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Data Descriptor

Information Competences and Academic Achievement: A Dataset

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Abstract: Information literacy (IL) is becoming fundamental in the modern world. Although several IL standards and assessments have been developed for secondary and higher education, there is still no agreement about the possible associations between IL and both academic achievement and student dropout rates. In this article, we present a dataset including IL competences measurements, as well as academic achievement and socioeconomic indicators for 153 Chilean first- and second-year engineering students. The dataset is intended to allow researchers to use machine learning methods to study to what extent, if any, IL and academic achievement are related.

Dataset: The dataset is available in the Mendeley Data repository. Doi: http://dx.doi.org/10.17632/7r5fnrhyky.1.

Dataset License: The license under which the dataset is made available is CC-BY 4.0.

Keywords: information competences; academic achievement; machine learning

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1. Summary

The last few decades have seen a widespread growth of both the World Wide Web, and the use of computers and mobile devices with access to it. Consequently, IL has become of great importance. According to the American Library Association, "information literate people know how to find, evaluate and use information effectively to solve a particular problem or make a decision" [1] (para. 19).

The relevance of IL in today's world can be seen in the development of various standards [2–6], as well as in its inclusion in standardized international tests such as PISA [7–9] and ICILS [10]. Several authors have developed instruments to assess IL competences in secondary or higher education. Some of them correspond to self-assessments [11,12], whereas others are designed as tests to measure actual competences [12–17]. Some researchers, such as [18], have developed rubrics. From a different perspective, there have also been efforts to build software tools to assess online inquiry competences [17,19–21].

Despite all the above, there is no agreement regarding how IL impacts academic achievement in higher education. Some studies, such as [22–25], state that there is an association between better grades and better information competences. However, there are also studies that did not find such an association [26,27]. Another study concluded that high self-efficacy in IL skills contributes to effective research academic skills [28]. It must be noted that, to the best of our knowledge, most of the research attempting to find associations between IL and academic achievement has been conducted by librarians who have assessed the impact of library instruction interventions.

In recent years, there has been a proliferation of works attempting to predict students' GPAs [29–31] or determine whether they will pass or fail certain courses [32]. These investigations rely on machine learning techniques applied to data typically stored in institutional repositories. Another interesting study used classification algorithms to analyze students' learning behaviors and predict the learning effect on students' IL [33]. To the best of our knowledge, no research has been conducted using such techniques to study the relationship between IL and academic achievement.

Given the above, the aim of this work is to describe a novel dataset comprising information literacy competences and first-semester academic achievement for 153 first- and second-year students from all 23 engineering programs imparted by a Chilean university. The intended use for the dataset is to build classification and regression models to predict the final status (pass or fail) or the final grade for a given course, as well as the first-semester grade point average (GPA). Nevertheless, it can also be valuable to increase the number of observations in new datasets of the same nature or to explore the existence of different student profiles, as well as other applications.

The remaining sections of this article are structured as follows. First, Section 2 provides a detailed description of the dataset. Afterwards, Section 3 describes both the instruments and methods used to gather the data. Finally, Section 4 presents conclusions and applications for further research.

2. Data Description

The study associated with the presented dataset aims to determine to what extent, if any, information competences can improve (compared to predictors broadly described in the literature, such as previous academic achievement, as well as socioeconomic and demographic variables) the prediction of first-semester students' academic achievements, which is understood as the final course grades and the first-semester GPA.

The study is being conducted at a Chilean University and considers first- and second-year students from all its 23 engineering programs, including the following branches: Chemical, Civil, Electrical, Informatics, Mechanical, Thermal, Biomedical, Industrial, Mechatronics, Mining, Environmental, Geotechnical, Metallurgical, Biotechnological and Telematics. For this purpose, invitations were sent to over 2000 students through the Faculty's social networks and their courses' virtual classrooms.

As part of the study, students were asked to complete an online survey (available during the first and second semesters of 2022). This survey included questions from two different questionnaires: one to assess self-perceived IL competences [12,34] and the other to evaluate students' observed IL competences [15,35]. The former considers the information search and evaluation dimensions, whereas the latter assesses the information search, evaluation, processing and communication dimensions. Both instruments were designed based on the definitions for each dimension provided in [14]:

- Information search: covers the abilities to locate and access information.
- Information evaluation: "to analyse and assess the quality of the information by recognizing its usefulness, credibility and relevance" [14].
- Information processing: involves the abilities and skills of handling tools and applications to organize, store and retrieve information, as well as to manage the bibliography.
- Information communication: "concerns the set of abilities for transferring knowledge, promoting information dissemination and developing virtual spaces for work and debate" [14].

Scores achieved in both instruments were later aggregated to first-semester final grades and GPA, as well as high school GPA, national university admission test scores, and other socioeconomic indicators.

2.1. Files

A single comma-separated values (CSV) file, IL_competences_and_grades.csv, is provided in the repository (http://dx.doi.org/10.17632/7r5fnrhyky.1).

2.2. Features

The features in the dataset, described in Table 1, are organized as follows:

Table 1. Dataset content, including names, variable types and descriptions. S_ and O_ prefixes correspond to self-perceived and observed information competences, respectively. G_ prefix indicates a final course grade.

Feature	Type	Description	Values
ID	Identifier	Unique identifier for the row.	
S_SEARCH	Integer	Total score for the search dimension of the self-perceived IL competences instrument.	0–10
S_EVAL	Integer	Total score for the evaluation dimension of the self-perceived IL competences instrument.	0–10
S_TOT	Integer	Total score for the self-perceived IL competences instrument.	0–20
O_SEACH	Numeric	Total score for the search dimension of the observed IL competences instrument.	0–10
O_EVAL	Numeric	Total score for the evaluation dimension of the observed IL competences instrument.	0–10
O_PROC	Numeric	Total score for the processing dimension of the observed IL competences instrument.	0–10
O_COM	Numeric	Total score for the communication dimension of the observed IL competences instrument.	0–10
O_TOT	Numeric	Total score for the observed IL competences instrument.	0–40
SEX	Categorical	Sex.	0: male, 1: female
SCHOOL_TYPE	Categorical	Indicates the type of high school a student attended. Lower values are associated with a lower family income.	0, 1, 2
FEE_EXEMPTION	Categorical	Indicates if a student has a fee exemption benefit.	0: no, 1: yes
FIRST_CHOICE	Categorical	Indicates if a student was admitted to the program of his/her preference.	0: no, 1: yes
SCHOOL_GPA	Numeric	Final high school GPA.	0–10
SCORE_LAN	Numeric	Score achieved in the language admission test.	0–100
SCORE_MAT	Numeric	Score achieved in the math admission test.	0–100
SCORE_SCI	Numeric	Score achieved in the sciences admission test.	0–100
SCORE_WAV	Numeric	Weighted average score achieved in the admission test. Includes the three above items, student high school ranking and high school GPA.	0–100
G_ALG	Numeric	Final grade in Algebra I.	0–10
G_CAL	Numeric	Final grade in Calculus I.	0–10
G_PHY	Numeric	Final grade in Physics I.	0–10
S1_GPA	Numeric	First semester GPA.	0–10
ST_ALG	Categorical	Final status in Algebra I.	0: fail, 1: pass
ST_CAL	Categorical	Final status in Calculus I. 0: fail, 1: pass.	0: fail, 1: pass
ST_PHY	Categorical	Final status in Physics I. 0: fail, 1: pass.	0: fail, 1: pass

- The first feature is a unique participant identifier.
- The next three features correspond to scores achieved in the self-perceived IL competences instrument.
- The following five features include scores achieved in the observed IL competences instruments.

- Next, four features present demographic and socioeconomic indicators.
- The following five features summarize previous academic achievement.
- Following that, four features include the final grades achieved in three common first-semester courses and the first-semester GPA.
- The remaining three features include the courses' final statuses (pass or fail).

It must be noted that students are required to achieve 5.0 or more to pass. Also, S1_GPA considers all first-semester courses, i.e., the three common courses included in the dataset as well as other courses which are specific for each program.

2.3. Data Distribution

The dataset includes n = 153 observations. Table 2 shows summary statistics for numeric features; namely, self-perceived (S_ prefix) and observed (O_ prefix) information competences (per dimension and overall), previous academic achievement, final course grades (G_ prefix) and first-semester GPA (S1_ prefix).

Table 2. Summary statistics for information competences, final course grades and GPA.

Feature	Min	Q1	Median	Mean	Q3	Max	SD
S_SEARCH	0.000	6.875	8.750	7.921	9.375	10.000	2.151
S_EVAL	1.000	6.500	8.000	7.529	9.000	10.000	2.030
S_TOT	1.500	14.000	16.125	15.450	18.375	20.000	3.866
O_SEARCH	2.357	6.000	6.893	6.763	7.500	9.286	1.205
O_EVAL	0.972	5.556	6.389	6.432	7.778	10.000	1.779
O_PROC	2.267	5.600	6.933	6.945	8.267	10.000	1.793
O_COM	1.625	6.167	7.833	7.455	8.667	10.000	1.712
O_TOT	10.499	25.032	27.871	27.595	30.412	36.589	4.401
SCHOOL_GPA	7.500	8.750	9.000	8.989	9.300	9.967	0.450
SCORE_LAN	39.000	55.714	62.714	63.006	70.000	93.714	10.008
SCORE_MAT	51.286	64.857	70.286	69.078	73.429	83.429	6.868
SCORE_SCI	22.714	59.714	64.286	63.464	70.143	85.286	9.889
SCORE_WAV	57.814	71.221	75.900	75.052	78.721	99.751	6.059
G_ALG	0.333	4.167	5.000	5.014	5.833	8.500	1.388
G_CAL	0.000	2.000	5.000	4.062	5.500	8.333	2.084
G_PHY	0.000	4.000	5.333	4.881	5.833	9.667	1.734
S1_GPA	1.118	4.886	5.946	5.667	6.543	8.220	1.191

Figure 1 shows that, for self-perceived information competences, most observations are concentrated near the top of the scale for both dimensions and that few participants perceive their information competences as less proficient. For observed information competences, most participants achieve scores above the center of the scale (Figure 2).

As can be seen in Figure 3, most students finished high school with a final GPA of 9.0 or above (where 10.0 is the maximum), which means that they are among the best in their schools.

Similarly, Figure 4 shows how national university admission test scores are distributed. It is interesting to notice that most students achieve scores of 60% or more in all tests, although there are some atypically low scores in the sciences tests. Weighted average scores are higher than the test scores, which can be explained by the fact that high school grades and school rankings have the highest weights.

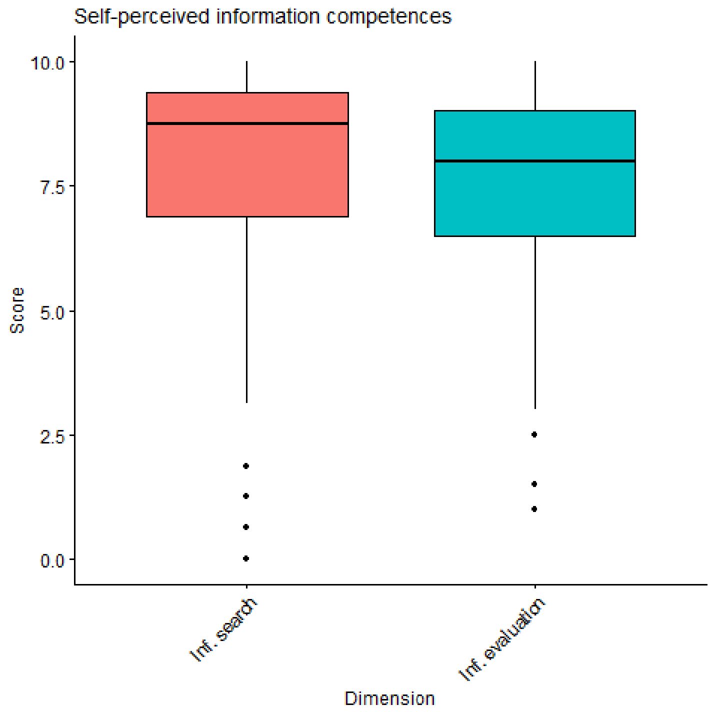

Figure 1. Distribution of self-perceived information competences scores per dimension.

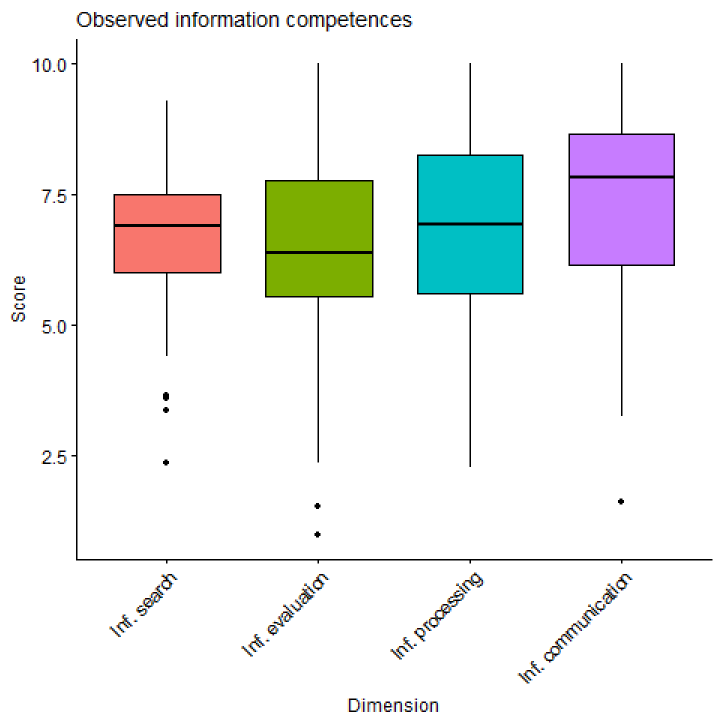

Figure 2. Distribution of observed information competences scores per dimension.

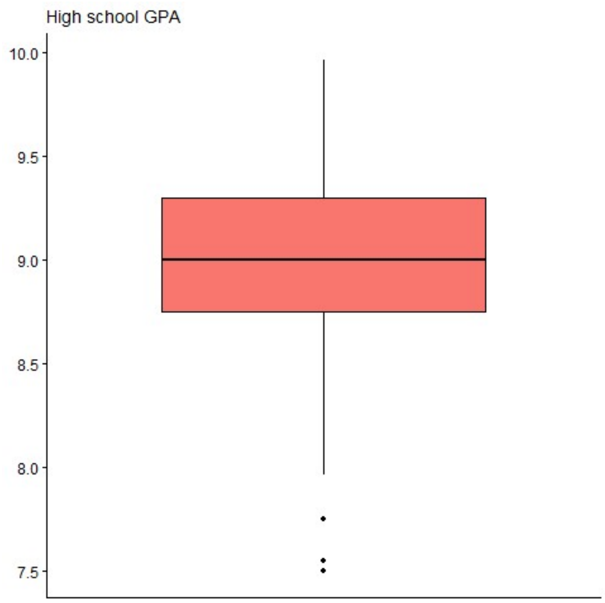

Figure 3. Distribution of high school GPA.

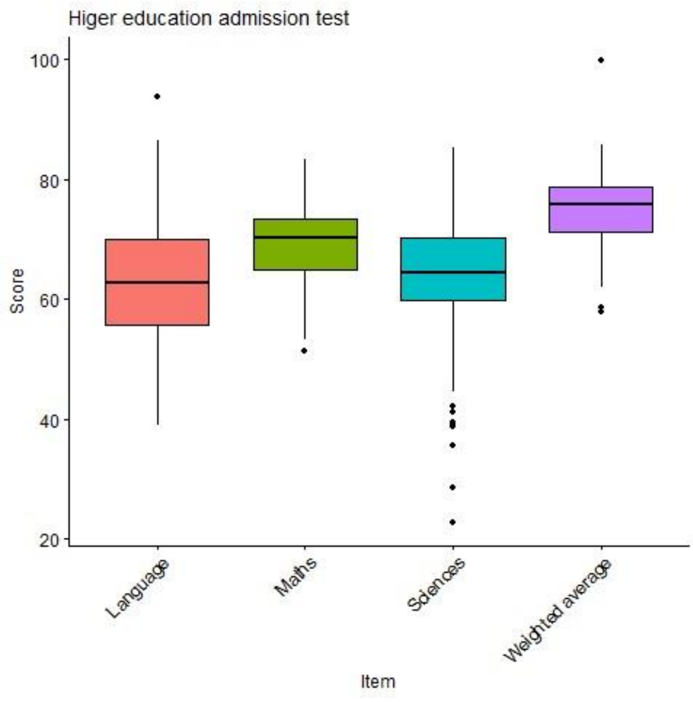

Figure 4. Distribution of higher education admission test scores.

As shown in Figure 5, final grades for all three courses and the first-semester GPA gather around 5.0 (the minimum grade required to pass). The highest variability can be found in Algebra I and, to a lower extent, Physics I. This variability mainly involves failing grades. It is worth noting that, in general, GPA is higher than the final grades in the reported courses, meaning that students had better grades in those courses that are specific to their programs.

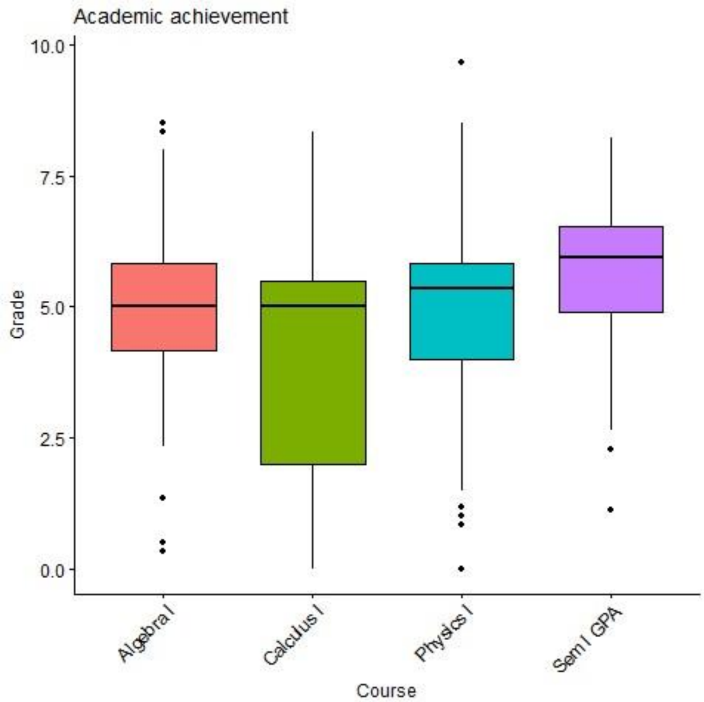

Figure 5. Distribution of final course grades and first-semester GPA.

Shapiro–Wilk normality tests found that only language and math admission test scores followed a normal distribution for a significance level of 0.05 (Table 3).

Table 3. Shapiro–Wilk normality tests for information competences, final course grades and GPA ($p < 0.05$ marked with *).

Feature	W	*p*
S_SEARCH	0.839	0.000 *
S_EVAL	0.904	0.000 *
S_TOT	0.875	0.000 *
O_SEARCH	0.980	0.027 *
O_EVAL	0.976	0.010 *
O_PROC	0.964	0.000 *
O_COM	0.952	0.000 *
O_TOT	0.978	0.015 *
SCHOOL_GPA	0.980	0.023 *
SCORE_LAN	0.993	0.716
SCORE_MAT	0.985	0.099
SCORE_SCI	0.933	0.000 *
SCORE_WAV	0.975	0.008 *
G_ALG	0.955	0.000 *
G_CAL	0.917	0.000 *
G_PHY	0.950	0.000 *
S1_GPA	0.965	0.001 *
S_SEARCH	0.839	0.000 *

Table 4 summarizes demographic and socioeconomic indicators both by sex and overall. It is interesting to note that 86.93% of the participants have achieved a fee exemption grant as is established in the Chilean law for higher education student funding [36]. Also, most students (57.52%) come from a school type frequently associated with a mid-low family income. Nearly half (54.25%) of the participants were admitted to the program of their preference, and this rate increases for female students (65.95%).

Table 4. Summary of demographic and socioeconomic indicators by sex and overall.

Feature	Level	Male n = 106	Female n = 47	Total n = 153
School type	Type 0	21.70%	23.40%	22.22%
	Type 1	57.55%	57.45%	57.52%
	Type 2	20.75%	19.15%	20.26%
Has fee exemption	Yes	87.74%	85.11%	86.93%
	No	12.26%	14.89%	13.07%
Program is first choice	Yes	49.06%	65.96%	54.25%
	No	50.94%	34.04%	45.75%

Similarly, Table 5 summarizes the final status (pass/fail) of participants in the three first-semester courses common to all undergraduate engineering programs, both by sex and overall. Although Physics I has a slightly lower pass rate than Algebra I and Calculus I, the pass rate is above 50% for all three courses. It is interesting to note that males have higher pass rates for both math courses, but females have higher pass rates in Physics I.

Table 5. Summary of course final status by sex and overall.

Course	Final Status	Male n = 106	Female n = 47	Total n = 153
Algebra I	Pass	65.09%	80.85%	69.93%
	Fail	34.91%	19.15%	30.07%
Calculus I	Pass	50.94%	72.34%	57.52%
	Fail	49.06%	27.66%	42.48%
Physics I	Pass	66.98%	59.57%	64.71%
	Fail	33.02%	40.43%	35.29%

3. Methods

The study for which the presented dataset has been gathered attempts to determine to what extent information competences can predict academic success. We first selected suitable instruments to measure such competences in students. Since we need to determine at-entrance IL, we selected instruments designed for secondary education. As mentioned earlier, two instruments were selected: one to assess self-perceived information competences [12,34] and the other to evaluate observed information competences [15,35]. Both instruments were designed in Spain. Hence, it was then necessary to make some adaptations for the Chilean context, which were validated by a panel of experts.

The adapted version of the instrument to measure self-perceived information competences comprised 9 statements for which participants had to indicate how much they agreed by using a 5-point Likert scale (1: totally disagree, 5: totally agree). The first 4 statements address information search competences, whereas the last 5 statements address those competences required to evaluate information. The final scores for each of these dimensions are calculated as the sum of the scores for all questions for each dimension. Similarly, the overall score is the sum of the scores for all 9 questions. It must be noted that the original instrument includes 18 questions and two more dimensions. However, two dimensions were excluded because they correspond to more general digital competences.

The instrument to assess observed information competences includes 18 close-ended questions. These questions are associated with various learning results in four dimensions: information search, information evaluation, information processing and information communication. Total scores for each dimension are normalized to range from 0 to 10. The overall score is the sum of the scores in all 4 dimensions.

Once the validation process was completed, both instruments were implemented as online surveys. Next, the study design and research protocol were approved on 19 January 2022, by the Institutional Ethics Committee No. 020/2022).

The overall questionnaire, implemented on LimeSurvey, consisted of 31 items including 2 agreement questions, 2 open-ended identification questions (national unique ID and university e-mail) and 27 close-ended questions.

Data collection was carried out in the following stages:

1. All students taking first- and second-year common courses for all 23 Engineering programs were invited to answer the survey. We obtained 195 complete answers.
2. Data were filtered to discard duplicates, students enrolled in non-engineering programs, students not in the cohorts of interest (2021 and 2022) and students who did not agree to participate in the study or did not authorize the use of their academic records.
3. Scores for both IL competences assessments were calculated.
4. Final grades for three common first-semester courses (Calculus I, Algebra I and Physics I), as well as the first-semester GPA were collected. After this stage, the resulting dataset contained 153 complete observations.
5. To ensure that individual students cannot be identified, we took several measures: (1) We pseudonymized the dataset by discarding personal information (national unique ID and e-mail), shuffling dataset rows and then adding a unique numeric row ID. (2) Data were then generalized by deleting answers for individual questions on the survey, keeping only the total scores per dimension and the overall totals. (3) Finally, course final grades, GPAs and higher education admission test scores were re-scaled.

4. User Notes

This article introduced a new dataset of first-semester course grades and both self-perceived and observed information competences for 153 first- and second-year Chilean engineering students.

Although IL has grown in importance during the past few decades, there is still no consensus about its importance for academic success and on how it relates to student dropout rates. As mentioned earlier in this article, to the best of our knowledge, most research in this field has been conducted by librarians who have attempted to assess the impact of an intervention, frequently for minority groups (e.g., [27,37–41]). The described dataset intends to let researchers further explore how IL and academic achievement are related, now incorporating machine learning methods into previously used quantitative tools.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and it was approved by the Ethics Committee of Universidad de Santiago de Chile (Ethical Report No. 020/2022, approved 19 January 2022).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The dataset is available in the Mendeley Data repository. Doi: http://dx.doi.org/10.17632/7r5fnrhyky.1.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. American Library Association Presidential Committee on Information Literacy: Final Report. Available online: https://www.ala.org/acrl/publications/whitepapers/presidential (accessed on 20 July 2019).
2. Bruce, C. The Seven Faces of Information Literacy. Available online: https://www.researchgate.net/publication/239229387_The_Seven_Faces_of_Information_Literacy (accessed on 4 April 2023).
3. Association of College and Research Libraries Information Literacy Competency Standards for Higher Education. 2000.
4. Bundy, A.L. *Australian and New Zealand Information Literacy Framework: Principles, Standards and Practice*, 2nd ed.; Australian and New Zealand Institute for Information Literacy: Adelaide, Australia, 2004.
5. Catts, R.; Lau, J. *Towards Information Literacy Indicators*; UNESCO: Paris, France, 2008; Available online: https://unesdoc.unesco.org/ark:/48223/pf0000158723 (accessed on 20 July 2019).
6. SCONUL. *National and University Libraries Perceptions of the SCONUL Seven Pillars of Information Literacy. A Brief Review*; SCONUL: London, UK, 2015.
7. Organization for Economic Cooperation and Development. *PISA 2015 Released Field Trial: Cognitive Items*; OECD: Paris, France, 2015.
8. Organization for Economic Cooperation and Development. Skills Studies. In *Skills Matter: Further Results from the Survey of Adult Skills*; OECD Publishing: Paris, France, 2016.
9. Organization for Economic Cooperation and Development. Statistics Canada. In *Literacy in the Information Age: Final Report of the International Adult Literacy Survey*; OECD Publishing: Paris, France, 2000.
10. Fraillon, J.; Ainley, J.; Schulz, W.; Duckworth, D.; Friedman, T. *IEA International Computer and Information Literacy Study 2018 Assessment Framework*; Springer: Cham, Switzerland, 2019; ISBN 978-3-030-19389-8.
11. Douglas, K.A.; Fernandez, T.; Purzer, Ş.; Fosmire, M.; Van Epps, A. A Self-Assessment Instrument to Assess Engineering Students' Self-Directedness in Information Literacy. In Proceedings of the 2015 IEEE Frontiers in Education Conference (FIE), El Paso, TX, USA, 21–24 October 2015; pp. 1–8.
12. García-Llorente, H.J.; Martínez-Abad, F.; Rodríguez-Conde, M.J. Evaluación de La Competencia Informacional Observada y Autopercibida En Estudiantes de Educación Secundaria Obligatoria En Una Región Española de Alto Rendimiento PISA. *Rev. Electrón. Educ.* **2020**, *24*, 24–40. [CrossRef]
13. Katz, I.R. Testing Information Literacy in Digital Environments: ETS's iSkills Assessment. *Inf. Technol. Libr.* **2007**, *26*, 3–12. [CrossRef]
14. Pinto, M. Design of the IL-HUMASS Survey on Information Literacy in Higher Education: A Self-Assessment Approach. *J. Inf. Sci.* **2010**, *36*, 86–103. [CrossRef]
15. Bielba Calvo, M.; Martínez Abad, F.; Herrera García, M.E.; Rodríguez Conde, M.J. Diseño de Un Instrumento de Evaluación de Competencias Informacionales En Educación Secundaria Obligatoria a Través de La Selección de Indicadores Clave. *Educ. Knowl. Soc.* **2015**, *16*, 124–143. [CrossRef]
16. Hollis, H.; Rachitskiy, M.; Leer, L. van der The Development and Face Validity Testing of the Open Test of Information Literacy with Context-Specific Add-Ons: OTIL. *LIBER Q. J. Assoc. Eur. Res. Libr.* **2019**, *29*, 1–21. [CrossRef]
17. Hahnel, C.; Eichmann, B.; Goldhammer, F. Evaluation of Online Information in University Students: Development and Scaling of the Screening Instrument EVON. *Front. Psychol.* **2020**, *11*, 562128. [CrossRef]
18. van Helvoort, J. A Scoring Rubric for Performance Assessment of Information Literacy in Dutch Higher Education. *J. Inf. Lit.* **2010**, *4*, 22–39. [CrossRef]
19. Coiro, J.; Kennedy, C. The Online Reading Comprehension Assessment (ORCA) Project: Preparing Students for Common Core Standards and 21st Century Literacies 2011. Available online: https://www.academia.edu/download/5672240/CCSS_ORCA_Alignment_June_2011.pdf (accessed on 22 July 2019).
20. González-Ibáñez, R.; Gacitúa, D.; Sormunen, E.; Kiili, C. NEURONE: oNlinE inqUiRy experimentatiON systEm. *Proc. Assoc. Inf. Sci. Technol.* **2017**, *54*, 687–689. [CrossRef]
21. González-Ibáñez, R.; Chourio-Acevedo, L.; Gacitúa, D.; Márquez, C.; Mellado, J.; Villarreal, F.; Becerra, C.; Köhler, J.; Proaño-Ríos, V.; Joglar, C.; et al. Let's Play: Toward an Effective Approach to Assess Online Inquiry Competences at School Level. In Proceedings of the 2021 40th International Conference of the Chilean Computer Science Society (SCCC), La Serena, Chile, 15–19 November 2021; pp. 1–8.
22. Catalano, A.J.; Phillips, S.R. Information Literacy and Retention: A Case Study of the Value of the Library. *Evid. Based Libr. Inf. Pract.* **2016**, *11*, 1–13. [CrossRef]
23. Ay, K.; Erdem, M. An Investigation on University Students' Online Information Search Strategies and Relationships with Some Educational Variables [Üniversite Öğrencilerinin Çevrimiçi Bilgi Arama Stratejileri ve Bazı Eğitimsel Değişkenlerle Ilişkilerinin Incelenmesi]. *Hacettepe Egitim Dergisi* **2020**, *35*, 843–857. [CrossRef]
24. Wittkower, L.R.; McInnis, J.W.; Pope, D.R. An Examination of Relationships Between Library Instruction and Student Academic Achievement. *J. Libr. Adm.* **2022**, *62*, 887–898. [CrossRef]
25. Jones, W.L.; Mastrorilli, T. Assessing the Impact of an Information Literacy Course on Students' Academic Achievement: A Mixed-Methods Study. *Evid. Based Libr. Inf. Pract.* **2022**, *17*, 61–87. [CrossRef]
26. Sharun, S. Enrollment in a Library Credit Course Is Positively Related to the College Graduation Rates of Full Time Students. *Evid. Based Libr. Inf. Pract.* **2015**, *10*, 156–157. [CrossRef]

27. Espe, T.W.; Dettman, D.M.; Noltze, M.; Harnett, D. Credit Score: Assessing a Library Course's Association with Graduation Rates and GPAs for at-Risk Students at a Regional Public University. *Coll. Undergrad. Libr.* **2021**, *28*, 243–252. [CrossRef]
28. Bacarrisas, H.P. College Student Self-Efficacy in Information Literacy: Influence on Their Research Academic Skills. *Br. J. Multidiscip. Adv. Stud.* **2023**, *4*, 12–19. [CrossRef]
29. Al-Fairouz, E.I.; Al-Hagery, M.A. Students Performance: From Detection of Failures and Anomaly Cases to the Solutions-Based Mining Algorithms. *Int. J. Eng. Res. Technol.* **2020**, *13*, 2895–2908. [CrossRef]
30. Baz, A.; Alshareef, F.; Alshareef, E.; Alhakami, H.; Alsubait, T. Predicting Students' Academic Performance Using Naïve Bayes. *Int. J. Comput. Sci. Netw. Secur.* **2020**, *20*, 182–190.
31. Pekuwali, A.A. Prediction of Student Learning Outcomes Using the Naive Bayesian Algorithm (Case Study of Tama Jagakarsa University). In Proceedings of the IOP Conference Series: Materials Science and Engineering, Kupang, Indonesia, 17–21 October 2020; Volume 823.
32. Köhler, J.; Hidalgo, L.; Jara, J.L. Using Machine Learning Techniques to Predict Academic Success in an Introductory Programming Course. In Proceedings of the 2022 41st International Conference of the Chilean Computer Science Society (SCCC), Santiago, Chile, 21–25 November 2022; pp. 1–8.
33. Shi, Y.; Sun, F.; Zuo, H.; Peng, F. Analysis of Learning Behavior Characteristics and Prediction of Learning Effect for Improving College Students' Information Literacy Based on Machine Learning. *IEEE Access* **2023**, *11*, 50447–50461. [CrossRef]
34. García Llorente, H.J.; Martínez Abad, F.; Rodríguez Conde, M.J. Validación de un Instrumento de Evaluación de Competencias Informacionales Autopercibidas en Educación Secundaria Obligatoria. *An. Doc.* **2019**, *22*, 1–14. [CrossRef]
35. Bielba Calvo, M.; Martínez Abad, F.; Rodríguez Conde, M.J. Validación psicométrica de un instrumento de evaluación de competencias informacionales en la educación secundaria. *Bordón Rev. Pedagog.* **2017**, *69*, 27–43. [CrossRef]
36. Ley N° 20.027 Establece Normas para el Financiamiento de Estudios de Educación Superior. 2005. Available online: https://transparenciaactiva.cultura.gob.cl/uploads2010/marcoNormativo/4f5e40ee9cff6525ebd2a7d4648f2ac77ce228e5.pdf (accessed on 13 April 2023).
37. Heady, C.; Morrison, M.M.; Vossler, J. Ecological Study of Graduation Rates and GPA in a Library Credit Course. *J. Acad. Librariansh.* **2018**, *44*, 642–649. [CrossRef]
38. Ahmed, S.T.; Roche, T. Making the Connection: Examining the Relationship between Undergraduate Students' Digital Literacy and Academic Success in an English Medium Instruction (EMI) University. *Educ. Inf. Technol.* **2021**, *26*, 4601–4620. [CrossRef]
39. Crawford-Visbal, J.L.; Crawford-Tirado, L.; Ortiz-Záccaro, Z.Z.; Abalo, F. Assessment of Digital Competences in Communication Students across Four Latin American Universities. *Educ. Knowl. Soc. (EKS)* **2020**, *21*, 14. [CrossRef]
40. Horn, A.; Maddox, A.; Hagel, P.; Currie, M.; Owen, S. Embedded Library Services: Beyond Chance Encounters for Students from Low SES Backgrounds. *Aust. Acad. Res. Libr.* **2013**, *44*, 235–250. [CrossRef]
41. Mortimore, J.M.; Wall, A. Motivating African-American Students through Information Literacy Instruction: Exploring the Link between Encouragement and Academic Self-Concept. *Ref. Libr.* **2009**, *50*, 29–42. [CrossRef]