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Generative AI, Learner Autonomy, and Online French Learning in Algerian Higher Education: A Typological Study

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Abstract: This exploratory study investigates the relationship between generative AI use (ChatGPT, Copilot, Gemini) and perceived learner autonomy among French as a Foreign Language (FFL) students in an online learning context. Based on a survey of 92 Algerian university students, a hierarchical cluster analysis (Ward's method) identified three distinct profiles of perceived autonomy: autonomous (40.2%), dependent (47.8%), and selective (12.0%). The selective profile exhibited high dependence on AI for text comprehension but autonomy for understanding instructions and solving exercises, suggesting that autonomy may be task-specific rather than global. Binary logistic regression indicated that students who reported using AI "to progress faster" were 3.45 times more likely to belong to the dependent profile (p = 0.033), regardless of frequency of AI use or response verification practices. No statistically significant between-cluster differences were found for interest in FFL, frequency of AI use, or response verification, although descriptive trends were consistent with the typology. These findings point to the importance of reflective AI training and differentiated pedagogical support based on learner profiles. The study offers insight into the conditions under which AI may support or hinder perceived learner autonomy.

Keywords: generative artificial intelligence, learner autonomy, French as a foreign language, online learning, Algerian higher education

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1. Introduction

Since the recent emergence of generative artificial intelligence tools such as ChatGPT, Copilot, and Gemini, foreign language learning practices have been undergoing rapid and profound change. These technologies provide learners with a wide range of instantly accessible resources, including translation, paraphrasing, language correction, idea generation, and complete text generation (Barrot, 2023; Kohnke et al., 2023). Their widespread adoption in higher education now raises questions not only about learning processes, but also about the learner's role in developing their own competencies.

In the field of language education, this issue is closely linked to the concept of autonomy, which has been regarded as a core competence since the seminal work of Holec (1981). Autonomy refers to the learner's ability to take responsibility for their own learning, particularly through planning their work, selecting appropriate strategies, monitoring their progress, and evaluating their achievements (Benson, 2011; Little, 2007). It is especially important in online learning environments, where pedagogical support is less continuous and students are expected to assume greater responsibility for managing their learning.

However, the integration of generative AI into these environments also creates an important tension. On the one hand, such tools can support learning by facilitating access to information, providing rapid feedback, and helping learners overcome specific difficulties (Lai & Zheng, 2018; Mohebbi, 2025). On the other hand, they may foster forms of dependency when learners systematically delegate cognitive operations that they should gradually learn to master themselves. Recent studies have suggested a link between intensive AI use, cognitive offloading, and the weakening of certain critical skills (Gerlich, 2025; Tian & Zhang, 2025).

The key issue, therefore, is not simply whether AI helps or hinders learning, but under what conditions it supports learner autonomy or, conversely, undermines it. This relationship is likely to be heterogeneous. Students do not all use these tools in the same way, pursue the same goals, or draw on the same self-regulatory resources (Bundgaard & Møller, 2025; Reinders & White, 2011; Sockett, 2014). While approaches based on broad comparisons (e.g., between users and non-users) or average effects provide valuable insights, they do not fully capture this diversity of learner configurations. A profile-based approach may therefore usefully complement them.

Despite the rapid growth of research on generative AI in education, few studies have adopted a person-centred approach to examine the relationship between AI use and autonomy in language learning. This gap is particularly evident in Global South contexts, and more specifically in Algerian higher education, where digital transformation intersects with specific linguistic and pedagogical challenges. The case of French as a Foreign Language (FFL) is especially relevant: it remains an important academic and professional language, while often being taught online through transversal modules that require a high degree of learner autonomy.

It is within this context that the present study was conducted among students at the University of Batna 1 (Algeria) enrolled in online FFL courses. It pursues two main objectives: (1) to identify differentiated profiles of self-reported autonomy based on academic tasks performed without assistance; and (2) to examine the extent to which these profiles are associated with broader patterns of AI use and orientations towards language learning. By adopting a typological approach based on hierarchical cluster analysis, this study seeks to contribute to a more nuanced understanding of the conditions under which generative AI may support – or hinder – the development of student autonomy.

2. Theoretical Framework

2.1. Language Learner Autonomy: A Multidimensional Construct

Since Holec's (1981) seminal definition – the ability to take charge of one's own learning – autonomy has become a central concept in language education. Subsequent research has highlighted its multidimensional nature: it is neither simply learning alone nor a lack of teacher guidance; rather, it refers to capacities for control, self-regulation, responsibility, critical reflection, and self-evaluation (Benson, 2011; Little, 1991, 2007). This perspective is closely aligned with models of self-regulated learning in cognitive psychology, which describe the ability to plan, monitor, and evaluate one's own learning processes (Zimmerman, 2000).

It is important to distinguish perceived autonomy from both behavioural and dispositional autonomy. Behavioural autonomy refers to what learners actually do in practice (e.g., completing a task without external assistance), whereas dispositional autonomy refers to a relatively stable learner trait across contexts. In contrast, perceived autonomy – operationalized in this study through self-reported capability – captures learners' beliefs about their ability to perform specific tasks without AI assistance. Such beliefs are known to influence effort, persistence, and strategy use (Bandura, 1997).

Focusing on perceived autonomy is particularly appropriate for an exploratory study because it allows us to examine learners' subjective sense of agency in AI-rich environments. Although this perception does not necessarily coincide with objectively observed performance, it strongly shapes learners' behavioural choices and their relationship with technological support. This distinction also resonates with domain-specific self-efficacy theory, according to which learners may feel capable in some tasks but not in others – a pattern that directly informs our interpretation of the selective profile discussed later in the paper.

From this perspective, autonomy is an evolving process shaped both by learner characteristics and by learning conditions. Rather than a fixed attribute, it develops through interactions among learners, tasks, and educational environments. In online learning settings, where guidance is less direct, autonomy becomes particularly crucial: learners are expected to organize their work, sustain their engagement, and manage difficulties independently. These demands may become even more complex in AI-rich environments, where learners must not only regulate their own learning processes but also critically evaluate and strategically integrate AI-generated support.

2.2. Digital Technologies and Autonomy: Between Opportunities and Regulatory Demands

The development of educational technologies has profoundly reshaped research on autonomy. Numerous studies have shown that digital tools can support self-directed learning by expanding access to resources, increasing practice opportunities, and offering greater temporal and spatial flexibility (Lai, 2017; Reinders & White, 2011).

In the field of language learning, these tools can support several dimensions of autonomy, including information seeking, individualized practice, immediate feedback, and personalized learning pathways. Lai (2017) notes that autonomous use of technology outside the classroom is an important means of extending learning. Similarly, Lai and Zheng (2018) show that self-directed use of mobile devices can strengthen learners' initiative and extend learning opportunities beyond the institutional setting. However, Sockett (2014) cautions that such informal uses do not automatically ensure self-regulation or sustained engagement.

Yet the mere availability of digital tools is not enough to guarantee the development of autonomy. Technology-rich environments themselves require skills such as planning, resource selection, attention management, and self-regulation (Reinders & White, 2011). In other words, while technology can support autonomy, it also presupposes its exercise.

These issues are now being intensified by the rise of AI-based tools. A recent systematic review suggests that certain AI applications, such as chatbots or adaptive feedback systems, can support different phases of self-regulated learning, provided that learners remain active in guiding their own activities (Lan & Zhou, 2025).

2.3. Generative Artificial Intelligence: Pedagogical Support or Cognitive Dependency?

In this context, the integration of generative AI raises questions about its potential effects on learners' cognitive processes. Sparrow et al. (2011) demonstrated that the mere accessibility of information through digital technologies can reduce its memorization, illustrating a mechanism of cognitive offloading that is also relevant to AI. More recent research suggests an association between intensive AI use and a weakening of certain dimensions of critical thinking, mediated by cognitive fatigue (Gerlich, 2025; Tian & Zhang, 2025).

Conversely, other studies emphasize that these effects are neither systematic nor uniform. AI can also support self-regulation when its use is reflective and learning-oriented (Mohebbi, 2025). Some studies have even shown that interventions incorporating ChatGPT can lead to greater gains in autonomy than traditional approaches, thereby highlighting the decisive role of pedagogical design (Nguyen & Doan Thi Hue, 2025).

From this perspective, the central issue is not merely whether learners use AI, but how they appropriate it: as occasional support, as a strategic tool, or as a systematic substitute. Recent surveys confirm the diversity of students' usage patterns, perceptions, and verification practices (Bundgaard & Møller, 2025; Langseth et al., 2025), while also pointing to the need for critical skills to evaluate the reliability of generated content (Baldrich et al., 2025).

Thus, the effects of AI on autonomy do not appear to be intrinsic to the technology itself, but rather linked to the configurations of use adopted by learners. These findings suggest that an approach based on global variables (frequency of use, interest) might mask differentiated profiles. A typological approach therefore seems particularly relevant for capturing this heterogeneity

3. Methodology

3.1. Research Objectives and Questions

Research on educational technologies often relies on broad comparisons (e.g., users versus non-users) or on estimating average effects. While such approaches provide useful insights, they may nevertheless obscure the heterogeneity of practices, as students develop different relationships with AI and draw on varied learning strategies.

From this perspective, a typological approach – focused on identifying profiles based on configurations of responses – can overcome this limitation by revealing contrasted groups of learners.

The present study aims to answer the following research questions:

1. What profiles of autonomy can be identified among online FFL students based on their perceived ability to perform different tasks without assistance?
2. To what extent do these profiles differ in terms of interest in FFL, learning strategies, frequency of AI use, response verification, and perceived impact of AI on autonomy?
3. Among these variables, which ones predict membership in the profile of students most dependent on AI?

3.2. Design

This study adopts a quantitative, cross-sectional, and exploratory approach. It aims to better understand the relationship between the use of generative artificial intelligence (AI) and learner autonomy in an online French as a Foreign Language (FFL) context at the university level. Given the still-emergent nature of these uses and the presumed heterogeneity of student practices, a typological approach was chosen. Rather than focusing solely on linear relationships between variables or estimating average effects applicable to the whole sample, this approach makes it possible to identify differentiated student profiles based on response configurations. This person-centred approach is particularly well suited to capturing learner heterogeneity and identifying subgroups with distinct response patterns (Bergman et al., 2017).

3.3. Participants

The study was conducted among third-year undergraduate students in Economics at the University of Batna 1 (Algeria) who were enrolled in online FFL courses. Instruction is delivered entirely online via the Moodle platform, with a weekly one-and-a-half-hour videoconference session. In addition, students complete autonomous activities (H5P activities, online tests, assignments to be submitted). This context – characterized by less direct teacher presence and a significant amount of individual work – is particularly relevant for examining the relationship between AI use and learner autonomy.

The sample comprises 92 students, of whom 66.3% are women and 33.7% men. The vast majority of participants (94.6%) are aged 20–25. Self-assessed French proficiency levels according to the CEFR are as follows: A1 (23.9%, n = 22), A2 (25.0%, n = 23), B1 (31.5%, n = 29), B2 (7.6%, n = 7), C (3.3%, n = 3), while 8.7% (n = 8) of respondents stated that they did not know their level. Although modest in size, the sample is acceptable for exploratory person-centred research aimed at detecting preliminary response patterns rather than producing population estimates.

3.4. Instrument

Data were collected using a purpose-built ten-item questionnaire designed for this study. Four items assess students' self-reported ability to perform common academic tasks without AI assistance: text comprehension, understanding instructions, writing an assignment, and solving exercises. These items reflect situation-specific perceived autonomy rather than objectively measured performance. Responses were collected on a five-point Likert scale (1 = not at all capable; 5 = completely capable).

These four items showed good internal consistency (α = 0.868). A principal component analysis (PCA) was conducted to examine the structure of the scale. The Kaiser-Meyer-Olkin measure (KMO = 0.805) and Bartlett's test of sphericity ($\chi^2(6) = 174.38$, $p < 0.001$) indicated the suitability of the data. A single component, retained according to the Kaiser criterion, explained 71.78% of the total variance. Factor loadings ranged from 0.818 to 0.871 (Table 1), justifying the use of a mean autonomy score.

Table 1

Component loadings of the autonomy items (PCA)

Item	Loading
Text comprehension	0.840
Understanding instructions	0.871
Writing an assignment	0.859
Solving exercises	0.818

Six additional items covered respectively:

- Interest in FFL (1–5 scale);
- Learning strategies (four options: no strategy, using AI to simplify tasks, using AI to progress faster, learning without AI);
- Frequency of AI use in courses (1–4 scale: never, rarely, sometimes, regularly);
- Verification of AI-generated responses (1–4 scale: copy-paste without verification, sometimes verify, always verify);
- Perceived impact of AI on autonomy (four options: more autonomous, as autonomous as before, less autonomous, I don't know).

The questionnaire was reviewed by two experts in FFL didactics and research methodology. A pre-test with ten students confirmed the clarity of the items. The use of single-item measures for certain dimensions follows methodological recommendations for exploratory research on simple constructs (Bergkvist & Rossiter, 2007; Fuchs & Diamantopoulos, 2009).

3.5. Procedure

The survey was distributed on the university's Moodle platform between 7 and 12 February 2026. The questionnaire was administered online via a Google Form; the average completion time was approximately five minutes. An information note preceding the questionnaire outlined the research objectives and the terms of participation. Students were explicitly informed that their participation was voluntary, that they could withdraw at any time without providing a reason, and that their decision would have no consequences for their grades, academic evaluation, or pedagogical relationship. Responses were collected anonymously, with no identifying information recorded. Informed consent was assumed upon voluntary submission of the completed questionnaire. The response rate was 76.7% (92 respondents out of 120 enrolled students).

3.6. Statistical Analyses

Analyses were performed using SPSS (version 25). A hierarchical cluster analysis was conducted on the four standardized autonomy items (z-scores) using Ward's method and squared Euclidean distance. The number of clusters was determined by examining the dendrogram and selecting the most interpretable and parsimonious solution.

The principal component analysis (PCA) presented in Section 4.3 was used solely to validate the unidimensional structure of the autonomy scale. The hierarchical cluster analysis pursued a distinct objective: to construct a typology of self-reported autonomy profiles. No factor scores from the PCA were used in the cluster analysis, thereby avoiding any risk of circularity.

One-way analyses of variance (ANOVA) were performed to compare clusters on the mean autonomy score as well as on continuous variables (interest in FFL, frequency of AI use, and response verification). Categorical variables (learning strategies and perceived impact of AI) were analysed using descriptive statistics only because the small sample sizes in some cells, particularly in the smallest cluster ($n = 11$), made chi-square tests unreliable.

Finally, a binary logistic regression was conducted to predict membership in the dependent cluster (coded 1) as opposed to the autonomous cluster (coded 0), using interest in FFL, learning strategies, frequency of AI use, and response verification as predictors. The threshold for statistical significance was set at $p < 0.05$.

4. Results

4.1. Three Autonomy Profiles

The hierarchical cluster analysis (Ward's method) applied to the four autonomy items yielded a three-cluster solution (Table 2). The first cluster ($n = 37$, 40.2%) comprised students who reported being able to perform all tasks without AI assistance; it was labeled "autonomous". The second cluster ($n = 44$, 47.8%) had the lowest scores on all dimensions and corresponded to a "dependent" profile. The third cluster ($n = 11$, 12.0%) combined low autonomy in reading comprehension with higher autonomy for instructions and exercises; it was named "selective".

Table 2

Mean autonomy item scores by cluster (1-to-5 scale)

Cluster	Text comprehension	Understanding instructions	Writing an assignment	Solving exercises
Autonomous (n=37)	4.11	4.24	4.14	3.89
Dependent (n=44)	2.02	2.05	2.16	2.27
Selective (n=11)	2.09	4.09	3.18	4.00

A one-way ANOVA performed on the mean autonomy score revealed statistically significant differences between the three clusters, $F(2,89) = 141.8$, $p < 0.001$. Tukey's post-hoc tests showed that all inter-cluster comparisons were significant ($p < 0.001$). The autonomy scale had good internal consistency ($\alpha = 0.868$).

4.2. Comparison of Profiles

One-way analyses of variance (ANOVA) were conducted for the continuous or ordinal variables (AI use, response verification, and interest in FFL), treated as approximately continuous in line with common practice in the social sciences. For the categorical variables (learning strategies and perceived impact of AI), the small sample sizes in some cells – particularly in the selective cluster ($n = 11$) – did not allow for reliable chi-square tests. These variables are therefore presented for descriptive purposes only.

4.2.1. Use of AI in courses

The distributions (Table 3) show that students in the selective cluster reported using AI "sometimes" more frequently (63.6%) than autonomous (40.5%) and dependent (34.1%) students. However, the ANOVA revealed no statistically significant difference between clusters, $F = 1.13$, $p = 0.321$.

Table 3

Use of AI in courses by cluster (%)

Cluster	No, never	No, rarely	Yes, sometimes	Yes, regularly
Autonomous	16.2	21.6	40.5	21.6
Dependent	20.5	25.0	34.1	20.5
Selective	0.00	18.2	63.6	18.2

4.2.2. Verification of AI-generated responses

The results in Table 4 indicate that autonomous students reported systematically verifying AI responses in 56.8% of cases, compared to 47.7% for dependent and 54.5% for selective students. Selective students also had the highest proportion of non-verification (copy-paste, 27.3%). The ANOVA revealed no statistically significant difference between clusters, $F = 1.02$, $p = 0.363$.

Table 4

Verification of AI generated responses by cluster (%)

Cluster	Copy-paste without verification	Verifies sometimes	Verifies always
Autonomous	5.4	29.7	56.8
Dependent	11.4	38.6	47.7
Selective	27.3	18.2	54.5

4.2.3. Interest in FFL

Table 5 shows that autonomous students reported high interest in FFL more frequently (48.6% “very interested”) than dependent (29.5%) and selective (18.2%) students. However, this difference was not statistically significant, $F = 1.31$, $p = 0.272$.

Table 5

Interest in FFL by cluster (%)

Cluster	Not very interested	I don’t know	Somewhat interested	Very interested
Autonomous	10.8	10.8	29.7	48.6
Dependent	22.7	4.5	43.2	29.5
Selective	9.1	18.2	54.5	18.2

4.2.4. Learning strategies

The distributions (Table 6) indicate that dependent students were more likely to use AI “to progress faster” (47.7%), whereas autonomous students preferred learning without AI (45.9%). Selective students were distinguished by more frequent use of AI “to simplify tasks” (27.3%). These results are presented for descriptive purposes only and were not subjected to inferential testing due to small cell sizes.

Table 6

Learning strategies by cluster (%)

Strategy	Autonomous	Dependent	Selective
No strategy	13.5	20.5	18.2
AI to simplify	10.8	6.8	27.3
AI to progress faster	29.7	47.7	18.2
Learning without AI	45.9	25.0	36.4

4.2.5. Perceived impact of AI on autonomy

Table 7 shows that students in the dependent cluster reported a negative impact of AI on their autonomy more frequently (52.3%) than autonomous (40.5%) and selective (27.3%) students. Selective students predominantly felt that their autonomy remained unchanged (54.5%).

Table 7

Learning strategies by cluster (%)

Perceived impact	Autonomous	Dependent	Selective
More autonomous	24.3	20.5	9.1
As autonomous as before	32.4	27.3	54.5
Less autonomous	40.5	52.3	27.3
I don’t know	2.7	0.0	9.1

4.3. Prediction of Membership in the Dependent Cluster

A binary logistic regression was performed to predict membership in the dependent cluster (coded 1) compared with the autonomous cluster (coded 0). The selective cluster (n = 11) was not included in this binary regression because its small size precluded reliable multinomial modelling, and its hybrid nature (autonomous for some tasks, dependent for others) places it conceptually in an intermediate position. The analysis thus focused on comparing the two more clearly contrasted profiles.

The model showed a good overall fit (Hosmer-Lemeshow test: $\chi^2 = 5.78$, $df = 8$, $p = 0.672$). The results (Table 8) indicate that only the learning strategy of using AI "to progress faster" was a significant predictor. Students who adopted this strategy had 3.45 times higher odds of belonging to the dependent cluster (95% CI [1.104–10.787], $p = 0.033$). None of the other predictors (interest in FFL, frequency of AI use, response verification) reached the threshold for statistical significance.

Table 8

Logistic regression: predictors of membership in the dependent cluster (ref. = autonomous)

Variable	*B*	*Wald*	*p*	*Exp(B)*	95% CI
Interest in FFL	-0.425	3.192	0.074	0.654	[0.410–1.042]
Strategy "AI to progress faster"	1.239	4.537	0.033	3.451	[1.104–10.787]
Frequency of AI use	-0.217	1.468	0.226	0.805	[0.567–1.143]
Response verification	-0.052	0.058	0.810	0.950	[0.624–1.446]
Constant	2.156	2.151	0.143	8.633	

5. Discussion

5.1. Discussion of Results

This exploratory study aimed to identify autonomy profiles among FFL students in an online learning environment and to examine the links between these profiles and certain reported uses of generative artificial intelligence. The analyses revealed three contrasting profiles: an autonomous profile, a predominantly dependent profile, and a smaller selective profile. Overall, these findings confirm the heterogeneity of relationships with autonomy and AI use within the same student population. This diversity is consistent with recent work showing that students do not necessarily perceive traditional instruction and AI as opposing alternatives, but rather as complementary resources mobilized according to their learning needs (Amzalag et al., 2025).

At the theoretical level, these results suggest that autonomy in the context of generative AI can be reduced neither to a stable trait nor to a uniform general ability. Instead, it appears as a situated configuration, likely to vary according to tasks, strategies used, and the goals pursued. In this sense, the typological approach makes it possible to move beyond a binary opposition between autonomous and non-autonomous learners by uncovering intermediate or hybrid profiles. This interpretation aligns with multidimensional conceptions of autonomy in language education, according to which capacities for regulation, decision-making, and control are actualized differently depending on the learning situation (Benson, 2011; Little, 2007). Importantly, autonomy should not be equated with the absence of external support, but with the capacity to regulate, evaluate, and critically orchestrate available resources, including AI tools. From this perspective, strategic and reflective use of AI may itself constitute an expression of autonomy rather than its opposite.

The selective profile is particularly instructive in this respect. The students in this profile report low autonomy for text comprehension while perceiving themselves as more autonomous for understanding instructions or solving exercises. This contrast suggests that support needs are not distributed uniformly across tasks. Autonomy may therefore be partial, context-dependent, and specific to certain domains of activity. However, this finding must be interpreted with caution due to the small size of this cluster ($n = 11$).

Why might text comprehension – rather than understanding instructions or solving exercises – be the specific dimension in which these students rely more heavily on AI? Several complementary explanations may be considered. First, reading comprehension in a foreign language is cognitively demanding, as it requires lexical, syntactic, inferential, and discourse-level processing. Students with lower levels of French proficiency may therefore experience reading as particularly effortful and use AI as a form of scaffolding, whereas instructions and exercises often involve shorter and more routinized language patterns. Second, this selective use of AI may reflect a strategic form of regulation rather than generalized dependence. Learners may deliberately mobilize AI to cope with tasks perceived as linguistically dense or cognitively demanding, while continuing to handle more predictable tasks independently. Third, from a self-efficacy perspective (Bandura, 1997), learners may develop differentiated perceptions of competence across tasks: they may feel capable of understanding instructions or solving exercises, but less confident in their ability to comprehend longer academic texts autonomously.

Although the present data do not allow these hypotheses to be tested directly, the existence of this selective profile suggests that AI dependence may itself be task-specific rather than global. This finding opens a promising avenue for future qualitative or mixed-methods research aimed at better understanding the subjective rationales underlying differentiated uses of AI. From a pedagogical perspective, it invites us to move beyond global judgments about learner autonomy and to identify more precisely the tasks for which targeted support remains necessary.

The most striking result concerns the predictive role of the learning strategy consisting of using AI "to progress faster". Students who adopted this strategy had 3.45 times higher odds of belonging to the dependent cluster. This finding can be interpreted in light of research on cognitive offloading, according to which systematic reliance on an external tool can reduce engagement in certain intellectual operations involved in learning, such as analysis, memorization, or verification (Sparrow et al., 2011). It is also consistent with recent studies highlighting an association between intensive AI use and lower levels of critical thinking (Gerlich, 2025; Tian & Zhang, 2025). Nevertheless, caution is warranted: the cross-sectional and self-report design of the study does not allow causal relationships to be established. The results merely suggest that use oriented primarily towards saving time may be associated with more pronounced forms of perceived dependence.

Comparisons between clusters concerning interest in FFL, frequency of AI use, and response verification did not reach statistical significance. This finding may be explained by the modest sample size, the imbalance between groups, the low variability of some responses, and the ordinal nature of several variables. Nevertheless, some descriptive trends appear consistent with the observed typology. Autonomous students are proportionally more likely to report high interest in FFL and to systematically verify AI-generated responses. Conversely, dependent students are the most likely to perceive AI as reducing their autonomy. While not allowing definitive conclusions, these trends suggest that autonomy may be less related to simple frequency of use than to the quality of disciplinary engagement and the critical stance adopted towards the tools used. This interpretation is also consistent with the findings of Galindo-Domínguez et al. (2026), who identify procrastination and low intrinsic motivation as factors associated with increased dependence on ChatGPT.

5.2. Limitations and Future Research

Several limitations should be acknowledged. First, the study relies on a purpose-built questionnaire and self-reported measures, which makes the results susceptible to biases related to perception, memory, or social desirability. Second, the modest sample size (n = 92), and particularly that of the selective cluster (n = 11), limits the statistical power of some comparisons and calls for caution in interpreting this profile. Because the selective cluster was excluded from the logistic regression due to its small size, the predictive findings reported in this study apply only to the contrast between autonomous and dependent profiles. Larger-scale studies are therefore needed to examine predictors of membership in the selective profile using multinomial or other polytomous models.

Furthermore, autonomy was assessed through perceived abilities rather than through actual performance observed in learning situations. In addition, the number of clusters retained is partly based on interpretability criteria inherent to exploratory classification approaches. Finally, the survey was conducted at a single Algerian university, and all participants were drawn from a single department (Economics) and a single cohort (third-year students). Consequently, the observed autonomy profiles may partly reflect cohort-specific pedagogical conditions, disciplinary learning cultures, or shared exposure to the same online learning environment, rather than solely individual learner characteristics. This limitation suggests that the profile-based implications proposed in this study should primarily be interpreted in relation to comparable online FFL contexts in Algerian higher education. Any generalisation to other institutional, linguistic, or cultural contexts should therefore be considered with caution.

Future research could draw on larger and more diverse samples to test the robustness of this typology. It would also be relevant to incorporate more objective measures of autonomy (digital traces, observations, standardized tasks) and to adopt longitudinal designs in order to examine how profiles evolve over time. Lastly, mixed-methods approaches combining quantitative analyses and qualitative interviews could help better understand the subjective rationales underlying differentiated uses of AI.

5.3. Pedagogical Implications

Despite these limitations, this research suggests several directions for online FFL teaching. First, it suggests the value of training students in a reflective use of AI, oriented towards supporting learning rather than substituting for cognitive effort. This perspective aligns with the recommendations of UNESCO (2023), which emphasize the protection of human agency and the development of educators' capacities in integrating AI technologies. Recent work also shows that experiential learning structured around a self-regulation cycle (planning, experimenting, evaluating) can strengthen AI literacies, self-efficacy, and students' sense of agency (Anders & Speltz, 2025).

Second, the results suggest a distinction between potentially facilitating uses of AI (clarification, feedback, idea generation, rewording) and uses that may hinder the development of certain skills when they become systematic or act as substitutes.

Third, the identified profiles argue in favor of differentiated support. Some students may require targeted assistance for specific tasks – for example, reading comprehension – while being autonomous in other dimensions. The pedagogical challenge, therefore, is not merely to regulate the use of AI, but to help learners make it a tool for the progressive development of their autonomy.

6. Conclusion

This exploratory study suggests that the typological approach offers a relevant heuristic framework for capturing the heterogeneity of relationships with AI among online FFL learners. Three profiles were identified – autonomous, dependent, and selective – with the latter inviting us to consider autonomy not as a uniform trait but as a potentially variable reality depending on the tasks encountered. Furthermore, the strategy of using AI "to progress faster" appears to be associated with the dependent profile, suggesting that usage intentions deserve to be examined beyond mere frequency of use. Based on this finding, the present study suggests that goal-oriented AI use (i.e., using AI primarily to progress faster) may constitute a stronger predictor of perceived dependence than frequency of use alone – a proposition that future research could test more directly through longitudinal or experimental designs.

Subject to replication with larger samples and in other contexts, these findings provide a preliminary empirical basis for understanding the relationship between generative AI and student autonomy. They point to the importance of promoting critical and pedagogically supported uses of AI, while also highlighting the need for future research based on objective measures and longitudinal designs.

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