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Digital Competencies and the Adoption of GenAI in Higher Education. Empirical Evidence and a Training Model Proposal for Accounting and Finance

Competencias digitales y adopción de IA generativa en la educación universitaria. Evidencia empírica y propuesta de modelo formativo en Contabilidad y Finanzas

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Abstract: The digitalization of accounting and financial work, and the growing adoption of generative artificial intelligence (GenAI), are reshaping the competencies required in higher education. This study examines the self-perceived digital proficiency of undergraduate and postgraduate students in key analytical tools (Excel, PivotTables, Analyze Data, Copilot, and ChatGPT) and proposes a progressive training model aligned with current market needs. A quantitative, descriptive–comparative, cross-sectional design was applied to a sample of 157 students from three universities in Spain, Italy, and Argentina. Findings reveal significant differences between educational levels. Postgraduate students report higher competence in traditional spreadsheet-based tools, whereas Undergraduate students display greater familiarity with GenAI tools. These patterns reflect differentiated educational trajectories and emerging cognitive shifts associated with the use of digital technologies. Based on these insights, the study proposes a three-stage training model aimed at strengthening digital tool proficiency, analytical reasoning, and the critical validation of GenAI-generated outputs. The model was evaluated using objective performance indicators, which showed substantial improvements in students' use of the tools assessed.

Keywords: Financial Analysis; Analytical Software; Generative Artificial Intelligence; Data Analysis Skills; Higher Education.

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Resumen: Las competencias necesarias en la formación universitaria están siendo redefinidas por la digitalización del trabajo contable y financiero, y por la adopción creciente de herramientas de inteligencia artificial generativa (GenAI). Este estudio analiza la autopercepción de estudiantes de Grado y Posgrado respecto a su dominio de herramientas digitales para el análisis (Excel, Tablas Dinámicas, Analizar Datos, Copilot y ChatGPT) y propone un modelo de entrenamiento progresivo alineado con las necesidades del mercado. Se empleó un diseño cuantitativo, descriptivo-comparativo y transversal, aplicado a una muestra de 157 estudiantes de tres universidades de España, Italia y Argentina. Los resultados evidencian diferencias significativas entre ambos niveles formativos. Los estudiantes de Posgrado manifiestan mayor competencia en herramientas tradicionales basadas en hojas de cálculo, mientras que los de Grado presentan una familiaridad superior con herramientas de GenAI. Estos patrones reflejan trayectorias formativas diferenciadas y cambios emergentes en los procesos cognitivos asociados al uso de tecnologías digitales. A partir de estos hallazgos, se propone un modelo formativo en tres etapas orientado a reforzar el aprendizaje de herramientas digitales, el razonamiento analítico y la validación crítica de los resultados generados por la GenAI. El modelo se evaluó basado en indicadores objetivos de desempeño, los cuales mostraron mejoras relevantes de los estudiantes en el uso de las herramientas evaluadas.

Palabras clave: Análisis financiero; Software analítico; Inteligencia artificial generativa; Competencias en análisis de datos; Educación superior.

1. INTRODUCTION

The digitalisation of accounting and finance has accelerated over the past decade. This shift has been driven by the growing availability of data, the increasing sophistication of spreadsheet applications and, more recently, the emergence of generative artificial intelligence (GenAI). Organisations now seek professionals who can combine rigorous numerical analysis with advanced digital skills and, crucially, assess the reliability of the outputs produced by these technologies (Balsategui et al., 2024; Zhao et al., 2021). Accounting and finance education must therefore do more than introduce emerging tools. It must integrate them without weakening the technical foundations on which financial information, professional judgement and effective control depend.

Research points to considerable variation in the digital competence of both students and educators, as well as a persistent gap between access to technology and the ability to use it effectively (Machado et al., 2024). Spreadsheets—particularly Excel—remain central to accounting and financial analysis in professional practice. Yet their more advanced capabilities are often underused, with users relying mainly on basic recording and calculation functions (Borthick & Schneider, 2023; Frownfelter-Lohrke, 2017). At the same time, students have adopted GenAI tools such as ChatGPT and Copilot remarkably quickly, often without explicit instruction on their limitations, embedded biases or ethically acceptable uses (Wecks et al., 2024).

This pattern exposes two distinct weaknesses in current accounting education. The first concerns depth. Instrumental familiarity with Excel does not necessarily develop strong analytical competence or disciplined practices for auditing and validating data. The second concerns integration. Students' informal use of GenAI is not always aligned with the learning objectives of accounting and finance programmes. When these tools are treated as substitutes for independent reasoning rather than as supports for it, they may weaken the very cognitive processes that higher education is expected to develop (Redecker, 2017).

Recent teaching innovations in accounting and finance suggest that these weaknesses cannot be addressed by adding isolated digital tools to existing courses. What is needed is a progressive learning pathway that connects established technologies with emerging ones through a coherent analytical logic. Students should begin by understanding the structure and meaning of data, move towards the assisted automation of analysis and ultimately learn to scrutinise systematically generated outputs with professional scepticism (Borthick & Schneider, 2023; Zhao et al., 2021).

This study develops that approach in two stages. It first examines how undergraduate and postgraduate students assess their own competence in a set of digital tools used in accounting and financial analysis. Then, it proposes a progressive training model designed specifically for the development of digital, analytical and critical capabilities among university students preparing for accounting and finance roles.

2. THEORETICAL FRAMEWORK AND RESEARCH OBJECTIVES

Digital competence has become a core component of university education, particularly in accounting and finance, where decision-making depends heavily on large volumes of quantitative information. European frameworks such as DigComp and DigCompEdu identify five broad dimensions: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving (Vuorikari et al., 2022; Zhao et al., 2021; Redecker, 2017). In accounting and finance, these dimensions take practical form in spreadsheet modelling, data cleaning and reconciliation, financial analysis, report preparation, and the communication of findings to different stakeholder groups.

Access to digital resources, however, does not necessarily translate into proficiency. Studies of accounting students suggest that they are generally comfortable with basic Excel operations but encounter difficulties when working with advanced functions, pivot tables, macros, and auditing tools (Borthick & Schneider, 2023; Frownfelter-Lohrke, 2017). The resulting pattern is one of frequent but shallow spreadsheet use. Excel remains present across accounting courses and professional tasks, yet its capacity to support analytical reasoning and deeper learning is not fully exploited.

Large language models and GenAI tools have added a further layer of complexity to university teaching. Their use among students is already widespread, although it is not always disclosed, and the consequences for academic performance remain uncertain. GenAI can reduce the time required for some tasks, but it may also be associated with poorer learning outcomes when it replaces rather than supports individual effort (Wecks et al., 2024). In accounting, these systems can propose journal entries, summarise accounting standards, explain financial ratios, and generate interpretations of financial statements. Their outputs, however, may contain errors, omissions, or biases that are difficult to detect without sound technical knowledge and professional judgement (Balsategui et al., 2024).

The educational challenge is therefore not whether GenAI should simply be prohibited or permitted. It must be treated both as an object of critical study and as a learning tool. Students need to learn how to formulate effective prompts, verify generated responses, identify weaknesses, and use the technology to extend their reasoning rather than outsource it. This requires changes to classroom activities, assessment design, and academic integrity policies. It also calls for competencies that have not traditionally occupied a central place in accounting curricula, including model-output auditing and digital ethics (Wecks et al., 2024; Zhao et al., 2021).

Evidence from different academic settings suggests that these technologies are shifting the cognitive demands placed on students. Less effort may be devoted to the mechanical execution of calculations, while greater emphasis falls on problem formulation, data structuring, and result validation. Spreadsheets and GenAI perform different but complementary functions in this process. Excel allows students to manipulate, trace, and visualise data while retaining substantial control over each analytical step. GenAI, by contrast, can rapidly generate explanations, formulas, and interpretative text. The central educational question is how these tools should be combined so that automation supports higher-order competence rather than encouraging uncritical dependence (Redecker, 2017).

Bai and Wang (2025) provide further support for this argument. Their findings indicate that both the quality of students' interaction with GenAI and the quality of the resulting outputs influence academic learning and motivation. They also identify creative thinking as a moderating factor within this cognitive process. The educational value of GenAI therefore depends not only on access to technology, but also on how students engage with it and how critically they assess what it produces.

This study treats perceived digital competence as an initial diagnostic indicator for the design of differentiated learning pathways. Undergraduate and postgraduate students are expected to display distinct competence profiles because of differences in their academic trajectories, professional experience, and exposure to digital working environments. Identifying these profiles provides a basis for developing a training model that progressively combines established digital tools with GenAI in accounting and finance education.

The proposed model is grounded in technology-mediated learning (TML). Alavi and Leidner (2001) use this concept to describe learning environments in which students' interactions with educational resources, peers, and instructors are facilitated through information technologies. From this perspective, technology is not an additional component placed alongside the curriculum. It shapes how students access information, perform analytical tasks, receive feedback, and construct knowledge. This framework is particularly appropriate for a model that moves from spreadsheet-based analysis towards AI-assisted interpretation while preserving verification, judgement, and active student participation.

The study pursues two objectives, which guide both the empirical analysis and the training model developed in the final part of the article.

1. To assess undergraduate and postgraduate students' perceived knowledge and ability in the use of digital tools associated with accounting and financial analysis**:** Excel, PivotTables, Analyze Data, Copilot, and ChatGPT. The assessment applies to the same structure and measurement criteria across all student groups. Participants work with a common practical case based on a financial dataset and use each tool to perform different analytical tasks according to its available capabilities.

2. To develop a progressive model for training, learning, and assessment based on empirical findings. The model integrates the digital tools required for financial roles in companies and other organisations, including accounting and financial analysis, business analytics, and report generation. Rather than treating these applications as separate technical skills, the model organises them as a sequence of increasingly complex activities, moving from controlled data manipulation to AI-assisted analysis and critical output validation. The effectiveness of the model is subsequently assessed using objective performance measures.

3. METHODOLOGY

The study examined students' self-reported digital competence after they had worked with a practical case and datasets provided by the instructor. A quantitative, cross-sectional, descriptive-comparative design was adopted to capture students' current use and perceived command of digital tools within a standardised and controlled teaching setting. This approach is consistent with previous research on digital competence in higher education, which commonly uses structured questionnaires and Likert-type scales to assess perceived proficiency and familiarity with technology (Zhao et al., 2021).

The sample was collected during 2025 and comprised 157 university students enrolled in accounting and finance courses at three institutions: Universidad Autónoma de Madrid (Spain), the University of Florence (Italy), and Universidad Nacional de Córdoba (Argentina). All courses were taught by the same instructor, which reduced variation in teaching criteria, task design, and administration procedures across institutions. The sample included 122 undergraduate and 35 postgraduate students.

The practical case was built around a database containing accounting and commercial transactions from a fictitious company. The instructor posed a series of financial, accounting, and business questions that students were required to address using each of the five selected tools. The complexity of the tasks increased progressively in line with the analytical and generative capabilities of the software. Students therefore encountered a common dataset and a comparable sequence of activities, while the demands placed on them evolved from basic data manipulation to more advanced analysis and interpretation.

Data was collected through a structured online questionnaire containing five self-assessment items, each corresponding to one digital tool. Students rated their competence using the following five-level ordinal scale:

- I have never used it
- I have completed some training
- I am familiar with it
- I am an advanced user
- I am an expert

The scale draws on established digital literacy frameworks (OECD, 2022; Vuorikari et al., 2022) and Bandura's (1997) theory of self-efficacy. It ranges from no previous experience to perceived expert-level proficiency. Comparable scales have been used in technology-adoption research to distinguish between limited exposure, general familiarity, and advanced use in educational and professional settings (Venkatesh et al., 2012).

The five tools assessed were:

- Excel
- Excel PivotTables
- Analyze Data in Excel
- Copilot within Excel
- ChatGPT

For each tool, students selected the category that best represented their perceived level of competence. The questionnaire was administered digitally by the instructor during scheduled class time. Before completing it, students were informed of the purpose of the study and the confidential treatment of their responses. Participation was voluntary and anonymous. The data were subsequently exported to a spreadsheet for cleaning, coding, and statistical analysis.

The analysis proceeded in several stages. Absolute frequencies and within-group percentages were first calculated for undergraduate and postgraduate students across each combination of tool and competence level. This descriptive analysis was used to identify patterns of familiarity and perceived proficiency within the two groups, as reported in Figure 1.

Two complementary procedures were then used to test whether the observed differences between undergraduate and postgraduate students were statistically significant. First, Pearson's chi-square test of independence (χ^2) was applied to compare the distribution of self-reported competence across the two groups. To satisfy the expected-frequency assumptions of the test, the original five-level scale was recoded into three categories:

- Low competence: "I have never used it" and "I have completed some training";
- Moderate competence: "I am familiar with it";
- High competence: "I am an advanced user" and "I am an expert."

Cramér's V was then calculated to estimate the strength of the association between study level and perceived competence. Effect sizes were interpreted using conventional thresholds: values of approximately 0.10 were treated as small, values around 0.30 as moderate, and values above 0.50 as large (Cohen, 1988; Ellis, 2010).

A complementary non-parametric analysis was also conducted using the Kruskal–Wallis test. With only two independent groups, this procedure produces an inference equivalent to that obtained from the Mann–Whitney U test. The analysis treated the original five-level responses as ordinal data and assessed whether the distributions and the central tendencies of undergraduate and postgraduate students differed significantly for each digital tool.

4. RESULTS

Figures 1 to 5 report the within-group percentage distribution of self-reported competence levels for undergraduate and postgraduate students across the five digital tools examined.

For Excel (figure 1), undergraduate responses are concentrated in the categories "I have completed some training" (50%) and "I am familiar with it" (22%). Postgraduate students report a stronger position at the intermediate and advanced levels, with 43% selecting "I am familiar with it," 26% "I am an advanced user," and 6% "I am an expert."

A similar contrast appears for PivotTables (figure 2). Among undergraduate students, 29% report that they have never used the tool, compared with 11% of postgraduate students. More than half of the postgraduate group (51%) place themselves in the "I am familiar with it" category.

Figure 1. Distribution of responses by digital tool: Excel (in percentage)

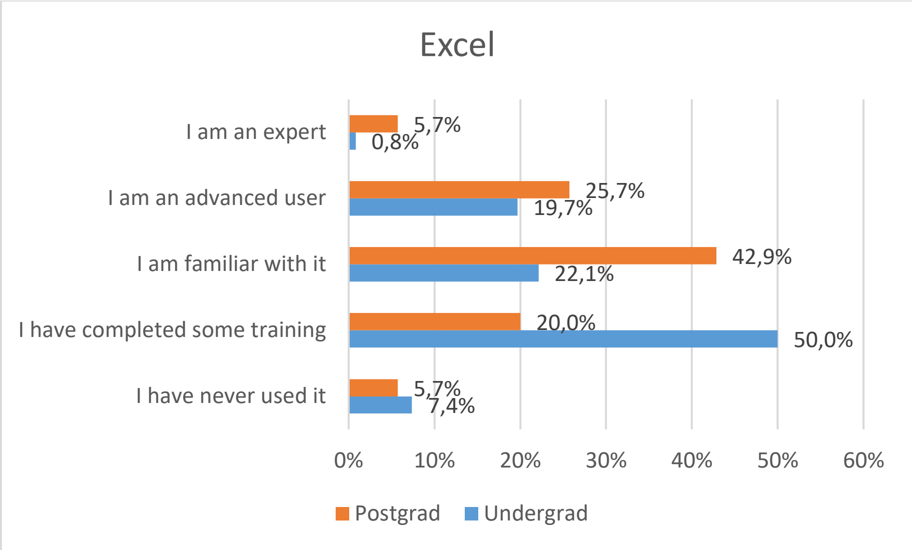
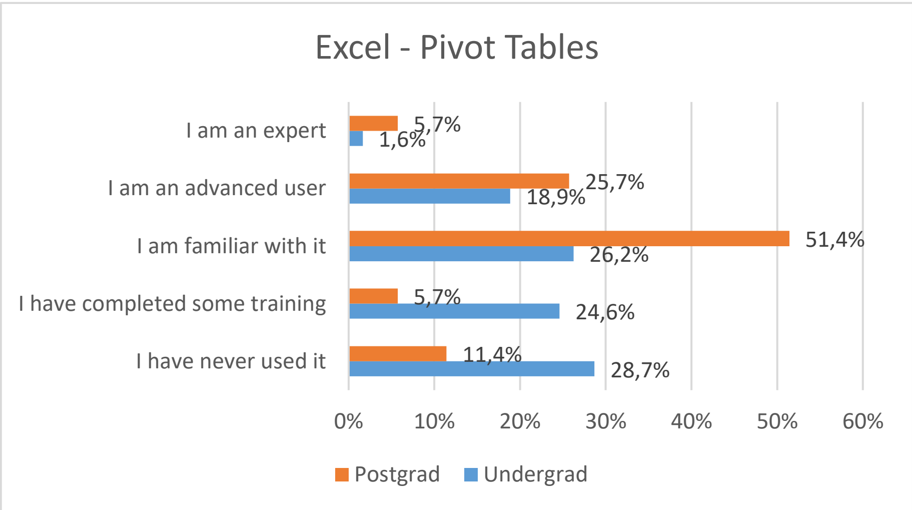


Figure 2. Distribution of responses by digital tool: Excel-Pivot tables (in percentage)



The pattern is more pronounced for Analyze Data (figure 3). Forty per cent of undergraduate students report no previous use, compared with 11% of postgraduate students. The difference at the upper end of the scale is also substantial: 23% of postgraduate students classify themselves as advanced users or experts, whereas only 2% of undergraduate students do so.

Copilot produces a different profile (figure 4). Experience remains limited in both groups. More than half of undergraduate students (52%) report that they have never used it. Although this proportion falls to 23% among postgraduate students, the overall distribution still points to a technology at an early stage of adoption.

Figure 3. Distribution of responses by digital tool: Excel-Analize data (in percentage)

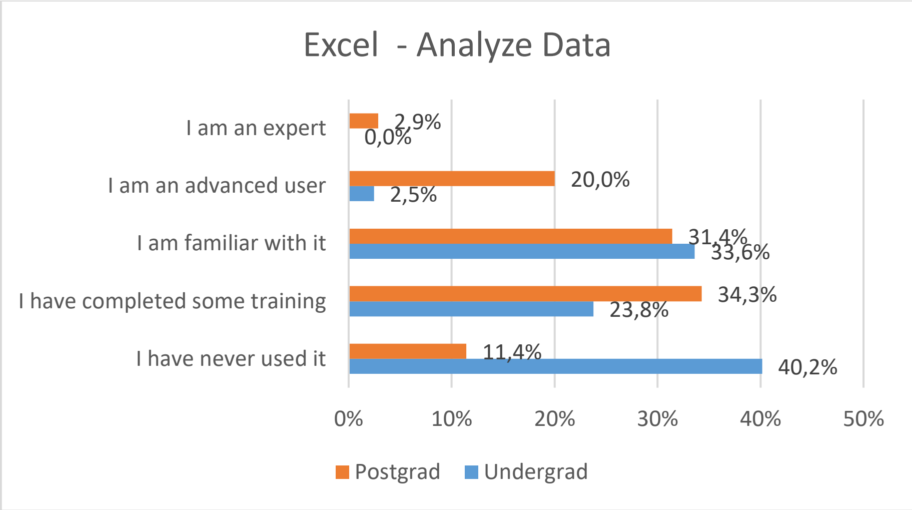
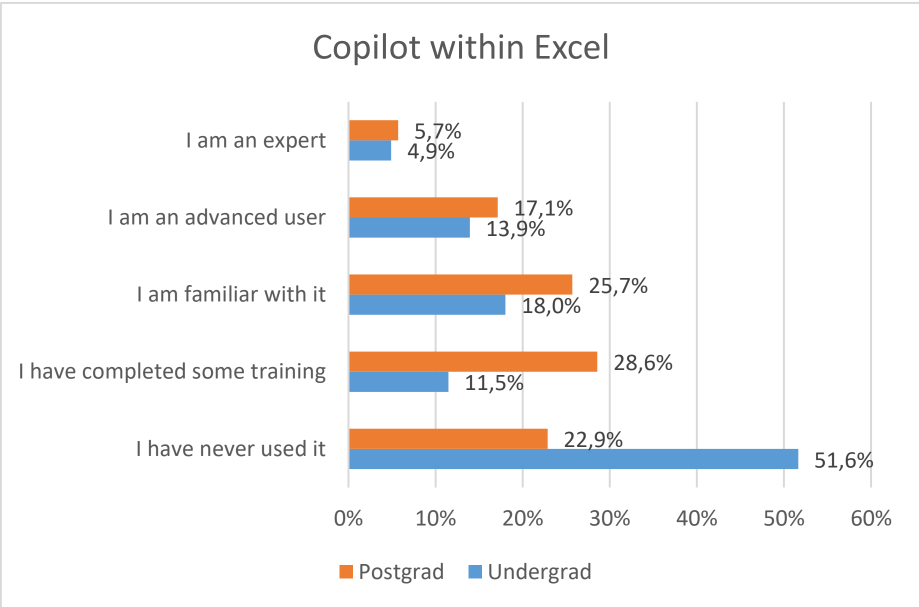
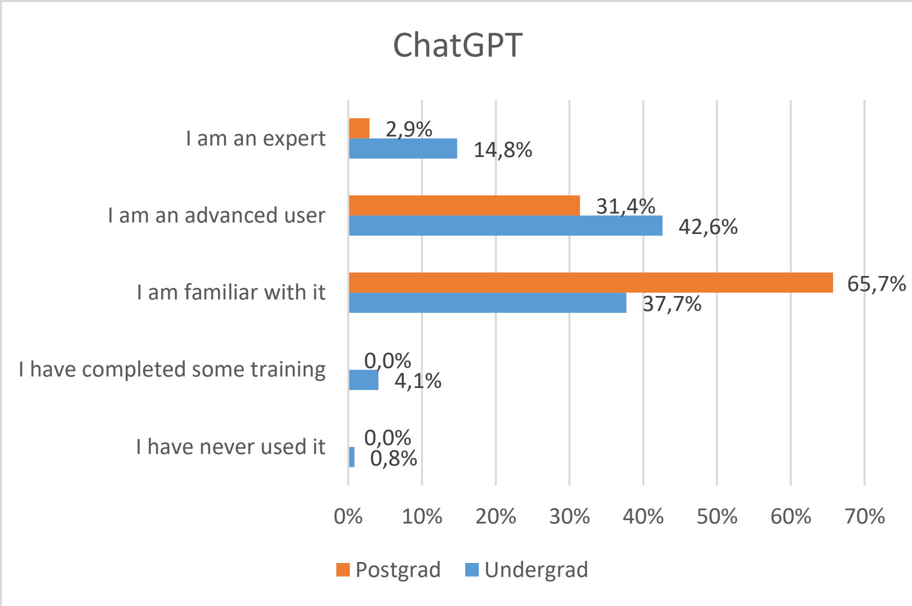


Figure 4. Distribution of responses by digital tool: Copilot (in percentage)



ChatGPT (figure 5) reverses the pattern observed for the spreadsheet-based tools. Undergraduate students report a more advanced competence profile: 38% classify themselves as familiar users, while 58% place themselves in the advanced or expert categories. No postgraduate student reports have never used ChatGPT, but responses are concentrated at the intermediate level. Sixty-six per cent select "I am familiar with it," while 31% identify as advanced users and 3% as experts. These figures suggest that undergraduate students have incorporated ChatGPT more intensively into their everyday academic practices.

Figure 5. Distribution of responses by digital tool: ChatGPT (in percentage)



After recoding the original five-level scale into three categories (low, moderate, and high competence), contingency tables were constructed, and Pearson's chi-square test of independence was applied separately to each tool. Table 1 presents the results.

Table 1. Pearson's chi-square results and Cramér's V effect sizes

Tool	χ^2	*p*	*Cramér's V*	*Effect*
Excel	11.20	0.004*	0.27	Small-to-moderate
PivotTables	14.69	< 0.001***	0.31	Moderate
Analyze Data	17.70	< 0.001***	0.34	Moderate
Copilot	1.65	0.440	0.10	Not significant
ChatGPT	9.35	0.009*	0.24	Small-to-moderate

Source: Author's own elaboration. *Note: *** p < 0.001; * p < 0.05.*

Statistically significant differences emerge between undergraduate and postgraduate students for four of the five tools. For Excel, PivotTables, and Analyze Data, the chi-square tests show that competence levels are distributed differently across the two groups, with effect sizes in the small-to-moderate or moderate range. In each case, postgraduate students are more strongly represented in the moderate and high competence categories.

ChatGPT also shows a significant group difference, although the association is weaker. Here the direction changes: undergraduate students report higher proportions of advanced and expert use, whereas postgraduate students are concentrated mainly in the familiarity category. Copilot is the only tool for which no statistically significant difference is found. Its use appears limited and uneven across both academic levels.

The Kruskal–Wallis analysis confirms the same broad pattern when the original ordinal scale is retained. As shown in Table 2, postgraduate students report consistently higher competence in the three established analytical tools: Excel, PivotTables, and Analyze Data. These results support the view that professional experience and repeated exposure to practical accounting and finance tasks contribute to stronger spreadsheet-based competence.

For ChatGPT, the direction of the difference is again reversed. Undergraduate students report significantly higher competence than postgraduate students. This finding is consistent with the argument that younger student groups adopt GenAI tools more rapidly and integrate them more extensively into their routine study practices (Tlili et al., 2023).

No significant difference is observed for Copilot. This reinforces the interpretation that adoption remains emergent and fragmented across both groups.

Table 2. Kruskal–Wallis test results

Tool	*H*	*p*	*Direction of difference*
Excel	7.41	0.006*	Postgraduate > Undergraduate
PivotTables	10.88	0.001***	Postgraduate > Undergraduate
Analyze Data	12.56	< 0.001***	Postgraduate > Undergraduate
Copilot	1.02	0.312	Not significant
ChatGPT	6.98	0.008*	Undergraduate > Postgraduate

Source: Author's own elaboration. *Note: *** p < 0,001; * p < 0,05*

All findings reveal a clear pattern of relative specialisation. Postgraduate students report stronger competence in established spreadsheet tools, probably reflecting greater exposure to professional settings in which Excel and its advanced functions remain the de facto standard for financial analysis and reporting. Undergraduate students, by contrast, report greater competence in ChatGPT. Their profile is consistent with earlier and more intensive adoption of GenAI in everyday learning activities.

The results therefore do not point to a single, uniform digital competence gap. They reveal two different competence trajectories. Postgraduate students appear stronger in structured, spreadsheet-based analysis, while undergraduate students are more confident in generative tools. The educational challenge is to bridge these trajectories as undergraduate students need deeper analytical and validation skills, whereas postgraduate students need more systematic exposure to GenAI and its critical use.

5. PROGRESSIVE TRAINING MODEL: PROPOSAL AND ASSESSMENT

5.1. Proposed training model

Drawing on the practical case, the students' reported competence profiles, and the literature reviewed, this study proposes a progressive model for developing digital competence in accounting, finance, and business-related tasks. Attention is given to the effective integration of large language models—specifically Copilot and ChatGPT—into learning environments and university curricula. Their inclusion requires more than access to technology. It demands a clearly defined educational strategy and an explicit pedagogical approach centred on critical thinking and systematic procedures for verifying information (Kasneci et al., 2023).

The pedagogical design follows the four components identified by Moon et al. (2005):

- Preparatory activity: identifying the learning needs of undergraduate and postgraduate students.
- Approach: supporting the progressive acquisition of digital competence.

- Design characteristics: defining the technical, analytical, and cognitive elements to be addressed by the course.
- Learner attributes: monitoring student development and assessing learning outcomes.

The model rests on four design principles.

- Data as the starting point. All activities begin with reliable accounting and financial datasets that require cleaning, organisation, analysis, and communication. The data should be structured in a database-like file so that students work with consistent records, defined variables, and traceable transactions rather than isolated exercises.
- Complementarity of tools. Excel and GenAI are used together, but each is assigned the role for which it is best suited. Excel provides a controlled environment for structured data manipulation, calculation, modelling, and verification. GenAI tools support the generation of explanations, formulas, analytical suggestions, interpretations, and written outputs. The model does not treat these technologies as interchangeable. Their educational value lies in the interaction between structured calculation and assisted interpretation.
- Cognitive progression. Activities increase in complexity as students move through the tools. Training begins with instrumental tasks such as entering functions, sorting records, applying filters, and performing basic calculations. It then advances towards interpretation, professional judgement, output auditing, critical evaluation, and the formulation of supported conclusions.
- Assessment of progress. Assessment is based on outputs that reproduce activities performed in the finance function. These include analyses, reports, models, dashboards, and written arguments. Students are evaluated not only on the technical correctness of the final answer, but also on the process used to obtain, verify, and communicate it.

The training model is organised into three stages that can be implemented across an academic course. Each stage can be adapted to students' prior knowledge, academic level, and professional profile.

Stage 1. Technical foundations in spreadsheets

This stage prioritises proficiency in Excel and its core applications in accounting and finance. Activities cover transaction processing, absolute and relative references, basic financial functions, PivotTables, filters, data validation, and formula auditing. The main objective is to ensure that undergraduate students attain at least a moderate-to-high level of spreadsheet competence before GenAI is introduced intensively. Establishing this technical foundation reduces the risk that students will accept model-generated answers without understanding the calculations, assumptions, or data structures on which those answers depend.

Stage 2. Analytical automation and modelling

Once the technical foundations have been consolidated, the second stage introduces more complex forms of automation and financial modelling. Students work with advanced filtering, parameterised templates, scenarios, basic simulations, Analyze Data in Excel and, where appropriate, introductory macros. At this stage, Copilot can support formula generation, the explanation of complex procedures, and the review of analytical models. Its role remains assistive rather than substitutive. Students are expected to examine the proposed solution, test its logic, and verify its results against the underlying data.

Stage 3. Critical integration of GenAI

The last stage focuses on the critical and reflective use of GenAI in tasks associated with accounting and finance roles. Students may use these tools to interpret financial statements, analyse ratios, prepare reports, draft explanatory notes, and discuss prospective scenarios. The emphasis shifts towards prompt design, source triangulation, comparison between GenAI-generated outputs and spreadsheet calculations, and the identification of errors, omissions, or biases in model responses. Assessment considers both the quality of the final output and the rigour of the process followed to produce and validate it.

The empirical findings indicate that the model should be differentiated by academic level. At undergraduate level, the immediate priority is to strengthen the technical foundations required for accounting and financial work in Excel while directing students' spontaneous use of ChatGPT towards more structured, transparent, and critically informed study practices. At postgraduate level, training can place greater emphasis on the integration of GenAI into complex financial analysis, dashboard design, scenario evaluation, and decision support. This approach builds on postgraduate students' stronger command of established analytical tools. The use of authentic business cases may further increase the perceived usefulness and professional relevance of the technologies introduced (Giménez Espín & Martínez Conesa, 2025).

5.2. Objective Performance Assessment and Validation of the Training Model

The findings presented in the preceding sections reveal significant differences in perceived digital competence between undergraduate and postgraduate students. Self-perception, however, remains an indirect measure of competence and may not correspond closely to performance in specific tasks (Bandura, 1997; Zhao et al., 2021). An additional assessment phase was therefore introduced to complement the perceptual evidence with objective performance measures.

This second phase has two purposes. The first is to determine whether a structured training intervention generated observable improvements in student performance. The second is to examine whether the progressive sequence proposed in this study (Excel → assisted automation → GenAI) is effective in developing applied competence for accounting and finance tasks.

The inclusion of objective measures moves the analysis beyond a descriptive account of students' perceptions. It provides a more robust evaluation of learning based on demonstrated performance and is consistent with recommendations in accounting education research and with the principles of authentic assessment (Borthick & Schneider, 2023; Frownfelter-Lohrke, 2017).

Quasi-experimental design

The model was tested through a quasi-experimental between-groups design involving undergraduate students enrolled in accounting and finance courses.

The sample was divided into two groups:

- Control group: 54 students who had not received specific prior training in the tools assessed;
- Experimental group: 52 students completed a structured intervention based on the progressive model proposed in this article.

Both groups completed four independent tests. Each test contained ten questions with only one correct answer. The Analyze Data functionality in Excel was incorporated into Test 2. The exercises covered the principal capabilities of each tool and were organised as follows.

Test 1. Basic Excel functions

- Cell references, Filters, Basic functions, Data sorting.

Test 2. Advanced Excel functions

- PivotTables, Lookup and reference functions, Data analysis, simple Modelling.

Test 3. Copilot within Excel

- Formula generation, Data interpretation, Assisted automation, Validation of results.

Test 4. ChatGPT

- Financial analysis, Interpretation of information, Prompt construction, Critical evaluation of responses.

The test structure reproduces the cognitive progression embedded in the training model. It therefore allows the effect of the intervention to be examined across different levels of technological and analytical complexity.

Table 3. Overall training results

Group	*Percentage of correct answers*
Control	62.22 %
Experimental	74.62 %

Source: Author's own elaboration.

The first analysis (table 3) compared the total proportion of correct responses in the two groups. The experimental group achieved 74.62%, compared with 62.22% in the control group. The difference of 12.40 percentage points provides initial evidence that the training intervention improved overall student performance.

Mean scores and standard deviations were then calculated for each test (table 4). The analysis also included 95% confidence intervals for the group means.

Table 4. Descriptive training results by test

Test	*Control Group*		*Experimental Group*		
	mean	**S.D.**	**mean**	**S.D.**	**Mean difference**
Basic Excel	5.91	1.78	7.35	1.71	+1.44
Advanced Excel	5.67	1.50	6.67	1.91	+1.01
Copilot	6.80	1.94	8.33	1.48	+1.53
ChatGPT	6.52	1.60	7.50	1.83	+0.98

Source: Author's own elaboration.

The experimental group obtained higher mean scores in all four tests. Copilot produced the largest absolute increase, with a mean difference of 1.53 points. In relative terms, the largest improvement occurred in Basic Excel, where the experimental mean was approximately 24.4% higher than the control mean, followed by Copilot, with an improvement of approximately 22.5%.

Welch's independent-samples t-test and the non-parametric Mann–Whitney U test were subsequently applied. Chi-square tests were used to examine differences in score distributions, while Cohen's *d* and Cramér's V were calculated to estimate effect size and strength of association (table 5). Combining parametric and non-parametric procedures strengthens the robustness of the findings by reducing dependence on the assumptions of a single statistical method (Cohen, 1988; Ellis, 2010).

Table 5. Statistical comparisons between the control and experimental groups

Test	***t***	***p***	***Cohen***	***M-Whitney***	***p***	***X²***	***V***
Basic Excel	4.23	< .001	0.82	2394	< .001	17.68	0.41
Advanced Excel	2.98	.004	0.58	1820	.008	10.41	0.31
Copilot	4.53	< .001	0.88	2036	< .001	19.00	0.42
ChatGPT	2.94	.004	0.57	1853	.004	11.32	0.33

Source: Author's own elaboration.

The differences between the control and experimental groups are statistically significant in all four tests (table 5). The largest effect sizes are observed for Basic Excel and Copilot, with Cohen's *d* values of 0.82 and 0.88, respectively. Advanced Excel and ChatGPT show moderate effects, with values of 0.58 and 0.57.

Three principal conclusions emerge from these results.

First, the training programme produces observable improvements across all the technologies assessed. Structured instruction therefore contributes not only to declarative knowledge but also to effective performance in tasks related to accounting and financial analysis.

Second, the largest absolute improvement occurs in Copilot. This finding is especially relevant because assisted automation represents the intermediate stage of the progressive model. The evidence suggests that the most substantial educational challenge may not lie solely in introducing generative tools, but in helping students move from conventional spreadsheet analysis towards forms of intelligent assistance that still require technical supervision and verification.

Third, although the improvement in ChatGPT performance is statistically significant, its effect size is lower than that observed for Copilot. One plausible explanation is the high level of prior familiarity that many students already have with general-purpose GenAI tools. Frequent use, however, should not be mistaken for professional competence. The improvement achieved by the experimental group indicates that structured instruction can still strengthen the analytical, critical, and professionally appropriate use of ChatGPT.

The objective assessment phase substantially strengthens the empirical contribution of the study. The first part of the research identifies distinct profiles of perceived digital competence. The second shows that a structured intervention can generate measurable improvements in actual performance. The proposed model therefore moves beyond a conceptually grounded pedagogical framework and becomes an educational intervention supported by initial empirical evidence.

6. DISCUSSION

The results for Excel, PivotTables, and Analyze Data underline the role of accumulated experience and professional exposure in the development of advanced digital competence. Postgraduate students, many of whom combine their studies with employment or already have experience in organisational settings, report higher levels of moderate and advanced competence. This finding is consistent with research showing both the continuing centrality of Excel in accounting practice and the difficulty university programmes face in fully preparing students for the digital demands of the labour market (Borthick & Schneider, 2023; Frownfelter-Lohrke, 2017).

The pedagogical implication is clear. Undergraduate accounting and finance programmes should require students to use advanced spreadsheet functions rather than treating Excel as a basic calculation tool. Learning activities should include PivotTables, analytical functions, formula auditing, data validation, and the automation of repetitive tasks. Greater exposure to these applications would help narrow the gap between elementary classroom use and the level of competence expected in professional practice before students enter postgraduate education or the labour market.

ChatGPT follows a different pattern. Undergraduate students report higher levels of competence, reflecting the speed with which younger cohorts have incorporated emerging technologies into their study routines. The findings are comparable with evidence reported by Microsoft for a sample of Australian university students, 72% of whom stated that they had used GenAI tools during the weekend before their examinations (Microsoft, 2025). Yet familiarity with GenAI should not be interpreted as evidence of pedagogically sound use. Intensive use may coexist with weak prompting, limited verification, and an inability to assess the reliability of generated content. Recent studies warn that GenAI can be associated with poorer academic outcomes when it is used to avoid the cognitive effort required by assessed tasks rather than to support that effort (Wecks et al., 2024).

Viewed through DigComp and DigCompEdu, technological familiarity represents only one component of digital competence (Redecker, 2017; Vuorikari et al., 2022; European Commission, 2024). Effective competence also requires the ability to analyse information, evaluate its quality, validate results, and make evidence-based decisions. The stronger self-reported ChatGPT competence among undergraduate students must therefore be interpreted cautiously. The relevant issue is not simply how frequently they use the tool, but how they use it: the quality of their prompts, the procedures adopted to verify responses, and the extent to which GenAI is embedded in structured learning processes.

The absence of statistically significant differences in Copilot supports a related conclusion. GenAI integrated into office-productivity environments remains at an early stage of adoption, and its educational potential has not yet been fully developed. Microsoft's continuing efforts to promote Copilot in educational settings also indicate that institutional adoption is still being constructed rather than consolidated (Microsoft, 2025).

The findings also support the central proposition of technology-mediated learning theory (Alavi & Leidner, 2001): the educational value of a technology depends less on its technical sophistication than on how it is embedded within a structured learning design. A powerful tool does not produce meaningful learning by itself. Its contribution emerges from the interaction between task design, instructional guidance, student engagement, feedback, and assessment.

This has direct implications for the design of accounting and finance curricula. Excel and its advanced functions should be tied explicitly to disciplinary learning outcomes, including data analysis, financial modelling, control, and professional judgement. GenAI should then be introduced gradually through activities that require students to compare, explain, challenge, and justify model-generated responses. Such activities position technologies as an object of scrutiny rather than an unquestioned source of answers.

Self-reported competence can provide a useful starting point for differentiated learning pathways, but it should not replace assessment based on observable performance in authentic tasks. The training model proposed in this study uses perceived competence to adjust the intensity and complexity of instruction while placing greater evaluative weight on verifiable evidence of learning. Clear protocols for source checking, result validation, and disclosure of AI use are essential to prevent excessive technological dependence and to reduce the risk of reproducing biases embedded in GenAI outputs (Vieriu & Petrea, 2025).

The experimental phase strengthens this argument by showing that the proposed model does more than organise students according to their perceived competence. It produces measurable improvements in performance. Compared with the control group, students who followed the structured sequence of spreadsheet foundations, assisted automation, and critical GenAI use achieved significantly better results in all four tests.

The strongest effects in Basic Excel and Copilot are particularly informative. They suggest that educational intervention adds most value where students must connect technical foundations with intelligent assistance. The central challenge is therefore not merely to teach a traditional tool and then add GenAI as a separate topic. It is to manage the transition between controlled spreadsheet analysis and AI-assisted work without weakening traceability, verification, or professional judgement.

The significant improvement in ChatGPT performance also shows that frequent prior exposure does not amount to professional competence. Students may be comfortable using a general-purpose GenAI interface while still lacking the ability to formulate precise prompts, assess the quality of responses, and integrate generated content into a defensible analytical process. Structured instruction remains necessary even for tools that students already use regularly.

The proposed model therefore moves beyond a conceptual pedagogical framework. The combination of perceived-competence profiles and objective performance evidence provides initial empirical support for a differentiated and progressive approach to digital training in accounting and finance. This is especially relevant for curriculum design in universities responding to rapid technological change without abandoning the technical and analytical foundations of the discipline.

7. CONCLUSION

This study identifies significant differences between undergraduate and postgraduate students in their perceived competence with digital tools used in accounting and finance. Postgraduate students report stronger command of established spreadsheet applications, whereas undergraduate students display greater familiarity with ChatGPT. These patterns reveal distinct competence trajectories rather than a single digital divide.

The findings support a progressive training model that connects technical foundations, analytical automation, and the critical use of GenAI. Such a sequence avoids two weaknesses that increasingly affect accounting education: excessive dependence on automated outputs and the persistence of teaching practices that no longer reflect the technological environment of professional work.

The study's main contribution lies in combining perceptual evidence with objective measures of student performance. The experimental results show that structured training produces significant improvements in Basic Excel, Advanced Excel, Copilot, and ChatGPT. The evidence therefore supports the underlying logic of the model: students benefit when digital learning progresses from controlled data manipulation to assisted automation and, finally, to the critical evaluation of AI-generated outputs.

Digital competence should not be taught as a collection of disconnected software skills. It should be developed through a coherent sequence in which analytical understanding precedes automation, and automation remains subject to verification and professional judgement. The value of the model lies not in privileging one technology over another, but in defining how different tools contribute to different stages of the accounting and financial reasoning process.

The study is nevertheless subject to several limitations. First, the initial analysis relies on self-reported competence, which may not accurately represent students' actual ability. Although the inclusion of objective tests partly addresses this weakness, the measures cover a restricted set of tasks and technologies. Second, the sample was drawn from three universities located in different national and cultural settings, but it cannot be considered representative of the broader population of accounting and finance students. The involvement of the same instructor across the participating groups increased procedural consistency, yet it may also limit the transferability of the findings to courses with different teaching approaches. Third, the cross-sectional design of the competence survey does not reveal how students' skills develop over time. The quasi-experimental phase provides evidence of differences following a structured intervention, but the design does not establish whether the gains are sustained, transferred to new tasks, or retained after the course has ended. The absence of random assignment also limits the strength of causal inference.

Future research should extend the analysis through longitudinal designs that follow students across different stages of their university education and into professional practice. Objective performance measures should include more complex and authentic accounting tasks, such as financial statement analysis, reconciliation, forecasting, model auditing, and the preparation of management reports.

Qualitative research could also examine how students combine spreadsheets and GenAI when solving real accounting and financial problems. Prompt strategies, verification routines, error detection, and the justification of final decisions deserve particular attention because they reveal forms of competence that conventional self-assessment scales may not capture.

The proposed training sequence should also be replicated across institutions, instructors, and course formats. Larger quasi-experimental or randomised designs could test whether the effects identified in this study remain stable across different student populations and teaching environments. Follow-up assessments would make it possible to determine whether the observed gains persist over time.

Finally, the model could be extended to include technologies such as Power Query and Power BI, as well as alternative GenAI systems including Gemini, Claude, and Perplexity. Their inclusion would increase the technological complexity of the programme, but it would also allow future studies to examine whether competence transfers across platforms or remains tied to specific applications.

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Appendix

Examples of Assessment Questions

The assessment activities were based on a multi-year sales database for a fictitious multinational company. The dataset contained transaction-level records organised by country, region, product, unit cost, unit selling price, units sold, and customer type, among other variables.

Excel Test

Skills assessed: filtering, calculation of totals, and use of basic formulas.

Students were instructed to use only the following functions: SUM, UNIQUE, COUNTA, SUMIF.

Examples of questions included:

- What was the total sales revenue during the period XXXX?
- Which customer generated the highest total sales?
- What was the average cost of product XXXX?

Excel and PivotTables Test

Skills assessed: summarising and analysing data by country, product, and year.

Students were instructed to use previous Excel functions and PivotTables.

Examples of questions included:

- Which two countries generated the highest revenue during the period XXXX?
- Which product generated the highest total profit margin in year XXXX?
- Which country sold the largest number of units of product XX in year XXXX?

Copilot within Excel Test

Skills assessed: using natural-language instructions within Excel to generate comparisons, calculations, and analytical interpretations.

Examples of questions included:

- What factors explain the decline in revenue between years XXXX and YYYY?
- What was the average percentage margin for the most profitable product?
- What was the growth rate of the selling price of product XX in country YY during the period XXXX?

ChatGPT Test

Skills assessed: synthesising information, explaining differences, interpreting financial results, and making recommendations in natural language.

Examples of questions included:

- Country XX has the highest percentage margin, but it does not generate the highest total margin. What explains this difference?
- In which country, product, or market segment should growth investment be prioritised to maximise its total impact on profit?
- From the Chief Financial Officer's perspective, which three financial metrics are most important for monitoring the quality of the company's performance?