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Using plithogenic n-SuperHyperGraphs to assess the degree of relationship between information skills and digital competencies

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Abstract. This study investigates the interdependence between informational skills and digital competencies, and how an educational intervention can strengthen this relationship in university students. Using Plithogenic n-SuperHyperGraphs as a modeling mechanism, 40 students were assessed through questionnaires and practical tests before and after a ten-week experiment.
Findings revealed new associations, such as a strong positive correlation (0.82) between information searching and digital literacy. Significantly, the percentage of students with high-level integrated skills increased from 12.5% to 37.5% after the intervention. Although the intervention improved all dimensions regardless of sociodemographic variables, female students, engineering students, and the 18-20 age group showed the greatest progress. The study proposes a novel approach to assess these multidimensional competencies and suggests the need to integrate these transversal skills into university curricula to better prepare students for the digital academic and professional environment.

Keywords: Information Skills, Digital Competencies, Integration, N-SuperHyperGraphs, Educational Intervention, Correlations, University Students.

1 Introduction

We are currently living in a technologically advanced society where information skills and digital competencies represent the required groundwork for current and future academic and career undertakings. Here, skills are needed to operate within technologically advanced environments, whether to seek out, evaluate, and acquire information or to use different technologies with finesse and skill. However, most importantly, the intersection of both sets of skills can foster better critical thinking and problem-solving abilities through creativity, especially in an information-rich world [1]. Recently, populations that directly relate include college students who study in a digitized world and require such skills to graduate or battle learned issues on a global scale [2]. Therefore, it is important to assess how these two types of skills relate—through cause and effect—and how they can build upon each other to strengthen newcomers' theory for present-day application. The last few decades of learning show a transformation of learning due to advancements in information technology. From the internet entering the classroom to increased computer usage to remote learning options, all have been unprecedented transformations in how we learn [3]. As such, immediate transformations in learning support the need for information skills—searching for information, evaluating it, and determining viable sources—and digital skills—creating products and using online safety [4]. Yet only through hypothetical assessments of these skills have they been utilized. Only rarely has the integration of such abstract skills been investigated despite their relevance in addressing real-world applications [5]. Thus, there is no better time than the present to approach this study based on the necessity of the past.

This gap is filled through the problem statement derived from the central research question: what is the relationship between information skills and digital competencies and can the interdependence thereof be enhanced through an educational intervention among university students? While such assessment of skills and competencies has been done relative to their comprehension over time [6], there is no relative information in the recent literature to suggest that researchers have tried to solidify a model of their dependent nature via such advanced means. The problem exists because it is relevant; university students are not prepared for a digitally driven transformed era where merely learning these integrative skills will put them ahead of the game come time for employment [7]. Thus, solving this problem will benefit theoretical and practical solutions and progress within higher education. As such, the study's problem helps form the purpose for assessment: to assess the relationship between information skills and digital competencies via plithogenic n-SuperHyperGraphs for mapping such relationships within an ontology. Secondly, the project seeks to assess the results of a 10-week educational intervention on the level of growth and integration of competencies among university students. Both purposes are goal-driven and relate to question developments that fulfill them and support this intention-focused approach with new findings relative to the symbiotic nature of such skills within academic settings [8,9].

2. Materials and methods

This section contains two subsections, the first one is dedicated to explaining the basic notions of the n-Plithogenic SuperHyperGraphs defined in [10]. Then, subsection 2.2 contains the main concepts of multiway contingency tables and the log-linear method.

2.1 n- Plithogenic superhypergraphs

Plithogenic n-SuperHyperGraphs were defined by Smarandache in the field of decision making in [10].

First, an n-SuperHyperGraph is defined as follows [11], [12]:

Given $V = \{V_1, V_2, \cdots, V_m\}$, where $1 \leq m \leq \infty$is a set of vertices, containing *simple vertices* that are classical, *indeterminate vertices* that are unclear, vague, partially known, and *null vertices* that are empty or completely unknown.

$P(V)$is the power set of$V$ including $\emptyset$. $P^n(V)$is the n-potential set of V, which is defined recursively as follows:

$P^1(V) = P(V)$, $P^2(V) = P\big(P(V)\big)$, $P^3(V) = P\big(P^2(V)\big)$, … , $P^n(V) = P\big(P^{n-1}(V)\big)$, for $1 \leq n \leq \infty$.
Where is also defined as $P^0(V) = V$.

An n- SuperHyperGraph (*n-SHG*) is an ordered pair $n - SHG = (G_n, E_n)$, where$G_n \subseteq P^n(V)$ and $E_n \subseteq P^n(V)$, for $1 \leq n \leq \infty$. Such that, $G_n$is the set of vertices and $E_n$is the set of edges.

$G_n$contains all possible types of vertices as in the real world:

- *Simple vertices* (the classic ones),
- *Indeterminate vertices* (unclear, vague, partially known),
- *Null vertices* (empty, completely unknown),
- *SuperVertex* (or *SubsetVertex*) contains two or more vertices of the above types grouped together (organization).
- *n-SuperVertex* which is a collection of vertices, where at least one of them is an *(n-1)-SuperVertex,* and the others may be *r-SuperVertex* for $r \leq$ n.

E_n contains the following types of borders:

- *Simple edges* (the classic ones),
- *Indeterminate borders* (unclear, vague, partially known),
- *Null edges* (totally unknown, empty),
- *HyperEdge* (connecting three or more individual vertices),
- *SuperEdge* (connecting two vertices, at least one of them is a SuperVertex),
- *n- SuperEdge* (connecting two vertices, at least one of which is an n-SuperVertex and may contain another which is an r-SuperVertex with $r \leq$ n).
- *SuperHyperEdge* (connects three or more vertices, where at least one of them is a SuperVertex),
- *n- SuperHyperEdge* (contains three or more vertices, at least one of which is an n-SuperVertex and may contain an r-SuperVertex with $r \leq$ n),
- *MultiEdge* (two or more edges connecting the same two vertices),
- *Loop* (an edge that connects an element to itself),

The graphics are classified as follows:

- Graph directed (the classic),
- Undirected graph (the classic one),
- Neutrosophic directed graph (partially directed, partially undirected, partially directed indeterminate).

Within the framework of the theory of Plithogenic n-SuperHyperGraphs, we have the following concepts [13,14, 15]

Enclosing vertex: A vertex that represents an object comprising attributes and sub-attributes in the graphical representation of a multi-attribute decision-making environment.

***Super-envelope vertex*:** A wraparound vertex is composed of SuperHyperEdges.

***Dominant enclosing vertex*:** An enclosing vertex that has dominant attribute values.

***Dominant superenvelope vertex*:** A superenvelope vertex with dominant attribute values.

The dominant enclosing vertex is classified into *input* , *intervention* and *output* according to the nature of the object representation.

***Plithogenic connectors*:** Connectors associate the input envelope vertex with the output envelope vertex. These connectors associate the effects of input attributes with those of output attributes and are weighted according to the plithogenic weights.

2.2 Multi-way contingency tables

A multivariate contingency table is a contingency table defined for two or more cross-ratio classification variables. Two-dimensional tables are usually referred to as contingency tables, while the term multivariate applies when the number of variables is at least three [16, 17, 18].

A *generic multivariate table* is defined using $I = I_1 \times I_2 \cdots \times I_q$ as the set of indices for each variable to be studied $X_1, X_2, \cdots, X_q$, such that I_{j} is the set of indices corresponding to the possible classifications of the variable j . Therefore, $n_{\mathrm{i}_1\mathrm{i}_2\cdots\mathrm{i}_q}$ is the frequency of occurrence of the classifications $\mathrm{i}_1, \mathrm{i}_2, \cdots, \mathrm{i}_\mathrm{q}$ for each of the corresponding variables.

Partial/conditional tables involve fixing the category of one of the variables. Fixed variables are indicated in parentheses. For example, partial tables XZ and YZ are indicated by $n_{\mathrm{i(j)k}}$ and $n_{\mathrm{(i)jk}}$, respectively. Furthermore, the *partial/conditional probabilities* are calculated by $\pi_{\mathrm{ij(k)}} = \pi_{\mathrm{ij/k}} = Prob(X = i, Y = j/Z = k)$. *The partial/conditional proportions* are defined by $p_{\mathrm{ij(k)}} = p_{\mathrm{ij/k}} = \frac{\pi_{\mathrm{ijk}}}{\pi_{\mathrm{++k}}}$ for $k = 1, 2, \dots, K$. Where $\pi_{\mathrm{++k}}$ is the frequency i and j configuration k, for more information see [16,17].

Next, we briefly explain what log-linear models consist of. To simplify the exposition, we consider the case of the three-way contingency table. If X, Y, and $Z$are the variables, then the following possible models are obtained [18]:

- Model (X, Y, Z): All variables are considered independent, the model is as follows:
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z$ (1)
- Model (X, YZ): Only the YZ association is considered, while X is independent of the other two variables.
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{jk}^{YZ}$ (2)
- Model (XY, YZ): X and Z are independent for each value of Y:
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{jk}^{YZ}$ (3)
- Model (XY, YZ, XZ): There is a pairwise association between all variables, but there is no joint association between the three.
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ}$ (4)
- Model (XYZ): If the above model does not fit the data well, then the association between the three variables should be considered:
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ}$ (5)

To compare two different models, *the statistic called likelihood ratio is used,* which is calculated as [19]:

$G^2 = 2\sum f ln(f/F)$ (6)

Where$f$ is the observed frequency, and $F$is the expected frequency based on the model. This statistic is distributed according to a chi-square test under the hypothesis that the model is correct, with degrees of freedom depending on the parameters used to fit the model [20.

To compare two models, simply subtract their respectiveG^2 or, in another case, among others, the *Bayesian Information Criterion* is used with the formula [21]:

$BIC = G^2 - \mathrm{df}\log\mathrm{N}$ (7)

Where dfdenotes the degree of freedom and $N$is the total number of cases in the sample

3. Case Study

In the research, three instruments were used for data collection, which were designed and validated by experts in the subject, based on their reliability during their application. They were the following:

Information Skills Assessment Questionnaire (CEHI)

The Information Skills Assessment Questionnaire, developed by Martínez et al. in 2018, was designed to objectively assess information search, evaluation, and use skills. It is considered a rapid and objective assessment tool with a qualitative scoring system, consisting of two parts: a self-administered questionnaire and a practical test. The questionnaire consists of 18 questions, each of which will be scored one point if answered correctly or zero if answered incorrectly. It includes three ungraded control questions, with a maximum score of 15.

The second part of the CEHI consists of a practical test that assesses the participant's ability to conduct effective searches, critically evaluate sources, and synthesize information. The score is obtained by adding the results of both parts; a score greater than 20 indicates a high level of information skills.

Digital Competence Test (DCT)

The Digital Competencies Test assesses technological skills in different dimensions. It uses an assessment rubric that measures five key areas: information and information literacy, communication and collaboration, digital content creation, security, and problem-solving. Each dimension is assessed through practical activities that the participant must complete while the evaluator records their performance on a scale of 1 to 5. This assessment is conducted in two sessions to measure initial and final performance after the educational intervention. The procedure has been standardized for different population groups, so adherence to these protocols is recommended.

Practical Application Integrated Test (PAPI)

The assessment of skills integration has been standardized thanks to the work of Dr. Roberto Méndez. This test is designed to identify the ability to integrate information and digital skills in solving real-world problems. During the exam, the evaluator will explain the procedure to the participant. The participant must solve a practical case that requires both searching for and evaluating information and using digital tools to present a solution. The test will be evaluated considering both the process and the final result.

To assess the integration of competencies, a holistic rubric is used for solving the practical case. The participant will receive a grade that determines:

- Basic level: limited integration of information skills and digital competencies
- Intermediate level: adequate integration of information skills and digital competencies
- Advanced level: excellent integration of information skills and digital competencies

The research was conducted in two locations: the facilities of the Faculty of Information Sciences at the Central University, and also at the facilities of the municipality's Digital Innovation Center, in the province of Quito.

Population and sample

The research population consisted of 48 university students, of whom 40 participants completed the 10-week intervention, with pre- and post-assessment. The remaining 8 participants were eliminated for not completing the full 10-week program or for not attending the final assessment, yielding a 95% confidence interval, with a 5% margin of error for university students.

Inclusion criterio

- Male or female students aged 18 to 30.
- Students enrolled in undergraduate university programs.
- Students who regularly use electronic devices for their studies.
- Students who have completed at least one full semester of university studies.
- Students who voluntarily agreed to participate in the study.

Exclusion criterio

- Students with prior professional certification in digital skills.
- Students working in the information technology sector.
- Students who do not have regular internet access at home.
- People who have participated in similar programs in the last 6 months.

The input object (V) in this study is Students, defined as the university students selected to study the relationship between information skills and digital competencies. The Enveloping Vertex (Super Enveloping Vertex or Dominant Enveloping Vertex or Super Enveloping Dominant Vertex) in this problem is related to the following attributes and subattributes:

V_1= Sociodemographic data, V_2= Information skills, V_3= Digital skills, V_4= Integration of skills.
Attribute sets = {Sociodemographic data, Information skills, Digital skills, Skills integration}.
Sociodemographic data = {Age (V_{11}), Area of study (V_{12}), Gender (V_{13})}.
Information skills = {Information seeking (V_{21}), Information evaluation (V_{22}), Information use (V_{23})}.
Age = {18-20 years (V_{111}), 21-25 years (V_{112}), 26-30 years (V_{113})}.
Area of study = {Humanities (V_{121}), Sciences (V_{122}), Engineering (V_{123}), Social Sciences (V_{124})}.
Gender = {Male (V_{131}), Female (V_{132})}.
Information search = {Initial (V_{211}), Final (V_{212})}.
Information evaluation = {Initial (V_{221}), Final (V_{222})}.
Information usage = {Initial (V_{231}), Final (V_{232})}.

Initial = {Low, Medium, High}. Final = {Low, Medium, High}.

Digital skills = {Information and literacy (V_{31}), Communication and collaboration (V_{32}), Content creation (V_{33}), Security (V_{34}), Problem solving (V_{35})}.

For each digital competency, the following levels are assessed: Initial = {Basic, Intermediate, Advanced}. Final = {Basic, Intermediate, Advanced}.

Integration of competencies = {Initial (V_{41}), Final (V_{42})}.

In the case of integration, the following is determined: Initial = {Low, Medium, High}. Final = {Low, Medium, High}.

These variables are summarized in Table 1:

Table 1. Vertex, Vertex Attributes, Vertex Subattributes, and Vertex Subattributes in the study.

Vertex	Vertex attributes	Secondary vertex attributes	Secondary vertex attributes
Sociodemographic data (V_1)	Age (V_{11})	18-20 years (V_{111})	Low (V_{2111})
		21-25 years (V_{112})	Medium (V_{2112})
		26-30 years (V_{113})	High (V_{2113})
	Study area (V_{12})	Humanities (V_{121})	Low (V_{2121})
		Sciences (V_{122})	Medium (V_{2122})
		Engineering (V_{123})	High (V_{2123})
		Social Sciences (V_{124})	Low (V_{2211})
	Gender (V_{13})	Male (V_{131})	Medium (V_{2212})
		Female (V_{132})	High (V_{2213})
Information skills (V_2)	Information Search (V_{21})	Initial (V_{211})	Low (V_{2221})
		Final (V_{212})	Medium (V_{2222})
	Information Evaluation (V_{22})	Initial (V_{221})	High (V_{2223})
		Final (V_{222})	Low (V_{2311})
	Use of information (V_{23})	Initial (V_{231})	Medium (V_{2312})
		Final (V_{232})	High (V_{2313})
			Low (V_{2321})
			Medium (V_{2322})
			High (V_{2323})

Note that the sub-attributes V_{211}, V_{221}, and V_{231} are input enclosing vertices, while V_{212}, V_{222}, and V_{232} are output enclosing vertices. The intermediate enclosing vertices are the others.

Table 2 contains the absolute frequency of each of the variables:

Table 2. Absolute frequencies obtained for each variable.

Vertex	Vertex attributes	Secondary vertex attributes	Secondary vertex attributes
Sociodemographic data (40)	Age (40)	18-20 years (12)	Low (14)
		21-25 years (19)	Medium (18)
		26-30 years (9)	High (8)
	Study area (40)	Humanities (8)	Low (5)
		Sciences (10)	Medium (15)
		Engineering (14)	High (20)
		Social sciences (8)	Low (16)
	Gender (40)	Male (18)	Medium (17)
		Female (22)	High (7)
Information skills (40)	Information search (40)	Initial (40)	Low (6)
		Final (40)	Medium (19)
		Initial (40)	High (15)

	Information evaluation (40)	Final (40)	Low (15) Medium (18) High (7)
	Use of information (40)	Initial (40)	
		Final (40)	Low (4) Medium (16) High (20)

Note that each of the absolute frequencies can be converted to relative frequencies by dividing them by 40.

Table 3 contains the vertices corresponding to digital competencies and integration, which is written separately for reasons of space and to make it more understandable, however, it should be understood as a continuation of Table 1:

Table 3. Vertex, Vertex Attributes, and Vertex Subattributes in the study conducted for digital competencies and integration.

Vertex	**Vertex attributes**	**Secondary vertex attributes**
Digital skills (V_3)	Information and literacy (V_{31})	Initial (V_{311})
		Final (V_{312})
	Communication and collaboration (V_{32})	Initial (V_{321})
		Final (V_{322})
	Content Creation (V_{33})	Initial (V_{331})
		Final (V_{332})
	Security (V_{34})	Initial (V_{341})
		Final (V_{342})
	Problem Solving (V_{35})	Initial (V_{351})
		Final (V_{352})
Integration of competencies (V_4)	Initial (V_{41})	Low (V_{411})
		Medium (V_{412})
		High (V_{413})
	Final (V_{42})	Low (V_{421})
		Medium (V_{422})
		High (V_{423})

Note that the sub-attributes V_{311}, V_{321}, V_{331}, V_{341}, V_{351}, and V_{41} are input wrapping vertices, while V_{312}, V_{322}, V_{332}, V_{342}, V_{352}, and V_{42} are output wrapping vertices.

Table 4 contains the absolute frequencies of the variables in Table 3.

Table 4. Absolute frequency obtained for each of the variables corresponding to digital skills and integration.

Vertex	Vertex attributes	Secondary vertex attributes
Digital skills (40)	Information and literacy (40)	Initial: Basic (18), Intermediate (16), Advanced (6)
		Final: Basic (5), Intermediate (17), Advanced (18)
	Communication and collaboration (40)	Initial: Basic (12), Intermediate (20), Advanced (8)
		Final: Basic (4), Intermediate (14), Advanced (22)
	Content creation (40)	Initial: Basic (21), Intermediate (15), Advanced (4)
		Final: Basic (8), Intermediate (19), Advanced (13)

	Security (40)	Initial: Basic (22), Intermediate (13), Advanced (5)
		Final: Basic (9), Intermediate (18), Advanced (13)
	Troubleshooting (40)	Initial: Basic (19), Intermediate (16), Advanced (5)
		Final: Basic (7), Intermediate (17), Advanced (16)
Integration of competencies (40)	Initial (40)	Low (20)
		Medium (15)
		High (5)
	Final (40)	Low (8)
		Medium (17)
		High (15)

Let's now use log-linear models to statistically process the data. To simplify the method, we'll use three-way contingency tables. We'll calculate the G^2 coefficient in each case.

Table 5 contains a summary of these results:

Table 5. G^2 result of the processed models.

Model	**G^2**
Age *Initial information search* Final information search	2.842761e-7
Age *Initial information assessment* Final information assessment	3.145926e-7
Age *Use of initial information* Use of final information	2.953184e-7
Age *Initial information and literacy Final* information and literacy	3.267458e-7
Age *Initial communication and collaboration Final* communication and collaboration	2.875326e-7
Study area *Initial information search* Final information search	4.125687e-7
Study Area *Initial Information Evaluation* Final Information Evaluation	4.265821e-7
Study area *Use of initial information* Use of final information	3.957432e-7
Study Area *Initial Content Creation* Final Content Creation	4.125789e-7
Study Area *Initial Problem-Solving* Final Problem Solving	4.032567e-7
Gender *Initial information search* Final information search	3.148562e-7
Gender *Initial information evaluation* Final information evaluation	2.985621e-7
Gender *Use of initial information* Use of final information	3.047826e-7
Gender *Security initial* Final Security	3.125478e-7
Gender *Initial Competence Integration* Final Competence Integration	2.954781e-7

Note that, for example, in the first model, three vertices were combined to form a SuperVertex, since uncertainty and indeterminacy exist due to the nature of the problem being addressed, and therefore statistics are used. Figure 1 serves to graphically illustrate this example; a similar graphical representation exists for each of the models.

Regarding dominance, two vertices were always dominant: the initial one (representing the input) and the final one (representing the output).

Show image

Regarding statistical interpretation, all G^2 values were < 0.01 with a log-linear fit, indicating that all the log-linear models obtained fit the data well. When the models were analyzed in more detail for all cases, it was concluded that there was a significant improvement among the variables analyzed. In other words, the intervention program was effective in improving both information and digital skills in all students, regardless of their age, field of study, and gender.

Analysis of relationships between information skills and digital competencies

To further analyze the relationships between information skills and digital competencies, we used plithogenic n-SuperHyperGraphs to model the connections between the different components evaluated. Table 6 shows the results of the correlation analysis between the different dimensions evaluated:

Table 6. Correlation coefficients between information skills and digital competencies

Information skills	Digital competence	Initial coefficient	Final coefficient	Change
Search for information	Information and literacy	0.65	0.82	+0.17
Search for information	Troubleshooting	0.48	0.71	+0.23
Information evaluation	Information and literacy	0.57	0.76	+0.19
Information evaluation	Security	0.42	0.68	+0.26
Use of information	Content creation	0.61	0.79	+0.18
Use of information	Troubleshooting	0.53	0.74	+0.21

These results show significant positive correlations between information skills and digital competencies, with these relationships strengthening after the educational intervention. To better visualize these relationships, we applied the plithogenic n-SuperHyperGraphs model, generating a representation of the connections between the different components.

Analysis of the plithogenic n-SuperHyperGraph allows us to identify the following key trends:

1. Information seeking shows a strong correlation with information and digital literacy (0.82), suggesting that both skills reinforce each other and share similar cognitive processes.
2. Information evaluation presents a significant correlation with digital security (0.68), indicating that critical capabilities developed to evaluate information also contribute to identifying risks in digital environments.
3. The use of information is closely related to the creation of digital content (0.79), demonstrating that the effective application of information facilitates the generation of new content in digital format.
4. The integration of competencies, represented as a central node in the n-SuperHyperGraph, shows connections with all information skills and digital competencies, confirming its holistic nature.

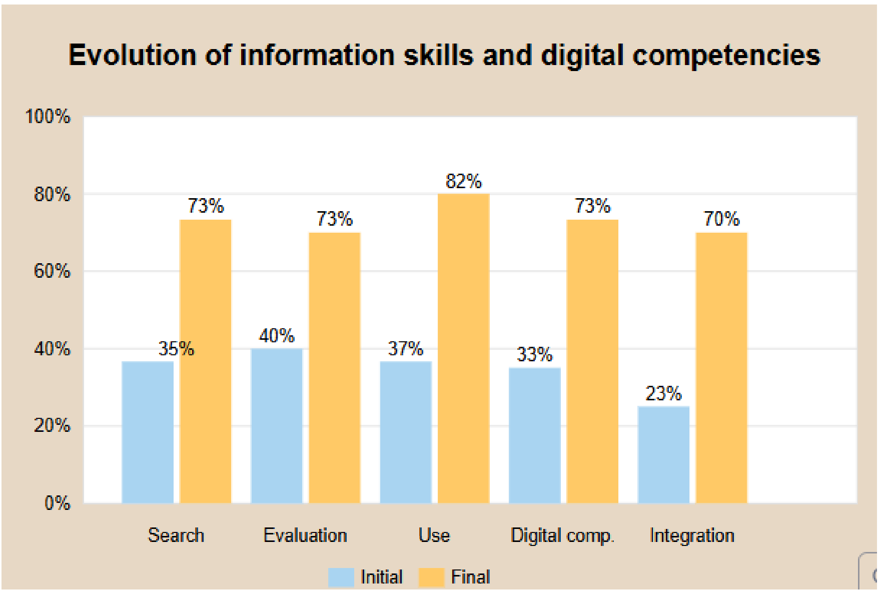

Figure 1. Evolution of information skills and digital competencies

Evolution of skills and competencies

Analyzing the evolution of information skills and digital competencies allows us to visualize the impact of the intervention program on the different components assessed. Figure 1 shows the evolution of the average levels achieved by students in each dimension.

As can be seen, all skills and competencies experienced significant growth after the educational intervention. Information use was the informational skill that showed the greatest growth (from 37% to 82%), while skills integration, although starting from the lowest level (23%), achieved a significant increase, reaching 70%.

Analysis of the integration of competencies according to sociodemographic variables

To better understand how sociodemographic variables influence the integration of information skills and digital competencies, we conducted a detailed analysis using log-linear and plithogenic n-SuperHyperGraphs models. Table 7 shows the results of the correlation between these variables:

Table 7: Integration of competencies according to sociodemographic variables

Variable	**Category**	**Initial integration**			**Final integration**		
		Low	Medium	High	Low	Medium	High
Age	18-20 years old	7 (58%)	4 (33%)	1 (8%)	3 (25%)	5 (42%)	4 (33%)
	21-25 years old	9 (47%)	7 (37%)	3 (16%)	3 (16%)	8 (42%)	8 (42%)
	26-30 years old	4 (44%)	4 (44%)	1 (11%)	2 (22%)	4 (44%)	3 (33%)
Study area	Humanities	4 (50%)	3 (38%)	1 (13%)	2 (25%)	3 (38%)	3 (38%)
	Sciences	5 (50%)	4 (40%)	1 (10%)	2 (20%)	4 (40%)	4 (40%)
	Engineering	6 (43%)	5 (36%)	3 (21%)	1 (7%)	6 (43%)	7 (50%)
	Social Sciences	5 (63%)	3 (38%)	0 (0%)	3 (38%)	4 (50%)	1 (13%)
Gender	Male	9 (50%)	7 (39%)	2 (11%)	4 (22%)	7 (39%)	7 (39%)
	Female	11 (50%)	8 (36%)	3 (14%)	4 (18%)	10 (45%)	8 (36%)

The results show improvements in skills integration across all demographic groups. However, some interesting differences are observed:

1. Engineering students showed the greatest increase in the high level of integration (from 21% to 50%).
2. The youngest students (18-20 years old) experienced the greatest positive change overall, going from 8% with a high level to 33%.
3. No significant gender differences were observed in the evolution of skills integration.

In the plithogenic n-SuperHyperGraph model, we can observe the connections between different information skills and digital competencies. Thicker lines indicate stronger correlations, and we can see that after the intervention, the relationship between information seeking and information literacy shows the strongest correlation (0.82), followed by the relationship between information use and digital content creation (0.79).

As can be seen, there is a clear increase in the percentage of students achieving a high level of skill integration (from 12.5% to 37.5%), information skills (from 18.3% to 45.8%), and digital skills (from 15.6% to 41.0%). This demonstrates the effectiveness of the intervention program in improving not only individual skills and competencies but also their integration.

While this study provides valuable insights into the relationship between information skills and digital competencies, it is important to acknowledge certain limitations. The sample size, although adequate, may restrict the generalization of the results to broader university populations. Additionally, the study focused on students from a specific region, which may introduce cultural or contextual biases. The methodology relies primarily on questionnaires and practical tests, which may not fully capture the complexity of integrated skills in real-world settings. Finally, although the educational intervention proved effective, the long-term effects and sustainability of the observed improvements were not evaluated.

4. Conclusions

This study demonstrated the effectiveness of using plithogenic n-SuperHyperGraphs to model and analyze the relationships between information skills and digital competencies. The main findings indicate that information skills and digital competencies are intrinsically related, with significant correlations between their different dimensions. Furthermore, the educational intervention program was effective in improving both information and digital skills among all university students, regardless of age, field of study, and gender. It was found that plithogenic n-SuperHyperGraphs allow complex relationships between multiple dimensions to be effectively visualized and analyzed, facilitating the identification of patterns that would be difficult to detect with traditional statistical methods. Moreover, there is a synergistic effect in the integrated development of information and digital skills, where improvement in one area contributes positively to the development of the other and the methodology applied in this study can be replicated to analyze relationships between different types of competencies in various educational contexts. In practical terms, these findings suggest that educational programs aimed at developing digital literacy should adopt an integrated approach that simultaneously addresses information skills and digital competencies, leveraging the synergistic relationships identified in this study.

Based on the results obtained, the following recommendations are proposed: design educational programs that explicitly integrate the development of information skills and digital competencies, recognizing the correlations identified between specific dimensions; implement diagnostic assessments that allow for identifying students' entry profiles and personalizing interventions based on their specific needs; and develop teaching materials that promote the resolution of complex problems requiring the integrated application of both capabilities. Additionally, it is recommended to establish ongoing monitoring and evaluation systems that allow for monitoring progress in the acquisition and integration of these skills, promote collaboration between teachers from different disciplines to enrich pedagogical approaches aimed at developing these transversal competencies, continue researching the applications of plithogenic n-SuperHyperGraphs for the analysis of complex relationships in the educational field, and integrate the development of these competencies across university curricula, recognizing their importance for students' academic and professional performance

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