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The Concerns Paradox: An Affective Model of ChatGPT Adoption in ESP Contexts

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Abstract

Purpose – This study examines the psychological determinants of ChatGPT utilisation among English for Specific Purposes (ESP) students in Albanian higher education, applying Self-Determination Theory to identify which factors predict actual adoption behaviour. Design/methodology/approach – A cross-sectional survey was administered to 202 ESP students at the Agricultural University of Tirana and the University of Tirana. The instrument measured Extrinsic Motivation, Competence/Autonomy, Relatedness/Trust, Challenges/Concerns, and Actual Utilisation using 31 Likert-scale items adapted from validated SDT scales. Data were analysed through Multiple Linear Regression and K-Means Cluster Analysis. Findings – Trusting ChatGPT as a safe, non-judgmental partner was the strongest predictor of usage, significantly outweighing digital competence. While extrinsic motivation also drove adoption, awareness of AI risks did not deter use. Cluster analysis revealed a "concerns paradox": frequent users and hesitant users reported identical levels of worry about AI limitations. Ultimately, affective trust, not risk assessment, separated the adopters from the sceptics. Originality/value – This study provides the first SDT-grounded empirical evidence on ChatGPT adoption in Balkan higher education and documents a "concerns paradox" whereby awareness of AI limitations does not inhibit utilisation. The affective quality of human-AI interaction—not utility alone—is the primary driver of adoption among instrumentally oriented ESP learners.

Keywords Generative AI; Self-Determination Theory; AI literacy; psychological safety; learner profiling.

1. INTRODUCTION

The integration of large language models (LLMs) into higher education has profoundly disrupted traditional paradigms of language learning. Systematic reviews tracking the first two years of ChatGPT's availability document a rapid accumulation of evidence across ESL and EFL populations, confirming that AI assistance facilitates measurable gains in writing proficiency, grammar accuracy, and vocabulary acquisition (Baig & Yadegaridehkordi, 2024; Kohnke et al., 2023). Within this landscape, English for Specific Purposes (ESP)—the teaching of English oriented toward the skills and communication strategies of a particular discipline (Hutchinson & Waters, 1987)—represents a particularly compelling, yet theoretically under-examined, site for AI adoption research. Because ESP students approach English instrumentally rather than for intrinsic linguistic interest, they utilise ChatGPT primarily for immediate, task-completion activities such as translation and paraphrasing (Ho, 2024; Sujannah et al., 2025).

The institutional response to this strategic adoption has been highly fractured. Universities find themselves caught between recognising the tool's undeniable utility and managing profound anxieties over academic integrity (Kasneci et al., 2023), prompting calls for fundamental assessment redesign (Cotton et al., 2024). Students, conversely, appear to bypass these concerns entirely. Emerging evidence indicates that an awareness of ChatGPT's risks does not inhibit usage and often coincides with widespread non-compliance regarding AI declarations (Gonsalves, 2025). This disconnect constitutes a "concerns paradox" that utilitarian technology acceptance models (such as TAM and UTAUT) struggle to resolve, as they traditionally treat risk perception as a behavioural deterrent (Shahzad et al., 2024; Strzelecki, 2024).

Self-Determination Theory (SDT), which posits that autonomy, competence, and relatedness drive sustained engagement (Ryan & Deci, 2017), offers a more robust psychological framework for dissecting this paradox. Recent applications of SDT to language learning suggest that ChatGPT adoption is dictated less by rational utility calculations or baseline digital competence than by the affective quality of the human-AI interaction (Annamalai et al., 2025; Li et al., 2025). However, the evidence supporting this affective shift remains geographically restricted primarily to Southeast Asia and the Gulf states, leaving Eastern Europe and the Balkans virtually absent from the empirical record (Mai et al., 2024). Albanian higher education—where English instruction serves as a vital gatekeeper to disciplinary knowledge in the absence of formal institutional AI policies (Mema et al., 2024)—is entirely unstudied. Furthermore, because existing scholarship relies heavily on intention-based measures (Polyportis, 2024), the psychological determinants of actual utilisation frequency remain empirically open.

The present study addresses these gaps by testing an SDT-derived predictive model among 202 ESP students at two Albanian universities. Employing Multiple Linear Regression and K-Means Cluster Analysis, the study investigates the relative

contributions of Extrinsic Motivation, Competence/Autonomy, Relatedness/Trust, and Challenges/Concerns on actual ChatGPT utilisation. Two research questions guide the investigation:

RQ1: Which psychological determinants (Motivation, Competence, Relatedness, or Concerns) most strongly predict the frequency and variety of ChatGPT utilisation among Albanian ESP students?

RQ2: What distinct AI-user profiles emerge among ESP students based on their motivational and affective orientations toward the technology?

2. LITERATURE REVIEW

2.1 Generative AI in English for Specific Purposes

Current systematic reviews confirm that ChatGPT enables the simulation of varied conversational scenarios with automated, highly adaptive corrective feedback, supporting enhanced academic writing, personalised learning, and vocabulary acquisition (Kohnke et al., 2023).

However, these findings derive overwhelmingly from General English contexts. Studies that have examined ESP populations show a distinct usage pattern: students prioritise task-completion activities over communicative practice (Ho, 2024; Sujannah et al., 2025). Experimental data confirms that ChatGPT produces significant gains in rule-based writing dimensions but non-significant improvements in higher-order discourse competencies, with lower-proficiency learners benefiting most (Mohamed et al., 2025). ESP learners thus approach ChatGPT strategically rather than linguistically, demanding a motivational theory capable of explaining why pragmatic learners deeply adopt a tool they know to be flawed.

2.2 Self-Determination Theory in AI-Assisted Language Learning

Self-Determination Theory (SDT) posits three basic psychological needs—autonomy, competence, and relatedness—whose satisfaction drives sustained engagement (Ryan & Deci, 2000, 2017). Applied to educational technology, SDT provides a psychologically grounded alternative to utilitarian models, offering explanatory mechanisms for why students persist with tools beyond initial acceptance (Chiu et al., 2024; Li et al., 2025).

The most comprehensive application of SDT to ChatGPT in language learning was conducted by Annamalai et al. (2025), who surveyed 324 EFL/ESL students in Malaysia. Their PLS-SEM model revealed a critical hierarchy: while initial usage predicted all three basic needs, only autonomy and relatedness emerged as significant predictors of continuous usage motivation; competence and challenges were non-significant. Systematic reviews corroborate this dominance of autonomy and relatedness (Li et al., 2025). The non-significance of competence in these models is theoretically interpretable: ChatGPT usage itself enhances perceived competence through repeated exposure rather than baseline technical confidence (Zhou & Li,

2023). In cross-sectional multivariate designs, competence may therefore lose predictive power once its shared variance with motivation and relatedness is partialled out.

2.3 The Pragmatic ESP Learner: Extrinsic Motivation and Competence

ESP learners engage with English primarily for career advancement and access to discipline-specific knowledge. SDT classifies this orientation as extrinsic motivation (Ryan & Deci, 2000), which aligns closely with the construct of "perceived usefulness" in TAM (Davis, 1989). Across diverse cultural contexts, perceived usefulness consistently operates as a primary driver of ChatGPT adoption in tertiary education, explaining substantial variance in behavioural intention while social influence generally remains non-significant (Strzelecki, 2024).

The relationship between this motivation and digital competence operates as a reciprocal loop, consistent with Bandura's (1977) social cognitive theory. ESP students who find ChatGPT useful invest effort into mastering it; this engagement builds competence, which subsequently reinforces its perceived utility. Most ESP students already exhibit sufficient self-regulatory capacity for AI tool use, allowing their motivation to operate directly through tool engagement to influence academic outcomes (Sujannah et al., 2025).

Accordingly, we hypothesise that:

H1: Extrinsic Motivation will have a positive relationship with ChatGPT Utilisation among ESP students.

H2: Competence/Autonomy will have a positive relationship with ChatGPT Utilisation among ESP students.

2.4 Relatedness, Trust, and Psychological Safety

While the construct of "relatedness" originally described human bonds, Ryan and Deci (2017) acknowledged it could extend to non-human entities that generate a sense of responsiveness. In the context of LLMs, relatedness manifests as psychological safety: the perception that a learner can make errors and receive non-evaluative feedback without social cost. This aligns directly with Edmondson's (1999) organisational construct of interpersonal risk-taking, and with Krashen's (1982) Affective Filter Hypothesis, which argues that anxiety blocks language acquisition.

Empirical evidence for this affective mechanism is substantial. ChatGPT-assisted practice significantly reduces foreign language speaking and reading anxiety for both high- and low-proficiency learners (Almineeai et al., 2025). The private, endlessly patient nature of the AI removes the fear of social evaluation (MacIntyre, 2017), allowing students to form a habitual, trusting connection to the technology. Trust functions as a critical enabler of this adoption, mediating the path from usefulness to loyalty (Dorobat & Corbea, 2025) and moderating the relationship between awareness and acceptance (Shahzad et al., 2024). Where language anxiety is

amplified by limited communicative exposure, the affective pathway to adoption may carry more weight than rational utility calculations.

Therefore, we hypothesise that:

H3: Relatedness/Trust will have a positive relationship with ChatGPT Utilisation among ESP students.

2.5 The Concerns Paradox: Academic Integrity versus Pragmatic Utilisation

While institutional alarm surrounding academic integrity and plagiarism is well-documented (Cotton et al., 2024; Kasneci et al., 2023), the empirical question remains whether these legitimate concerns actually deter student usage. The evidence suggests they do not.

Counterintuitively, awareness of ChatGPT's limitations is often positively related to intention to use (Al Murshidi et al., 2024). Active users simultaneously hold strong positive views about utility and strong concerns about risks, without the latter diminishing the former (Farhi et al., 2023). Perceptions of academic dishonesty show no direct inhibitory relationship with usage (Ortiz-Bonnin & Blahopoulou, 2025). From an SDT perspective, this paradox occurs because abstract challenges do not frustrate the three basic needs: students maintain autonomy over tool choice, retain operational competence, and still experience psychological safety (Annamalai et al., 2025). Abstract awareness of risk is simply outweighed by the concrete reward of task completion.

We therefore hypothesise that:

H4: Perceived Challenges will have a negative relationship with ChatGPT Utilisation among ESP students (though this effect is expected to be weak or non-significant).

2.6 The Present Study

The empirical patterns established in the literature, namely, the primacy of relatedness/trust, the strength of extrinsic motivation, and the negligible deterrent effect of academic concerns—have been validated almost exclusively in Southeast Asian, East Asian, and Gulf state contexts (Al Murshidi et al., 2024; Annamalai et al., 2025; Ho, 2024; Sujannah et al., 2025). The European dimension remains sparse, largely limited to studies confirming cross-cultural TAM variables in Poland, Romania, and Croatia (Dorobat & Corbea, 2025; Strzelecki, 2024).

The Balkan tertiary context is notably absent. Currently, Mema et al. (2024) provide the sole empirical data point on ChatGPT in Albanian higher education, identifying a consensus on learning effectiveness but highlighting a lack of institutional digitalisation. No study has tested an SDT-derived predictive model within a post-socialist educational system where English instruction is deeply instrumental and AI integration proceeds without formal regulatory frameworks. Moreover, by measuring actual utilisation frequency rather than intention, the present study

addresses the persistent intention–behaviour gap in technology adoption research, providing a vital cross-cultural counterpoint to the Asian and Middle Eastern cohorts that currently define the field.

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative, cross-sectional survey design (Creswell & Creswell, 2018). The cross-sectional approach is appropriate for examining predictive relationships among variables at a single point in time, and has become the prevailing design in ChatGPT adoption research within higher education (Annamalai et al., 2025; Shahzad et al., 2024; Strzelecki, 2024). Furthermore, this correlational approach directly addresses the methodological gap identified by Sujannah et al. (2025), who noted that the majority of existing studies regarding ChatGPT in ESP contexts remain exploratory or descriptive. Data were collected from two Albanian universities to enable an inter-institutional comparison of utilisation patterns across distinct disciplinary orientations within the same national framework.

3.2 Participants and Context

The sample (N = 202) was drawn from two Albanian tertiary institutions. The first site is the Agricultural University of Tirana (AUT), Faculty of Economics and Agribusiness, where undergraduates in Finance, Agribusiness Management, Economics, and Business Informatics are enrolled in mandatory ESP courses. The second site is the University of Tirana (UT), Faculty of Natural Sciences, where students in science-oriented programmes study English for academic communication. Both institutions serve students who approach English instrumentally—as a tool for disciplinary access rather than a subject of intrinsic interest—providing a robust basis for a within-country comparison of distinct academic disciplines.

Purposive sampling (Etikan et al., 2016) was employed based on two inclusion criteria: (a) current enrolment in an ESP course at the undergraduate or master's level, and (b) having used ChatGPT at least once for an English-related task. This screening filter, consistent with Annamalai et al. (2025) and Sujannah et al. (2025), ensured that all respondents possessed baseline experience with the technology. Minimum sample size requirements were established using the formula $N \ge 50 + 8m$, where m represents the number of predictors (Tabachnick & Fidell, 2013). For a model with four independent variables, the required minimum is 82; the obtained sample of 202 exceeds this threshold substantially.

3.3 Instrumentation

Data were collected via a two-part online questionnaire grounded in Self-Determination Theory (Ryan & Deci, 2017) and adapted from validated scales within the ChatGPT adoption literature (Annamalai et al., 2025; Sujannah et al., 2025). Items

were adapted rather than replicated verbatim to ensure functional equivalence and face validity for the Albanian ESP context.

Part 1 collected demographic and usage profile data (e.g., age, gender, study programme, ChatGPT version used). Part 2 measured five constructs using a 5-point Likert scale. The four predictor constructs, anchored from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*), included: Extrinsic Motivation (EM, 7 items), measuring instrumental reasons for usage such as academic progression; Competence/Autonomy (COM, 5 items), assessing self-efficacy in using the tool; Relatedness/Trust (REL, 4 items), capturing habitual engagement and the perceived non-judgmental quality of the AI; and Challenges/Concerns (CHC, 5 items), measuring apprehensions regarding bias, inaccuracy, and academic dishonesty. The dependent variable, Actual ChatGPT Utilisation (USE, 10 items), was adapted from Sujannah et al. (2025) and anchored from 1 (*Never*) to 5 (*Very Often*), measuring the frequency of use for specific ESP tasks (e.g., translation, paraphrasing, field-specific terminology). Composite scores were calculated as the mean of the respective items.

3.4 Data Collection Procedures

The survey was administered via Google Forms during the spring semester of 2026 which was distributed via institutional email to students enrolled in ESP courses at two state universities; Agricultural University of Tirana (AUT) and University of Tirana (UT). Participation was strictly voluntary. Prior to accessing the survey, respondents were presented with an electronic informed consent form detailing the study's purpose, data anonymization protocols, and their right to withdraw at any time, consistent with established ethical guidelines (Annamalai et al., 2025; Sujannah et al., 2025).

3.5 Data Analysis

Data were analysed using IBM SPSS version 28. Distributional normality for all composite variables was verified against the ±2.0 skewness and kurtosis thresholds recommended by George and Mallery (2019). Internal consistency was assessed using Cronbach's alpha, applying the conventional $\alpha > .70$ threshold for acceptability (Nunnally & Bernstein, 1994).

To compare the AUT (economics/agribusiness) and UT (natural sciences) cohorts, independent-samples t-tests were conducted, substituting the non-parametric Mann-Whitney U test where normality assumptions were violated. A simultaneous-entry Multiple Linear Regression (MLR) was then performed to identify the predictive strength of the four independent variables (EM, COM, REL, CHC) on Actual Utilisation (USE). Standard MLR assumptions were verified prior to estimation: multicollinearity (VIF < 5.0; Hair et al., 2019), normality of residuals (Shapiro-Wilk), homoscedasticity (Breusch-Pagan), linearity (Ramsey RESET), and the absence of autocorrelation (Durbin-Watson; Tabachnick & Fidell, 2013). Effect sizes for both the comparative

tests (Cohen's *d*) and individual regression predictors (Cohen's f^2) were calculated to quantify practical significance (Cohen, 1988).

Finally, to complement the variable-centred regression, a K-Means Cluster Analysis was executed on the standardised scores of the predictor constructs to identify distinct student AI-user typologies. Silhouette coefficients were evaluated across k=2 to k=4 configurations to determine optimal cluster retention, and the resulting profiles were validated via one-way ANOVA.

4. RESULTS

4.1 Demographic Profile of Participants

A total of 202 usable responses were obtained following data screening and the removal of incomplete submissions. Table 1 presents the demographic and background characteristics of the sample. The respondents were predominantly female (n = 144, 71.3%), which is consistent with the gender composition of the Faculty of Economics and Agribusiness at the Agricultural University of Tirana. Nearly half of the sample (49.0%) were enrolled in Finance and Accounting, followed by Agribusiness Management (8.9%), Business Informatics (5.4%), and Economics (4.0%), while 28.7% came from programmes outside the four target departments.

The majority of participants reported intermediate (B1, 37.6%) or upper-intermediate (B2, 36.1%) English proficiency, with only 2.5% self-identifying at the beginner (A1) level. Regarding ChatGPT access, 90.1% of respondents used the free version exclusively, and only 5.0% subscribed to ChatGPT Plus. Teacher awareness of students' ChatGPT use was mixed: 29.2% reported that their teacher was aware and encouraged use, 24.8% indicated neutral awareness, while 32.7% were unsure whether their teacher knew. The mean age of the sample was 19.23 years (SD = 1.72), and more than 62% of respondents reported having used ChatGPT for over one year.

Table 1. Demographic and Background Profile of Participants

Variable	Category	*n*	%
Gender	Female	144	71.3
	Male	58	28.7
Study programme	Finance and Accounting	99	49.0
	Agribusiness Management	18	8.9
	Business Informatics	11	5.4
	Economics	8	4.0
	Other	58	28.7
Self-reported English proficiency	Beginner (A1)	5	2.5
	Elementary (A2)	19	9.4

	Intermediate (B1)	76	37.6
	Upper-Intermediate (B2)	73	36.1
	Advanced (C1/C2)	28	13.9
ChatGPT version used	Free version only	182	90.1
	Paid version (Plus)	10	5.0
	Don't know	10	5.0
Teacher awareness of use	Yes, and encourages it	59	29.2
	Yes, but neutral	50	24.8
	Yes, but discourages it	11	5.4
	No, not aware	13	6.4
	Not sure	66	32.7

Note. N = 202. Percentages are based on valid responses per variable. "Other" programmes include Engineering Mathematics & Informatics, Business Management, Biotechnology, Mathematics, Informatics, and miscellaneous entries. English proficiency: 1 missing response. Teacher awareness: 3 missing responses.

4.2 Descriptive Statistics, Reliability, and Correlations

All five constructs exceeded the conventional threshold of α ≥ .70 (Nunnally & Bernstein, 1994), indicating acceptable to excellent internal consistency. Extrinsic Motivation demonstrated the highest reliability (α = .942, 7 items), followed by Utilisation (α = .933, 10 items), Competence (α = .918, 5 items), Relatedness (α = .878, 4 items), and Challenges (α = .751, 5 items). The adapted instrument thus performs reliably in the Albanian ESP context across all constructs.

As detailed in Table 2, all composite variables clustered around the midpoint of the 5-point scale (M = 3.10–3.44, SD = 0.90–1.14). Skewness (−0.71 to −0.26) and kurtosis (−0.58 to 0.21) values fell within the ±2.0 range recommended by George and Mallery (2019), confirming distributional adequacy for parametric testing. The three positive predictor constructs (EM, COM, REL) were strongly intercorrelated (r = .765–.819, p < .001) and showed strong positive associations with Utilisation (r = .628–.723, p < .001). Relatedness exhibited the highest bivariate correlation with Utilisation (r = .723). Notably, Challenges showed near-zero, non-significant correlations with all other constructs, including Utilisation (r = –.097, p = .170), indicating that it operates orthogonally to the motivational factors.

Table 2. Descriptive Statistics, Reliability Coefficients, and Pearson Correlation Matrix

Variable	Items	*α*	*M*	*SD*	1	2	3	4	5
1. Extrinsic Motivation	7	.942	3.31	1.14	—				
2. Competence	5	.918	3.44	1.06	.765***	—			
3. Relatedness	4	.878	3.17	1.08	.819***	.793***	—		
4. Challenges	5	.751	3.10	0.90	.029	.078	–.025	—	
5. Utilisation	10	.933	3.15	1.01	.688***	.628***	.723***	–.097	—

Note. N = 202. α = Cronbach's alpha. All scales measured on a 5-point scale (1 = *Strongly Disagree/Never* to 5 = *Strongly Agree/Very Often*). Reliability thresholds: α ≥ .70 acceptable, ≥ .80 good, ≥ .90 excellent (Nunnally & Bernstein, 1994). *** $p < .001$.

4.3 Regression Assumption Checks

Prior to the regression analysis, all standard MLR assumptions were verified. Variance Inflation Factors ranged from 1.03 to 3.89, all below the threshold of 5.0 (Hair et al., 2019). The Shapiro-Wilk test (W = .994, p = .657), Kolmogorov-Smirnov test (D = .040, p = .892), and Jarque-Bera test (JB = 0.292, p = .864) confirmed residual normality. The Breusch-Pagan test indicated homoscedasticity (LM = 3.89, p = .421). The Ramsey RESET test detected no significant non-linearity (F = 0.361, p = .698), and the Durbin-Watson statistic (DW = 2.14) confirmed independence of errors. All assumptions were satisfactorily met.

4.4 Multiple Linear Regression

Table 3 presents the results of the simultaneous-entry MLR predicting Actual ChatGPT Utilisation from the four predictor constructs.

The overall model was statistically significant, $F(4, 197) = 63.35$, $p < .001$, explaining 56.3% of variance in ChatGPT Utilisation (Adjusted $R^2 = .554$). Relatedness/Trust was the strongest predictor (β = .426, p < .001), followed by Extrinsic Motivation (β = .276, p = .002). Challenges/Concerns was a significant negative predictor (β = –.101, p = .035), though this effect became marginally non-significant under heteroscedasticity-consistent (HC3) robust standard errors (p = .083), warranting cautious interpretation.

Table 3. Multiple Linear Regression Results Predicting ChatGPT Utilisation (N = 202)

Predictor	*B*	*SE*	**β**	*t*	*p*	**95% CI**
(Constant)	1.146	0.228	—	5.035	< .001	[0.697, 1.594]
Extr. Motivation	0.245	0.077	.276	3.165	.002	[0.092, 0.397]
Competence	0.083	0.079	.088	1.061	.290	[–0.072, 0.238]
Relatedness	0.398	0.087	.426	4.580	< .001	[0.226, 0.569]
Challenges	–0.113	0.053	–.101	–2.121	.035	[–0.219, –0.008]

Note. R^2 = .563, Adjusted R^2 = .554. F(4, 197) = 63.35, p < .001. B = unstandardised coefficient; SE = standard error; β = standardised coefficient; CI = confidence interval.

Competence/Autonomy was not a significant independent predictor (β = .088, p = .290), despite its strong bivariate correlation with Utilisation (r = .628). This pattern is consistent with multicollinearity-induced attenuation of its unique contribution, driven by high shared variance with Extrinsic Motivation (r = .765) and Relatedness/Trust (r = .793). Figure 1 displays the standardised regression coefficients.

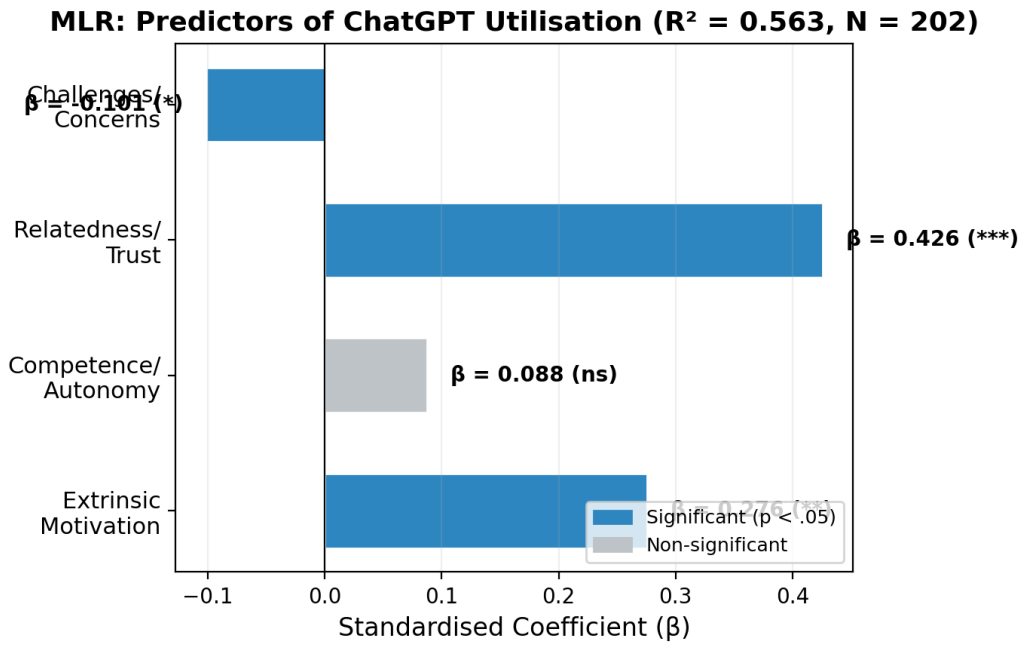


Figure 1. Standardised Regression Coefficients Predicting ChatGPT Utilisation

4.5 Hypothesis Testing

Table 4 summarises the hypothesis testing outcomes.

Table 4. Summary of Hypothesis Testing Results

	Hypothesis	Key Statistics	Verdict	Remark
H1	EM → USE (+)	β = .276, p = .002	**Supported**	2nd strongest
H2	COM → USE (+)	β = .088, p = .290	**Not Supported**	Suppression effect
H3	REL → USE (+)	β = .426, p < .001	**Supported**	Strongest predictor
H4	CHC → USE (–)	β = –.101, p = .035	**Supported***	Borderline; HC3 p = .083

Note. * H4 is supported under conventional OLS (p = .035) but becomes marginally non-significant under HC3 robust standard errors (p = .083). EM = Extrinsic Motivation; COM = Competence/Autonomy; REL = Relatedness/Trust; CHC = Challenges/Concerns; USE = Actual Utilisation.

4.6 K-Means Cluster Analysis

To complement the variable-centred regression approach with a person-centred perspective, a K-Means Cluster Analysis was performed on the four predictor constructs (EM, COM, REL, CHC) using standardised scores. The optimal number of clusters was determined by comparing silhouette coefficients across solutions ranging from k = 2 to k = 4. The two-cluster solution yielded the highest silhouette coefficient (0.378), indicating the clearest partition of the data, and was retained as the final model.

Table 5. K-Means Cluster Profiles (k = 2, N = 202)

Cluster	*n*	%	EM	COM	REL	CHC	USE
Disengaged Sceptics	81	40.1	2.24	2.46	2.16	3.11	2.45
Engaged Adopters	121	59.9	4.03	4.09	3.84	3.10	3.62

Note. EM = Extrinsic Motivation; COM = Competence/Autonomy; REL = Relatedness/Trust; CHC = Challenges/Concerns; USE = Actual Utilisation. Values are construct means (1–5 scale). Cluster labels assigned by USE mean ranking.

The two clusters differed sharply on all motivational constructs. One-way ANOVA confirmed statistically significant between-cluster differences for Extrinsic

Motivation ($F = 303.45$, $p < .001$, $\eta^2 = .603$), Competence/Autonomy ($F = 259.12$, $p < .001$, $\eta^2 = .564$), Relatedness/Trust ($F = 281.32$, $p < .001$, $\eta^2 = .585$), and Utilisation ($F = 97.69$, $p < .001$, $\eta^2 = .328$). The critical finding is that Challenges/Concerns did not differ between clusters ($F = 0.007$, $p = .932$, $\eta^2 < .001$). Both the Disengaged Sceptics and the Engaged Adopters reported virtually identical levels of concern about inaccuracy, bias, and academic dishonesty ($M = 3.11$ vs. $M = 3.10$). What distinguishes the high-use group is not the absence of concern but the presence of trust: Engaged Adopters scored substantially higher on Relatedness/Trust (3.84 vs. 2.16), the construct that also emerged as the strongest predictor in the regression model.

Figure 2 displays the cluster profiles.

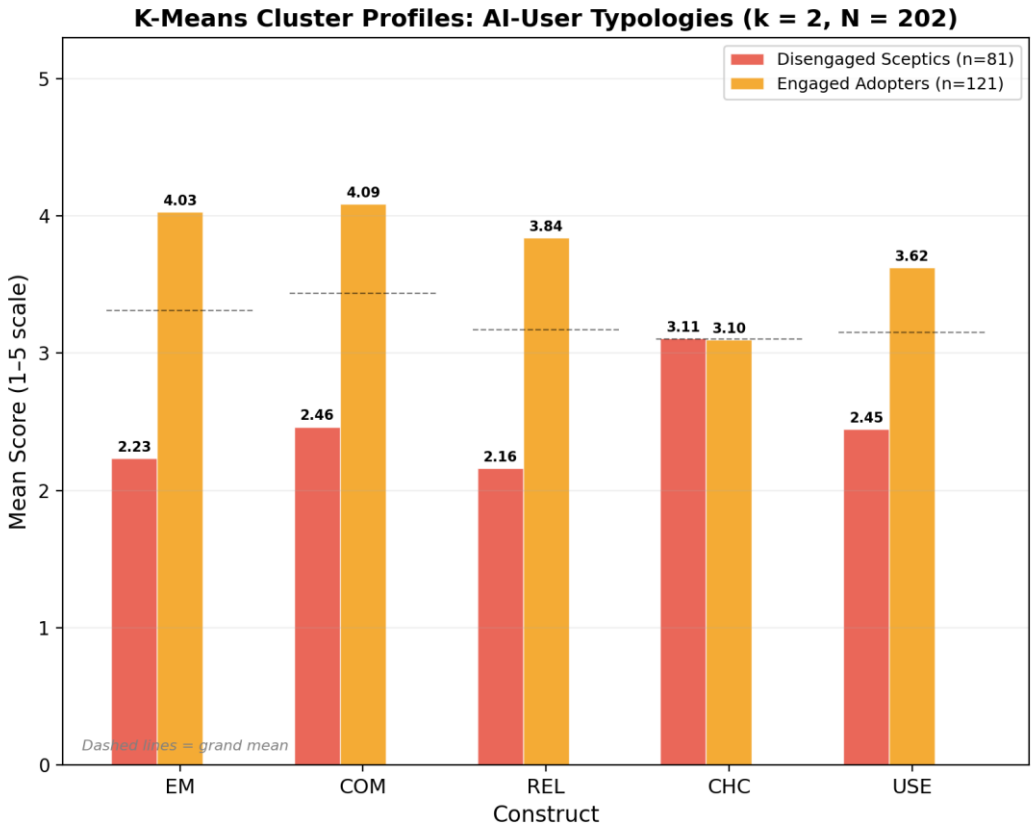


Figure 2. K-Means Cluster Profiles: AI-User Typologies

5. Discussion

5.1 The Primacy of Trust and the Suppression of Competence

Relatedness/Trust was the strongest predictor of ChatGPT utilisation, whereas Competence/Autonomy was non-significant. This contradicts utilitarian adoption models like TAM (Davis, 1989) and UTAUT (Strzelecki, 2024), which emphasize

usefulness and self-efficacy. For these Albanian ESP students, feeling safe with the tool outweighed feeling skilled in using it. This finding aligns with Annamalai et al. (2025), who noted that relatedness and autonomy, rather than competence, drove continuous usage among Malaysian EFL/ESL learners, and supports Li et al. (2025), whose systematic review identified relatedness as a primary need in AI-assisted language education.

This dynamic reflects the specific ESP context. Students learn English instrumentally to access disciplinary texts or pass exams (Hutchinson & Waters, 1987) and frequently experience anxiety when evaluated by peers or instructors (MacIntyre, 2017). ChatGPT mitigates this pressure by providing a non-judgmental practice space, aligning with psychological safety (Edmondson, 1999) and a lowered affective filter (Krashen, 1982). Extensive research confirms that generative AI reduces foreign language anxiety through private, low-risk interaction (Almineeai et al., 2025), developing habitual engagement built largely on trust (Shahzad et al., 2024). The non-significance of Competence/Autonomy likely indicates a suppression effect rather than irrelevance. Due to high intercorrelations among the motivational constructs, baseline competence lost its unique predictive value. This supports Zhou and Li (2023), who observed that repeated ChatGPT use organically enhances perceived competence. Once trust is established, the baseline technical skill required for engagement is simply too low to meaningfully differentiate users.

5.2 The “Concerns Paradox” in ESP Contexts

The negligible influence of Challenges/Concerns on actual utilisation is particularly instructive. This replicates the near-zero effect observed by Annamalai et al. (2025) and reinforces a well-documented paradox across tertiary populations: students widely recognise ChatGPT's inaccuracies, biases, and academic integrity risks, yet still use it frequently (Al Murshidi et al., 2024; Farhi et al., 2023).

Viewed through Self-Determination Theory (SDT; Ryan & Deci, 2017), abstract concerns do not frustrate basic psychological needs. They do not impair autonomy, technical competence, or interactional comfort. Therefore, the disconnect between institutional warnings and student behaviour represents a gap in motivational relevance rather than knowledge. Alternative theories offer partial explanations. Cognitive dissonance theory (Festinger, 1957) suggests students rationalise their usage by downplaying risks (Seran et al., 2025), while risk compensation theory (Wilde, 1998) posits that feeling supported encourages students to take manageable risks. Although both frameworks offer valuable insights (Gonsalves, 2025), SDT provides the clearest mechanism: concerns simply fail to deter adoption when a student's basic psychological needs are actively being met.

5.3 Pedagogical Implications for Tertiary ESP

Because integrity concerns do not deter usage, prohibition-based policies are highly likely to fail. Restrictive measures typically generate strategic non-compliance rather

than genuine behavioural change (Gonsalves, 2025). With formal AI policies still developing in Albanian universities (Mema et al., 2024), institutions must shift their focus from policing usage to building critical AI literacy.

Three practical interventions emerge from these findings. First, since trust drives adoption, ESP instructors should normalise rather than stigmatise AI. Integrating ChatGPT into classroom activities where students critically evaluate its output transforms private reliance into structured academic practice (Sujannah et al., 2025). Second, leveraging the strong influence of extrinsic motivation, instructors should highlight the tool's disciplinary utility. Demonstrating how AI accelerates tasks like drafting professional emails directly appeals to the pragmatic orientation typical of ESP learners (Ho, 2024). Finally, because risk awareness alone does not deter use, verbal warnings about hallucinations are insufficient. Assessments should instead require students to document their prompts, verify output accuracy, and reflect on the tool's limitations to build the critical AI literacy essential for modern graduates (Cotton et al., 2024).

5.4 Limitations and Future Research

Several limitations qualify these findings. First, the cross-sectional design captures associations at a single point in time, precluding causal inferences. The direction of influence between trust and utilisation may be reciprocal—frequent use may build trust just as trust drives use—a dynamic that requires longitudinal investigation (Polyportis, 2024). Second, utilisation was measured via self-report, which may not perfectly align with objective usage logs. Third, the sample is restricted to ESP students at two Albanian universities; the findings may not generalise to other national contexts or disciplinary settings. Finally, the high intercorrelations among the positive motivational constructs raise discriminant validity concerns that future research should address through Structural Equation Modelling or exploratory factor analysis. Future studies should also prioritise longitudinal designs to clarify the temporal emergence of trust, which carries direct pedagogical consequences. Additionally, mixed-method approaches incorporating qualitative interviews are needed to illuminate the lived experience behind these statistical patterns, particularly the subjective meaning of "psychological safety" for students lacking English-language support outside the classroom. Finally, comparative research across Eastern European tertiary institutions would determine whether the primacy of trust is specific to the Albanian context or a broader characteristic of educational systems with instrumental English instruction and developing AI policy frameworks.

6. CONCLUSION

This study set out to identify the psychological determinants of ChatGPT utilisation among Albanian ESP students and to determine whether distinct AI-user profiles exist within this population. The findings systematically challenge the prevailing assumption, which is embedded in both traditional technology acceptance models and institutional policies, that AI adoption is primarily a rational, utility-driven

decision modulated by risk awareness. The results show it is not. Namely, the data demonstrate that ChatGPT adoption among instrumentally oriented language learners is, at its core, an affective phenomenon. The strongest predictor of use is not how useful students believe the tool to be, nor how competent they feel operating it, but how safe, trusted, and non-judgmental they experience the interaction to be. The cluster analysis confirms this at the person level: the critical difference between an Engaged Adopter and a Disengaged Sceptic is not what they fear about the technology, but how they feel toward it.

The practical consequence is stark. Policies designed to curb ChatGPT use by amplifying concerns will not achieve their intended effect, because these concerns operate outside the motivational system that drives adoption. Meaningful pedagogical design must build trust through transparent integration of ChatGPT into coursework, channel instrumentally motivated use toward critical evaluation, and replace prohibition with rigorous AI literacy. For Balkan higher education, this carries particular urgency. Students are already using ChatGPT extensively, guided not by policy but by the psychological reality that the tool feels safe to use. The question is whether institutions will catch up.

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APPENDIX

Extrinsic Motivation (IV)
1. I use Chatbot to study English because I think it is useful.
2. I use Chatbot to study English because I want to be proficient in English usage.
3. I use Chatbot to study English because I want to have mastery in English writing.
4. The reason why I study English using Chatbot is that I think it will advance my academic studies.
5. I study English using Chatbot because it is important for my future.
6. I study English using Chatbot because it is an important subject for my career path.
7. I study English using Chatbot because it helps me to get good grades.
Competence (IV)

1. I believe I am talented at using Chatbot for learning English.
2. I do pretty well in using Chatbot in learning English as compared to my other friends.
3. I feel pretty confident about my Chatbot usage skills for learning English.
4. I am satisfied with my ability to use Chatbot in learning English language.
5. My instructor understands my choice to use Chatbot in learning English language.
Relatedness (IV)
1. I can trust Chatbot in helping me to learn English.
2. I like the opportunity to interact with Chatbot more often for English language learning.
3. I feel Chatbot usage for English language learning has become my habit.
4. I enjoy interacting with chatbot for English language learning.
Challenges (IV)
1. Using Chatbot is not perfect for learning English language because it sometimes provides incorrect or misleading information (accuracy and reliability).
2. Chatbot is trained on data that may contain bias against the English language and can result in biased outputs which perpetuate harmful stereotypes.
3. Over-reliance on Chatbot for my English language learning can reduce my critical thinking and problem-solving skills, as well as motivation to actively engage with course materials (dependence).
4. Chatbot could be used for academic dishonesty, such as plagiarism or coyping answers (cheating).
5. Using Chatbot to learn English may be impacted by technical issues, such as network connectivity or software compatibility, which could disrupt the practical and interactional experience (technical issues).
Actual ChatGPT Use (DV)
1. I use ChatGPT to help me translate English texts into Albanian for better understanding.
2. I use ChatGPT to look for the meaning of words that I do not understand.
3. I use ChatGPT to help me translate the English texts into Albanian for better understanding.
4. I use ChatGPT to help me look for the meaning of words that I don't understand.
5. I use ChatGPT to help me paraphrase the English sentences for my assignments in my ESP class.

6. I use ChatGPT to help me fix my grammatical mistakes in my assignments in my ESP class.
7. I use ChatGPT to help me generate ideas for my assignments in my ESP class.
8. I use ChatGPT to help me understand complex English texts relevant to my field of study.
9. I use ChatGPT to help me improve my English writing skills by providing feedback on my compositions.
10. I use ChatGPT to help me prepare for English tests in my ESP class.