling offers a practical framework for understanding and supporting responsible AI integration in higher education.

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Introduction

ChatGPT and similar generative-AI tools have rapidly entered academic workflows for drafting, explaining concepts, brainstorming, and feedback generation. Evidence on acceptance is expanding, often using UTAUT2 with structural models that estimate average effects (Venkatesh et al., 2012). Implementation decisions, however, are commonly made for segments rather than for an average user. A segment-level view can reveal barriers that remain invisible in net-effect models, such as a group that reports high ease-of-use and adequate support but does not develop stable usage routines (Moradi, 2025). The analysis focuses on the intention-to-routine problem. In the source dataset, habit is generally the lowest-scoring construct in descriptive results, and the journal study concludes that habitual use is not yet widespread (Strzelecki et al., 2024) . Building on that observation, the present paper treats the transition from positive beliefs to repeated behavior as a design problem: how can adoption support convert capability and readiness into routine, responsible practice?

Literature Review

UTAUT2, or the Unified Theory of Acceptance and Use of Technology 2, (Venkatesh et al., 2012) provides the conceptual basis for explaining why users may be willing to adopt ChatGPT and whether that willingness is translated into actual use. In this framework, performance expectancy (PE) refers to the belief that ChatGPT can improve academic performance, effort expectancy (EE) captures perceptions of ease of use, social influence (SI) reflects the effect of important others on adoption decisions, and facilitating conditions (FC) refer to the resources and support that make use possible (see Figure 1).

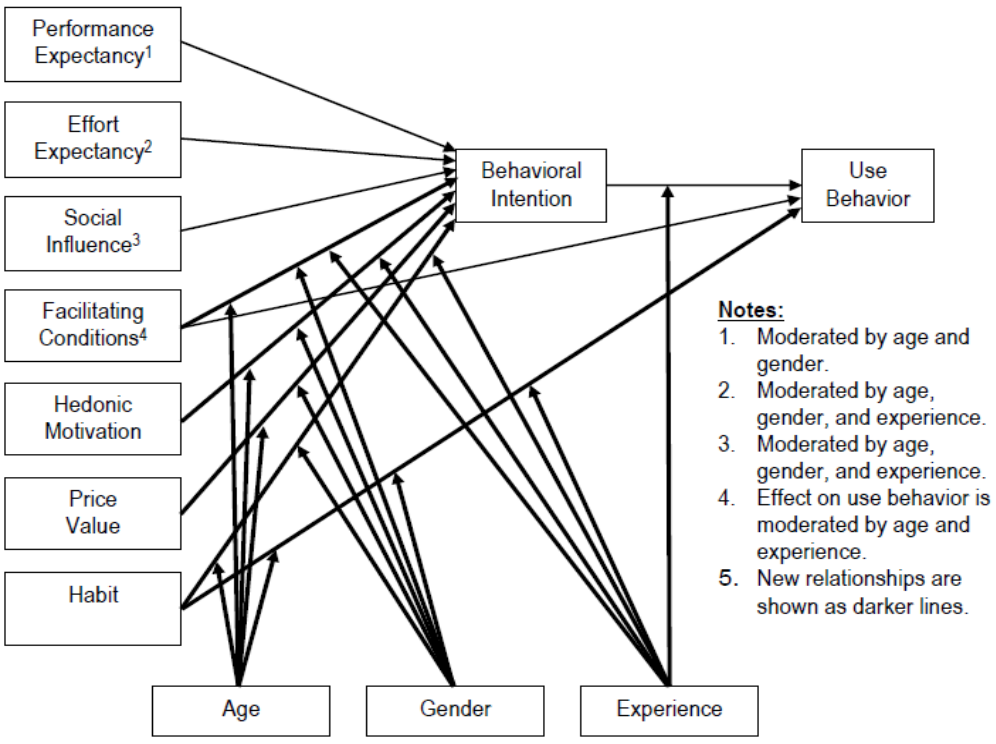


Figure 1. UTAUT2 (Venkatesh et al., 2012)

In addition, hedonic motivation (HM) represents the enjoyment associated with using the tool, price value (PV) concerns the perceived balance between benefit and cost, habit (H) reflects the extent to which use becomes automatic through repetition, behavioral intention (BI) refers to the willingness to use ChatGPT, and use behavior (UB) captures actual use. For the newly introduced conversion indicator, the present paper adopts Capability-to-Habit Discrepancy Index (CHDI) as the appropriate label.

Within UTAUT2, habit is positioned as a key driver of both behavioral intention and actual use, alongside performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2012). For emerging tools such as ChatGPT, however, strong beliefs about usefulness and ease of use do not necessarily lead to routine adoption. This is especially likely when use is optional, when legitimacy norms remain unclear, and when academic tasks do not repeatedly cue the use of the tool.

Recent UTAUT2-based research in higher education also suggests that acceptance dynamics differ across academic roles and learning contexts. Strzelecki et al. (2024) showed that academics' willingness to use ChatGPT is shaped by a combination of performance-related beliefs, social influence, and habit, indicating that the framework remains useful beyond student-only samples. Similarly, Moradi (2025) found that, among university EFL learners, habit and facilitating conditions were especially important for actual ChatGPT use, reinforcing the relevance of examining whether supportive conditions are converted into repeated practice.

Research on habit formation further shows that repetition in stable contexts, environmental cueing, and reinforcement help move behavior from conscious decision-making to automaticity (Wood & Neal, 2007; Lally et al., 2010). In learning environments, this process also relates closely to self-regulated learning, because sustained tool use depends not only on access and perceived usefulness but also on goal-setting, monitoring, and strategic adaptation. From this perspective, generative AI use can be understood as a workflow habit that develops through both recurring situational cues, such as repeated course tasks, and reflective controls, such as checking and verification routines.

In the present study, the habit formation gap refers to the pattern in which capability-related drivers, particularly effort expectancy and facilitating conditions, are relatively high, while habit and actual use frequency remain comparatively low. To capture this pattern more precisely, two conversion indicators are introduced. The first is the Capability-to-Habit Discrepancy Index (CHDI), calculated as the mean of effort expectancy and facilitating conditions minus habit. The second is the Intention-to-Use Residual (IUR), calculated as the deviation between observed use frequency and the use level predicted from behavioral intention. In practical terms, CHDI estimates how much perceived capability remains unconverted into routine use, whereas IUR indicates whether actual use falls below or exceeds the level that would normally be expected from intention.

Taken together, these conceptual relationships provide the basis for the study's empirical focus on adoption profiles, conversion dynamics, and variation across student groups:

1. What adoption profiles emerge when users are clustered by UTAUT2 driver constructs (PE, EE, SI, FC, HM, PV, Habit)?

2. How do profiles differ on conversion indicators that capture capability-to-routine and intention-to-use translation?
3. Does profile composition vary across faculties and student school years?

Method

Dataset and Participants

The study was conducted at a small English-medium university in Eastern Europe. The institution includes approximately 10,000 students and 500 instructors distributed across six faculties. Because the university hosts students and instructors from multiple countries and places strong emphasis on modern instructional technologies, it offers a suitable context for examining ChatGPT adoption in higher education.

Participants were recruited through convenience sampling. In other words, the study included students and instructors who were accessible through the institution and who voluntarily agreed to participate. This approach was considered practical given the size of the university, the diversity of its academic units, and the time and resource limitations of the study. Although convenience sampling has limitations in terms of representativeness, the inclusion of participants from all six faculties, both genders, and different academic roles improved the breadth of the sample. In addition, the university's active engagement with digital and AI-supported educational practices made it a particularly relevant site for investigating the acceptance and use of ChatGPT.

In the first phase of data collection, 378 responses were obtained. The dataset was then screened to improve data quality. This process involved removing incomplete responses, identifying outliers, and excluding cases with little meaningful response variation. After cleaning, 351 valid responses remained for analysis. Of these, 320 were students (91.2%) and 31 were instructors (8.8%).

A faculty-level breakdown shows that Engineering had the highest representation (127 participants), followed by Fine Arts and Design (64) and Business (58). Arts and Sciences contributed 45 participants, Communication 33, and Medicine 24. This distribution suggests that the sample captures perspectives from a wide range of disciplinary contexts.

Table 1. Participants

Faculty	Total participants	Percentage
Engineering	127	36.2%
Fine Arts and Design	64	18.2%
Business	58	16.5%
Arts and Sciences	45	12.8%
Communication	33	9.4%
Medicine	24	6.8%
Total	351	100%

Among students, first-year participants formed the largest group, accounting for 51.0% of the student sample.

Second-year students represented 19.7%, third-year students 15.9%, and fourth-year students 13.3%. This spread indicates that the study includes views from students at different stages of academic development, from those who are new to university life to those with more experience in higher education.

Overall, the sample offers a broad picture of ChatGPT adoption within a technologically engaged university setting. While the use of convenience sampling limits strong claims about generalizability, the inclusion of participants from different faculties, school years, and roles increases the value of the findings for understanding patterns of AI acceptance in higher education.

Measures

Data were collected using a seven-point Likert scale designed to measure participants' UTAUT2-based drivers of ChatGPT use in the university context (see Appendix A) (Strzelecki, 2024). For these items, response options ranged from strongly disagree to strongly agree. The item measuring 'use behavior' employed a separate seven-point frequency scale, with response categories ranging from never to several times a day.

The questionnaire was distributed by one of the researchers through multiple channels over a two-month period. Instructors received the survey by email every other Wednesday, QR-code leaflets linking to the questionnaire were distributed across campus, and the survey was also made available to both students and instructors through the university's learning management system. Using multiple distribution methods helped increase visibility and accessibility for potential participants.

Several measures were taken to ensure data security and accuracy. All responses were anonymized to protect participant confidentiality, and no personally identifiable information was collected, stored, or linked to the dataset. Participation was entirely voluntary, and informed consent was obtained from all respondents before data collection. In addition, the data were stored on encrypted platforms with restricted access and could be accessed only by the researchers involved in the study.

To assess the quality of the measurement model, reliability and validity indicators were examined, including Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). All constructs met accepted thresholds for reliability and validity. Specifically, Cronbach's alpha and CR values were above .70, indicating satisfactory internal consistency, while AVE values exceeded .50, supporting convergent validity.

Analytic Approach

A person-centered analytic approach was used in this study to identify distinct patterns of ChatGPT adoption among participants. More specifically, k-means clustering was applied to the standardized scores of the seven UTAUT2 driver constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. Standardizing these variables ensured that no construct disproportionately shaped the clustering solution because of differences in scale or variance. Behavioral intention

and use behavior were not used to form the clusters; instead, they were reserved for interpreting and comparing the resulting profiles.

K-means clustering was selected because the aim of the study was not simply to examine average relationships among variables, but to identify meaningful user segments with different combinations of adoption-related perceptions and habits. This makes k-means especially suitable, since it groups individuals into clusters that are internally similar but externally distinct. In this context, the method helps reveal whether some users are ready to adopt ChatGPT but have not yet turned that readiness into routine use, while others already demonstrate stable use patterns or remain detached from the tool.

This choice is also supported by recent methodological literature. Person-centered methods are particularly valuable when researchers seek to understand heterogeneity within a population rather than relying only on overall sample averages. As Woo et al. (2024) explain, person-centered modeling shifts attention from relationships among variables to differences among people, making it useful for identifying subgroups with shared characteristics. Similarly, Saqr et al. (2024) emphasize that educational data often contain meaningful learner differences that are better captured through person-centered approaches than through exclusively variable-centered models. This logic is also consistent with recent person-centered work in higher education showing that profile-based analyses can reveal substantively meaningful subgroups and then validate them through links with predictors and outcomes (Cano et al., 2024). After clustering, the profiles were compared using descriptive statistics and cross-tabulations, and additional conversion indicators were computed to examine the extent to which capability and intention were translated into routinized ChatGPT use.

Results

Adoption Profiles

The k-means analysis identified three distinct adoption profiles that differed meaningfully across the UTAUT2 driver constructs, behavioral intention, and use behavior. These profiles can be interpreted as Capability-Ready Explorers, Routine Adopters, and Skeptical/Detached Users. Table 2 presents the mean scores for each construct and outcome by profile. Figure 2 complements these profile means by visualizing the standardized UTAUT2 driver scores (z-scores) for each segment, making it easier to compare the relative shape of the three profiles across constructs. As shown in Figure 2, Routine Adopters consistently score above the sample mean across all drivers, Skeptical/Detached Users remain below the mean across constructs, and Capability-Ready Explorers display a mixed pattern characterized by relatively stronger effort expectancy and facilitating conditions but notably weaker habit. This visual pattern reinforces the interpretation that the largest segment is defined not by low capability, but by a gap between readiness and routinized use.

Capability-Ready Explorers formed the largest segment of the sample (n = 167). This group reported relatively high effort expectancy (EE = 5.29) and facilitating conditions (FC = 4.89), suggesting that they generally perceive ChatGPT as easy to use and believe that the necessary support or conditions for use are present. However, their habit score was much lower (Habit = 2.44), indicating that this readiness has not yet developed into routinized

use. Their behavioral intention (BI = 3.77) and use behavior (UB = 3.26) were moderate, which suggests that they occupy a transitional position between early readiness and regular use.

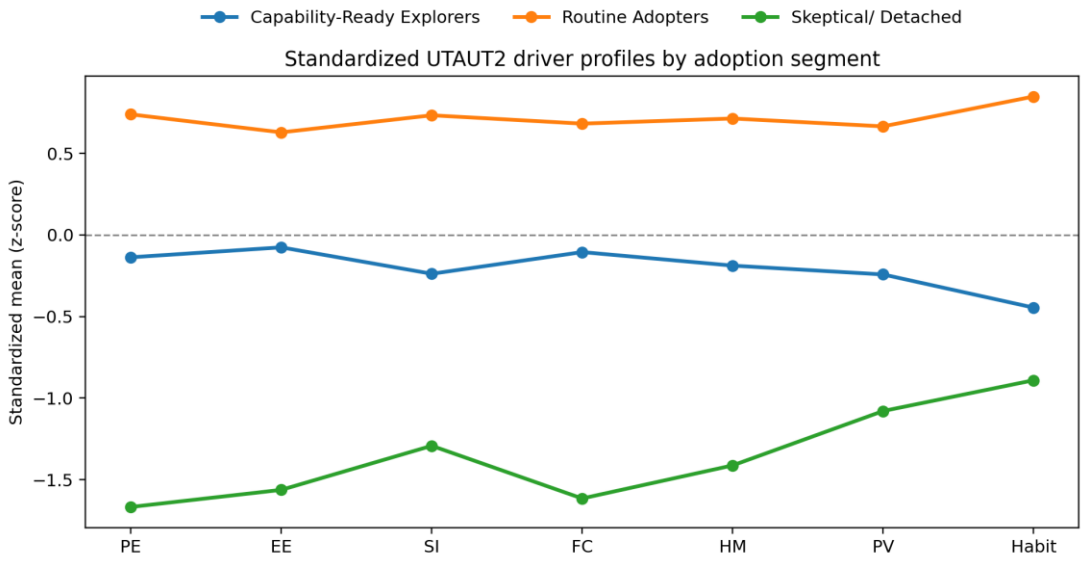


Figure 2. Standardized UTAUT2 Driver Profiles (z-scores) by Adoption Segment

Routine Adopters (n = 137) showed the highest scores across nearly all constructs. In particular, they reported strong levels of performance expectancy (PE = 6.00), effort expectancy (EE = 6.25), facilitating conditions (FC = 5.99), hedonic motivation (HM = 6.24), and habit (Habit = 4.53). This group also recorded the highest behavioral intention (BI = 5.64) and use behavior (UB = 4.71), indicating that positive attitudes and enabling conditions are more fully translated into repeated use.

By contrast, Skeptical/Detached Users (n = 47) had the lowest scores across all constructs. Their lower levels of performance expectancy, social influence, facilitating conditions, and habit suggest limited engagement with ChatGPT and weaker perceived relevance of the tool for their academic work. Their behavioral intention (BI = 1.94) and use behavior (UB = 2.19) were also the lowest among the three profiles.

Table 2. Profile Means and Outcomes

Profile	n	PE	EE	SI	FC	HM	PV	Habit	BI	UB
Capability-Ready Explorers	167	4.70	5.29	3.69	4.89	4.71	3.62	2.44	3.77	3.26
Routine Adopters	137	6.00	6.25	5.32	5.99	6.24	4.96	4.53	5.64	4.71
Skeptical/Detached	47	2.44	3.27	1.93	2.76	2.65	2.39	1.72	1.94	2.19

Conversion Indicators and the Habit Formation Gap

To interpret the profiles more precisely, Table 3 reports several conversion indicators that show whether supportive perceptions and intentions are actually translated into routine use. These indicators help move the analysis beyond simple mean differences and make it possible to identify where adoption may be stalling.

The most notable finding concerns the Capability-Ready Explorers, who show the largest Capability-to-Habit Discrepancy Index (CHDI = 2.64). Their average capability score, calculated from effort expectancy and facilitating conditions (5.09), is much higher than their habit score (2.44). This indicates that although this group feels able to use ChatGPT and perceives supportive conditions, these advantages have not yet developed into automatic or repeated use. Their habit-to-capability ratio (0.48) reinforces this interpretation, showing that less than half of their perceived capability is reflected in habit. In addition, their IUR (-0.13) is slightly negative, which suggests that their observed use falls somewhat below what would normally be expected from their level of behavioral intention.

Routine Adopters show a different pattern. Although they also display a gap between capability and habit, the discrepancy is clearly smaller (CHDI = 1.59), and their habit-to-capability ratio (0.74) is the highest of all groups. This means that they are more successful in converting readiness into routinized use. Their positive IUR (0.19) further suggests that their actual use slightly exceeds the level predicted by intention, which is consistent with stronger habitualization and more established academic integration.

For Skeptical/Detached Users, the CHDI is the smallest (1.29), but this should not be interpreted as a more successful pattern. Rather, both their capability level (3.01) and their habit level (1.72) are low from the outset. In other words, the smaller discrepancy reflects generally weak adoption conditions rather than effective conversion into use. Their low BI (1.94) and UB (2.19) confirm that this profile remains distant from routinized adoption.

Table 3. Conversion Indicators by Profile

Profile	n	Capability mean (EE, FC)	Habit	CHDI	BI	UB	BI–UB gap	IUR	Habit/Capability
Capability-Ready Explorers	167	5.09	2.44	2.64	3.77	3.26	0.52	-0.13	0.48
Routine Adopters	137	6.12	4.53	1.59	5.64	4.71	0.93	0.19	0.74
Skeptical/Detached	47	3.01	1.72	1.29	1.94	2.19	-0.25	-0.08	0.57

Discipline Variation (Faculty Patterns)

Profile composition also varied across faculties, suggesting that ChatGPT adoption is shaped partly by disciplinary context. Engineering had the largest share of Routine Adopters, indicating a stronger tendency toward established and repeated use. In contrast, Fine Arts and Design had the largest share of Skeptical/Detached Users, suggesting lower levels of perceived relevance, support, or routinization in that context. Figure 3 illustrates these differences by showing the proportional distribution of the three adoption profiles across faculties. The figure makes clear that profile membership is not evenly distributed across disciplinary areas; rather, some faculties are more strongly associated with routinized adoption, whereas others contain larger proportions of exploratory or detached users. This visual evidence supports the argument that institutional adoption is shaped not only by individual attitudes but also by disciplinary context and workflow compatibility.

Variation also appeared across student year levels. First-year students were most concentrated in the Capability-

Ready Explorer profile (52.4%), which suggests that many newer students perceive ChatGPT as accessible and potentially useful but have not yet incorporated it into regular academic routines. In contrast, third-year students (51.0%) and fourth-year students (46.3%) showed the highest proportions of Routine Adopters. This pattern suggests that routinized use may strengthen as students advance through university and encounter repeated academic demands that make AI use more functionally embedded.

Taken together, these faculty- and year-based differences suggest that ChatGPT adoption is not uniform across the institution. Instead, it appears to develop in relation to disciplinary expectations, academic maturity, and the extent to which repeated tasks create opportunities for habit formation.

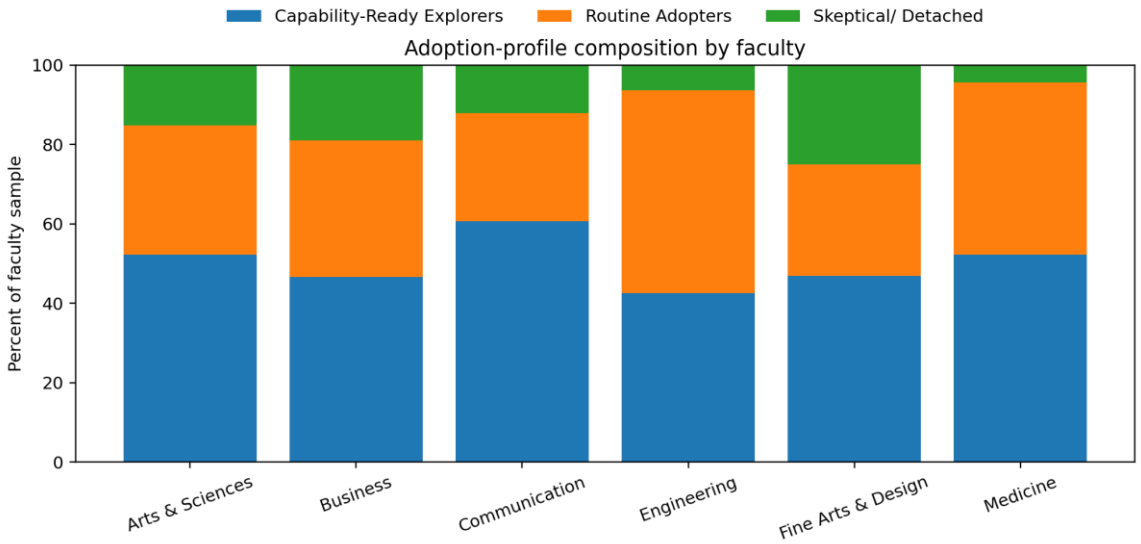


Figure 3. Adoption-profile Composition by Faculty

Discussion

What a Person-centered Lens Adds

Net-effect models explain which predictors matter on average; the profile perspective explains which combinations of beliefs and constraints co-occur in practice. The largest segment in the dataset is not characterized by low capability. Instead, the Capability-Ready Explorer profile combines relatively high effort expectancy and facilitating conditions with low habit and moderate use. This pattern matters because it redirects institutional response: if capability is already present, generic awareness workshops are unlikely to be enough.

Recent adoption studies similarly show that intention is often explained well by usefulness, trust, and enjoyment, yet repeated educational use depends on whether those attitudes are stabilized in everyday academic routines (Shahzad et al., 2024; Strzelecki, 2024). Kaya and Adıgüzel (2025) established that habit was the weakest construct in their study, while the present person-centered analysis identifies which subgroup is carrying that weakness most strongly. The finding that 167 of the 351 screened participants fall into the capability-ready cluster shows that the main implementation challenge is not persuasion alone, but conversion from readiness to routine.

This interpretation is also in line with broader higher-education evidence arguing that institutions must respond to generative AI not only as an innovation opportunity but also as a governance challenge requiring context-sensitive policy and support (Yusuf et al., 2024).

Interpreting the Habit Formation Gap

Habit theory suggests that repetition under stable cues is required for automaticity. In academic settings, cues can be created through recurring assignments, prompt templates embedded in the learning management system, and assessment rubrics that reward process transparency. The Explorer profile shows comparatively lower social influence and price value perceptions than Routine Adopters, suggesting that routinization may be constrained by normative ambiguity and by cost–benefit hesitation. This interpretation also fits recent comparative research. Strzelecki and ElArabawy (2024) showed that acceptance pathways differ across learner groups, which implies that the same ChatGPT tool may be normalized in one context yet remain tentative in another. Faraon et al. (2025) likewise found that performance expectancy and habit remained central across regions, but the exact pathway to use varied by context. Together, those studies support the claim that capability does not mechanically become habit. Students may know how to use ChatGPT and still refrain from integrating it into coursework when academic norms are unclear, when instructors send mixed signals, or when the perceived value of subscribing, documenting, and verifying outputs is uncertain. The CHDI therefore captures a substantively meaningful gap rather than a mere statistical artifact.

From SRL to Responsible Routine

Routine use of generative AI can be productive or harmful depending on verification and attribution practices. SRL-oriented routines emphasize planning (selecting an appropriate AI role), monitoring (checking outputs against course resources), and reflection (documenting what was accepted, revised, or rejected). A practical implication is that routinization support should not merely increase frequency of use; it should stabilize responsible sequences, such as draft–critique–revise cycles and evidence-check routines. This point is reinforced by recent work on academic integrity and disclosure. Kofinas et al. (2025) showed that generative AI can undermine even authentic assessment if institutional safeguards are weak (Göçen & Bulut, 2024), while Qu et al. (2025) demonstrated that students experience emotional and ethical tension about whether and how to disclose AI use. In other words, sustainable routine is not simply a behavioral frequency issue. It is also a governance issue: students are more likely to routinize tools when expectations for permissible use, disclosure, and verification are explicit and teachable. The conversion indicators in Table 2 provide a monitoring approach for that governance problem, because successful interventions should reduce CHDI and improve the intention-to-use residual without encouraging careless dependence.

Relatedly, students may perceive AI-generated feedback as useful while still viewing teacher feedback as more trustworthy for consequential academic decisions, which supports the argument that routinization should be guided by verification and pedagogical framing rather than by convenience alone (Henderson et al., 2025).

Why Discipline and Progression Matter

The cross-tabulations also suggest that routinization is socially and academically situated rather than uniform across the institution. Engineering has the largest share of Routine Adopters, whereas Fine Arts and Design has the largest share of Skeptical/Detached users. This distribution should not be reduced to a simple technical-versus-creative divide; rather, it may reflect differences in task structure, perceived legitimacy, and workflow compatibility. In disciplines where assignments are iterative, problem-based, and textually scaffolded, students may find it easier to insert ChatGPT into repeatable stages of work. In disciplines where originality, voice, or design authenticity are more strongly foregrounded, students may experience stronger hesitation about routinization. The school-year pattern points in the same direction. Freshmen are more concentrated in the capability-ready group, while juniors and seniors are more likely to appear among Routine Adopters. This suggests that time in the institution may gradually provide the cues, exemplars, and confidence necessary for routine formation. The practical lesson is that adoption policy should be differentiated by discipline and academic stage, not delivered as a single institution-wide message (Baig & Yadegaridehkordi, 2024; Faraon et al., 2025).

Practical Implications

Segment-specific Support Principles

Capability-Ready Explorers: the highest-leverage target. Adoption supports should prioritize routine scaffolds rather than general training. Recommended moves include: (i) curricular embedding of repeated low-stakes tasks that require AI-assisted steps; (ii) weekly prompt libraries aligned to course outcomes; (iii) explicit legitimacy scripts that define acceptable uses and documentation expectations; and (iv) verification checklists that reduce perceived risk.

Skeptical/Detached users: legitimacy and relevance first. Support should emphasize discipline-specific exemplars, privacy and integrity reassurance, and opt-in demonstrations tied to concrete tasks (e.g., explanation, language practice, brainstorming).

Routine Adopters: sustain and govern. Advanced guidance should focus on hallucination detection, source triangulation, and over-reliance prevention, including assessment designs that reward critical evaluation rather than output volume.

Routine-scaffolding Checklist for Professional Development

A professional development module intended to close the habit formation gap can be designed as a checklist: (1) Cue: define when the tool is used (task trigger). (2) Routine: specify a short, repeatable sequence (prompting, output evaluation, revision). (3) Accountability: require a trace (prompt/output excerpt, reflection note, or citation). (4) Feedback: provide a rubric-based response to the trace. (5) Norms: restate boundaries (what is not allowed). These steps create socially legitimate repetition, which is a prerequisite for habit formation.

For implementation, this checklist is likely to be most effective when converted into discipline-facing templates rather than remaining a generic policy statement. For example, a writing-intensive course might ask students to attach one prompt-output excerpt and a short verification note, whereas a design or problem-solving course might require a process log showing where AI support was accepted, modified, or rejected. Such design makes AI use visible enough to support feedback, yet bounded enough to discourage invisible over-reliance. It also aligns with the source article's emphasis on institutional support, because routinization depends not only on willingness but on whether the environment supplies reusable scripts, exemplars, and accountability mechanisms.

Institutional Implementation Roadmap

An additional implication of the present findings is that universities should treat AI routinization as a staged implementation problem. Stage 1 should focus on legitimacy: institutions need concise guidance explaining acceptable, unacceptable, and disclosure-based uses of generative AI. Stage 2 should focus on curricular embedding: departments should identify recurring assessment points where AI can be used transparently for brainstorming, outlining, language support, feedback rehearsal, or critique. Stage 3 should focus on monitoring: course teams can track whether students move from exploratory use to stable, responsible routines by observing CHDI-like gaps, self-reported verification practices, and assessment-quality indicators. Stage 4 should focus on staff development, because inconsistent instructor expectations can unintentionally widen the capability-to-habit gap. A roadmap of this kind is more actionable than a one-time training event. It creates a feedback loop between policy, pedagogy, and observed student behavior, which is especially important in a rapidly changing generative-AI environment (Baig & Yadegaridehkordi, 2024; Kofinas et al., 2025; Qu et al., 2025).

Limitations and Future Research

The dataset reflects a single institutional context and relies on self-reported measures. Habit is inherently longitudinal; future work should track adoption trajectories over time and test whether routine scaffolds causally increase habit and responsible use. Clustering yields discrete groups; latent profile analysis may be used to test robustness under probabilistic modeling and to evaluate profile stability across institutions. Future studies may also incorporate behavioral trace data, course-based usage records, or task-level observations to complement self-reports and provide a more fine-grained picture of actual AI use. Finally, comparative research across disciplines (Birgili et al., 2025; Bulut et al., 2026; Kaya et al., 2026; Kaya et al., 2026), institutional types (Rahman et al., 2026), and national settings would help clarify whether the identified profiles are context-specific or represent broader patterns of ChatGPT adoption in higher education.

Conclusion

This study examined ChatGPT adoption in higher education from a person-centered perspective and showed that intention alone does not adequately explain routinized use. By identifying distinct adoption profiles, the analysis demonstrated that a substantial proportion of users are not resistant to ChatGPT, but rather remain in a transition zone between capability and habit. In particular, the Capability-Ready Explorer profile revealed that relatively

high effort expectancy and facilitating conditions can coexist with weak habit and only moderate use frequency. This finding suggests that the central challenge for institutions is not simply increasing awareness or improving attitudes, but supporting the conversion of readiness into stable, responsible academic routines (Adıgüzel et al., 2026). The introduction of the Capability-to-Habit Discrepancy Index (CHDI) and the Intention-to-Use Residual (IUR) contributes a practical way to monitor this transition more precisely (Bulut et al., 2025; Yurdunkulu et al., 2025). These indicators help explain whether users possess the conditions for adoption without yet integrating the tool into repeated practice. Overall, the findings indicate that effective ChatGPT implementation in higher education requires discipline-sensitive, developmentally appropriate, and pedagogically structured support (Karanfiloğlu & Bulut, 2025). Universities should therefore move beyond one-size-fits-all training and instead design environments in which AI use becomes legitimate, repeatable, transparent, and instructionally accountable (Bulut, 2026; Bulut & Karanfiloğlu, 2026). In this sense, habit formation should be treated not as an incidental outcome, but as a strategic goal of institutional AI integration.

Statements and Declarations

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The authors used ChatGPT solely for language editing and clarity enhancement during the preparation of this manuscript. All conceptual development, analysis, interpretation, and final responsibility for the content remain with the authors.

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Data Availability: The materials supporting the findings of this study are available within the article and its supplementary materials. Requests for additional information may be directed to the corresponding author.

Ethics Approval: This study involving human participants was reviewed and approved by the Ethics Committee of Izmir University of Economics. All procedures were carried out in accordance with relevant institutional requirements and local regulations.

Informed Consent: Written informed consent was obtained from all participants prior to their participation in the study.

Conflicts of Interest: The authors declare that the study was conducted in the absence of any commercial or

financial relationships that could be interpreted as a potential conflict of interest.

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