AI and Data Literacy: A Disciplinary Divide

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ABSTRACT: Artificial intelligence (AI), data literacy now influences the study, work, and social life. However, little is known about the distribution of such capabilities within disciplines in developing-country contexts in universities. It was a cross-sectional study that involved 317 undergraduates of the University of Sargodha on self-judged proficiency, objective knowledge, and perceptions and exposure. Internal consistency was high in the questionnaire (Cronbachs =.90). Students expressed moderate confidence and strong interest in further learning. They had a weaker knowledge of the world. The self-assessed proficiency in female students was higher than in male students, $t(315) = -3.231$, $p = .001$, $d = 0.37$. The analysis provided did not show gender difference in objective knowledge and perceptions and exposure. The means of Science students were a little higher than Social Science students in each of the three measures, but none of the differences was statistically significant. Results do not indicate a definite disciplinary split. Instead they demonstrate a mutual desire towards more profound conceptual and critical study. A shared AI and data literacy base should be offered by universities, and related to the issues, skills, and ethical challenges of disciplines.

KEYWORDS: AI Literacy, Data Literacy, Higher Education, Gender, Academic Discipline

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Introduction

The knowledge production, communication, and evaluation processes are now influenced by artificial intelligence and data-intensive decision-making (Mubarak, 2026). Not only do university graduates need to use digital tools, but also to know how machine learning systems take in data, assess the reliability of machine-generated material, identify bias, safeguard privacy, and responsibly use evidence (Zhou et al., 2025). These expectations cross-cut across the professions. The social scientist familiar with the algorithmic classifications, the biologist operating with the predictive models, and the teacher assessing the generative content all need the functional combination of AI consciousness, data logic, as well as critical evaluation (Hackl et al., 2026).

Higher education has not been even-handed in reacting to this change. The courses offered by technical programs are more inclined to direct sightlines to the fields of computation and data, but students in the social sciences and humanities might be introduced to AI indirectly through research methods, communication platforms, research questions, or emergent professional practice (Yu et al., 2026). Such an imbalance may give the assumption that AI and data literacy owes all to disciplinary affiliation itself. However, regular access to generative AI, informal learning and the proliferation of easy-to-use tools may be helping to close the traditional divide, even as a lack of conceptual understanding still prevails (Battistig & Raffaghelli, 2026; Fu & Cao, 2026). This issue was explored in the current study at the University of Sargodha, a government-run institution with a heterogeneous undergraduate student body in Pakistan. It considered three related yet separate dimensions: self-reported AI and data literacy competence in students; objective knowledge of foundational concepts; and perceptions and exposure to AI and data literacy. It also tested the differences in these dimensions by gender and by broad academic discipline. The research hypothesized whether there is an expected Science- Social Science divide in the data and whether confidence corresponds to the realized knowledge. It adds value by combining self-report, knowledge items, curricular exposure, gender, and disciplinary comparisons into a one-place institution-level analysis that can be directly used to inform a curriculum plan.

Literature Review

AI Literacy as a Multidimensional Ability

AI literacy can be defined as an ability to comprehend, apply, challenge and discuss AI. It is distinctly different to the skill of coding. A student can comfortably utilize a chatbot and still fail to understand how models learn, where they get their output and why the results can be biased. Long and Magerko (2020) described AI literacy based on the following competencies: awareness of AI, its capabilities and restrictions, and assessment of impact. The field was subsequently organized around four related areas by Ng et al. (2021), who are knowing and understanding AI, using and applying AI, evaluating and creating with AI, and AI ethics. These descriptions set critical evaluation next to the application. According to the latest reviews, the concept is still developing. Almatrafi et al. (2024) discovered a wide consensus regarding technical knowledge, social consequences, and ethics; however, a smaller consensus regarding the inclusion of creation and advanced assessment in the basic AI literacy. Nearly the same conclusion was arrived at by Lintner (2024) when examining AI literacy scales. Available instruments vary in intent, sample, design, and demonstrations of soundness. There is no single measure that describes all the aspects. It is important for higher education research. A high rating of self could be familiarity, confidence, or use frequency and not secure knowledge.

Measuring Confidence and Knowledge

The combination of more than one form of evidence should therefore be applied in measurement. The Meta AI Literacy Scale divides AI literacy into understanding, use, detection, ethics, creation, self-efficacy, and self-management (Carolus et al., 2023). This modular design does not consider AI literacy a unified characteristic. An objective AI literacy test of university students was also designed by Hornberger et al. (2023). Their work demonstrates the usefulness of performance questions. They are able to bring into light the illusions that self-evaluation fails to pick up. A subsequent multinational study revealed that a large proportion of university students had only basic literacy in spite of high levels of interest and rather positive views on AI (Hornberger et al., 2025). Self-report remains valuable. Confidence, preparedness and perceived ability are captured. These are the factors which determine whether students will take part in new tools. However, self-report and performance provide answers to different questions. Confidence relates to what students think they are capable of doing. Objective items test their ability to demonstrate something under certain conditions. Solid research ought to keep these results apart. It must also check on the quality of items. When there are a small number of questions in a test, an objective score may be distorted by the use of ambiguous wording or weak distractors.

Critical Judgment and Data Literacy

AI literacy is based on data literacy. AI systems are learned with data, express trends in data and can recapitulate issues present in data. It is thus important that the student learns about sources, quality, uncertainty, privacy and representation. Data literacy involves data interpretation and application in an argument as well. A multidimensional Data Literacy Self-Efficacy Scale was validated by Kim et al. (2025) among university students. Their results affirm that there are multiple related skills to data literacy as opposed to having a single generic skill. Critical data literacy is more. It inquires about the data producer, the interests that lead to the analysis, and those who might suffer from a decision. According to Raffaghelli et al. (2020), universities ought to establish equitable data cultures both in teaching and institutional practice. This is a valuable strategy for AI education. Students should challenge prejudice, lack of data, false certainty, and social impacts of algorithms. These questions are applicable to science, social science, health, business, law and the humanities.

Curriculum, Exposure and Perceptions

Students have become acquainted with AI in formal courses, social media, commercial applications, and independent research. Familiarity can be achieved through informal use. It is not necessarily constructive for accurate perception. Chan and Hu (2023) determined that university students perceived educational and career advantages of generative AI to be clear. Accuracy, ethics, privacy, and the impact of AI on learning were also the concerns of the same students. The adoption, interaction, evaluation, and ethical awareness were demonstrated by Chen et al. (2024) to develop unevenly as well. The frequent use should not be considered as evidence of literacy. The universities require a response plan. Southworth et al. (2023) suggested an AI-across-the-curriculum guiding model, which is a combination of common ideas and discipline-specific uses. This prevents two feebleminded extremes. Computer science should not be seen as the only AI education. It must also not turn out to be a generic workshop that has minimal relation to the areas of students. Mechanisms, data, verification, bias, privacy and responsible use can be covered by a common ground. The departments can then implement these concepts in their own evidence, work, and standards.

Gender and Disciplinary Context

The results of gender in technology studies are not completely clear due to the interplay of confidence, access, social expectations, and previous experience. Self-assessment differences are not necessarily differences in knowledge. It can be a confidence calibration or engagement patterns. This is why gender comparisons need to be reported on perceived proficiency and the objective performance separately. They must also provide effect sizes and not just p-values. Different cultures of knowledge and use of tools are developed by academic disciplines. Qu et al. (2024) discovered that the use of generative AI among students was different in tasks and fields. Other fields made more use of AI to analyze, whereas others would make use of it to write or develop an idea. These discrepancies might mediate exposure without a significant discrepancy in general literacy scores. Another study conducted by Kong et al. (2024) demonstrated the possibility of AI-based problem-based learning that integrates knowledge and application, evaluation, and ethics to cultivate AI literacy. It is not merely a question of whether the students of Science know more or not. It is also a question of whether every student is sufficiently familiar with AI to be able to apply AI skeptically in their disciplines or not.

The majority of AI literacy data has been found in technologically advanced environments or in special courses. There is little evidence on the basis of the public universities in Pakistan. As well, there is a necessity for studies that will compare confidence, objective knowledge and perceptions within the same sample. This gap is being filled in the present study. It explores gender and general disciplinary differences in three outcomes. It also proves the widespread belief that Science students have a definite edge over Social Science students.

Research Methodology

This research employed a quantitative cross-sectional survey at the University of Sargodha, Pakistan. A sample was taken with a total of 317 undergraduates (141 men and 176 women). Among them, 133 were studying the subjects of Science and 184 were studying the subjects of Social Science. Three outcomes were measured with the use of a structured questionnaire. Ten Likert items with five points measured self-reported AI and data literacy proficiency. Basic objective knowledge was measured by eight multiple-choice items. Another 10 Likert-scale items were used to measure perceived relevance, curricular exposure, faculty guidance and interest in additional training. The questionnaire was content-checked and pilot tested to check its clarity. It had a high overall internal consistency (Cronbach 3 = .90). Since the items were locally assembled, the instrument is said to perform well in this sample, but not as a whole validated standardization scale. The responses were summarized using frequencies, percentages, means, and standard deviations. The scores were compared (independent-samples t-tests) by gender and by academic discipline. The desired p-value was $p < .05$. Only self-assessed proficiency had the full range of gender statistics supplied. It declared that the other two gender comparisons were insignificant without giving their numerical test value. Estimation of those values was not made. The three comparisons of disciplines were included. It is cross-sectional; therefore, it finds out the patterns of the groups but cannot determine the causes.

Results and Analysis

Self-Assessed AI & Data Literacy Proficiency

Table 1

Self-Assessed AI & Data Literacy Proficiency

No.	Item	SD	D	N	A	SA	mean	SD
1	Explain AI	13 4.1%	12 3.8%	91 28.7%	175 55.2%	26 8.2%	3.60	.854
2	Understand algorithm learning	18 5.7%	50 15.8%	85 26.8%	156 49.2%	8 2.5%	3.27	.952
3	Identify bias/limitations	7 2.2%	45 14.2%	93 29.3%	160 50.5%	12 3.8%	3.39	.856
4	Use basic AI tools	9 2.8%	28 8.8%	51 16.1%	180 56.8%	49 15.5%	3.73	.925
5	Evaluate AI output	10 3.2%	24 7.6%	76 24.0%	179 56.5%	28 8.8%	3.60	.871
6	Understand data concepts	11 3.5%	13 4.1%	81 25.6%	183 57.7%	29 9.1%	3.65	.838
7	Interpret charts/statistics	6 1.9%	15 4.7%	96 30.3%	165 52.1%	35 11.0%	3.66	.810
8	Understand privacy/security	6 1.9%	18 5.7%	69 21.8%	188 59.3%	36 11.4%	3.73	.810
9	Adapt to new AI	10 3.2%	15 4.7%	77 24.3%	187 59.0%	28 8.8%	3.66	.830
10	Find/use relevant data	11 3.5%	17 5.4%	50 15.8%	208 65.6%	31 9.8%	3.73	.843

The students rated their competencies in a positive manner. The strongest mean ratings were recorded for using basic AI tools, understanding privacy and security, and finding and using relevant data (all M = 3.73). The lowest scores were related to the knowledge of AI algorithm learning (M = 3.27, SD =.952) and the discovery of bias or limitations (M = 3.39, SD =.856). In this way, real-life comfort and overall data confidence were enhanced over more profound conceptual or critical knowledge. The unweighted average of the reported item means across the ten items was 3.64, suggesting moderately positive self-perceptions but not equal opportunity to show improved proficiency.

Objective AI & Data Literacy Knowledge

Table 2

Objective AI & Data Literacy Knowledge

Knowledge item	Keyed option	Selected %
Definition of AI	B	67.2
Ethical concern: bias/discrimination	B	53.9
Meaning of machine learning	B	55.8
Confidently stated factual error	C	20.2
Daily AI application	D	47.0
Meaning of data literacy	B	61.8
Fair AI decision-making	B	53.3
Data-quality challenge	B	54.9

Note. Percentages reproduce the supplied response table.

There was inequitable performance in terms of objectivity. 67.2% of students picked the intended definition of AI. 1.8% were correct in data literacy. Machine learning, bias, fairness, and data quality had correct responses of between 53.3 and 55.8 percent. In the case of Item 4, the response with 20.2% was Fantasy (AI hallucination). The average percentage of the eight item-level correct responses was 51.8%. This is below the trend of self-rating. The contrast indicates that familiarity with AI tools is not necessarily based on trustworthy knowledge of concepts.

Perceptions and Exposure to AI & Data Literacy

Table 3

Perceptions and Exposure to AI & Data Literacy

No.	Item	SD	D	N	A	SA	mean	SD
1	Career relevance	14 4.4%	17 5.4%	93 29.3%	171 53.9%	22 6.9%	3.54	.873
2	Impact on field	16 5.0%	20 6.3%	92 29.0%	149 47.0%	40 12.6%	3.56	.965
3	Program prepares AI use	7 2.2%	26 8.2%	104 32.8%	151 47.6%	29 9.1%	3.53	.855
4	Program prepares evaluation	6 1.9%	45 14.2%	98 30.9%	142 44.8%	26 8.2%	3.43	.900
5	Ethics in coursework	7 2.2%	40 12.6%	99 31.2%	144 45.4%	27 8.5%	3.45	.898
6	Department encourages AI	7 2.2%	36 11.4%	102 32.2%	141 44.5%	31 9.8%	3.48	.899
7	Professors can guide AI use	15 4.7%	24 7.6%	115 36.3%	137 43.2%	26 8.2%	3.43	.920
8	External AI learning	10 3.2%	36 11.4%	100 31.5%	136 42.9%	35 11.0%	3.47	.943
9	Interest in more training	8 2.5%	30 9.5%	74 23.3%	165 52.1%	40 12.6%	3.63	.911
10	Essential for all majors	16 5.0%	29 9.1%	68 21.5%	141 44.5%	63 19.9%	3.65	1.056

Gender differences in Self-Assessed AI & Data Literacy Proficiency

Table 4

Gender differences in Self-Assessed AI & Data Literacy Proficiency

Variable	Gender	n	mean	SD	df	t	p
Self-Assessed AI & Data Literacy Proficiency	Male	141	34.93	5.88	-3.231	315	.001
	Female	176	36.88	4.87			

Female students reported higher self-assessed proficiency (M = 36.88, SD = 4.87) than male students (M = 34.93, SD = 5.88). The 1.95-point difference was statistically significant, $t(315) = -3.231$, $p = .001$. Standardized mean difference using the pooled standard deviation was approximately $d = 0.37$, which is a small-to-moderate effect. The analysis provided indicated that there was no significant difference between genders in objective knowledge or perceptions and exposure, since the means and test statistics of the groups together in the analysis were omitted.

Academic Discipline Divide

Table 5

Academic Discipline Divide

Variable	Gender	n	mean	SD	df	t	p
Self-Assessed AI & Data Literacy Proficiency	Science	133	36.69	5.66	1.924	315	.055
	Social Science	184	35.57	5.21			
Objective AI & Data Literacy Knowledge	Science	133	35.83	6.01	1.778	315	.076
	Social Science	184	34.70	5.22			
Perceptions and Exposure to AI & Data Literacy	Science	133	18.93	2.54	1.461	315	.145
	Social Science	184	18.47	2.97			

The numerically higher means of the three measures were statistically significant in science students, although none of the differences was below the.05 significance level. Self-assessed proficiency approached significance, $t(315) = 1.924$, $p = .055$, as did objective knowledge, $t(315) = 1.778$, $p = .076$; perceptions and exposure showed a smaller difference, $t(315) = 1.461$, $p = .145$. In line with this, there is no statistically reliable Science-Social Science divide in this sample. The near-threshold p values ought not to be re-packaged into significance; they actually encourage replication with a clearer scoring of constructs and larger samples.

Discussion

There is no evident disciplinary division in the results. The means of science students were a bit higher on all three measures, but the p values were all above.05. The simplest answer is that there is no statistically valid evidence in this sample that Science students were more AI and data literate than Social Science students. This outcome is important since higher educational institutions tend to believe that technical subjects have such abilities whilst other subjects do not. A higher significance pattern can be observed in the three measures. Students were quite confident. They were familiar with simple AI tools and utilizing information. Artificial intelligence was also viewed by them as career-relevant. There was less strength of objective knowledge. The average correct-response percent in the eight items was approximately 51.8%. The lack of confidence in the false output was least secure among the students. This difference cannot be termed as evidence of overconfidence on an individual level since the research did not match each student's self-rating with the individual test results. At the group level, though, it does indicate that there was positive confidence that co-existed with unequal knowledge. Such a difference suits the present-day theory.

Long and Magerko (2020) and Ng et al. (2021) consider AI literacy to be the combination of understanding, use, assessment, and ethics. The model of ease of use takes only a fraction of that. The same is stated in the measurement literature. Carolus et al. (2023) make a distinction between literacy and self-efficacy, whereas Hornberger et al. (2023) conduct objective testing to determine real knowledge. The review by Lintner (2024) cautions that there is no uniformity in instruments and they should not be used as substitutes. The current results favour an ambivalent methodology. Universities must quantify what students think, what they know and what they do. The attitudes of the students provide a handy point of departure. There was a high interest in other courses. The majority also assumed that AI literacy is important in majors. Ratings of faculty instruction, morality talk, and readiness to assess AI outputs were, however, more circumspective. There was also an appreciation of enthusiasm and concern found by Chan and Hu (2023). This is also demonstrated by Chen et al. (2024), who showed that use, evaluation, and ethical awareness are not built at a similar rate. Institutions must capitalize on student interest; however, institutions must not confuse interest with readiness. The gender outcome must be presented with delicate wording. Women had more self-rated proficiency as compared to men. The statistical significance was small to medium, and the effect $d = 0.37$.

The analysis provided did not report any gender variations in objective knowledge or perceptions and exposure. This implies that the difference was in terms of perceived proficiency and not the knowledge demonstrated. It is not to be defined as a statement that either of the genders is more inherently gifted. It may include confidence, previous experience, classroom atmosphere, as well as tool-use patterns. These explanations cannot be separated using the current data. The disciplinary outcomes are also more suitable than a STEM benefit. Qu et al. (2024) discovered that disciplines determine the tasks students apply generative AI to. That can alter the nature of interaction without making much differentiation in overall literacy. Informal access can also generate an overlaying floor of fields. Simultaneously, the oversized Science and Social Science can conceal variations within the departments. Computer Science, Biology, Psychology and English are not exposed to the same or have the same evidence practices. This point should be kept in the future. The results lead to an AI-across-the-curriculum model. Southworth et al. (2023) suggest common principles and practices, along with discipline. The latter method is suitable for this sample. All students should have a fundamental description of how models learn, how training data influence output, why AI may be misguided and how bias and privacy threats occur. Repeated practice in source checking and describing the situations when AI is suitable is also required of students. These skills can then be applied by the departments to cases that are specific to the field. Data literacy cannot exist in this curriculum, but in addition to it. Unless the students are able to question the data quality, representation, uncertainty, or provenance, they cannot judge AI. Raffaghelli et al. (2020) put these questions in the context of a broader culture of fairness and responsibility. Kim et al. (2025) indicate that data literacy in itself has its competencies. A good curriculum must thus be based on a strong technical explanation coupled with critical reading, ethical reasoning and real-life decision-making.

Limitation

There are definite limitations to the study. It is based on a single university and was cross-sectional. The division into general categories of disciplinary trends can mask the patterns at the department. For Objective AI & Data Literacy Knowledge and Perceptions and Exposure to AI & Data Literacy, gender tests showed no significant difference. It was a short objective test. The internally consistent locally assembled questionnaire had strong internal consistency, but reliability does not determine construct validity. These boundaries define interpretations of results.

Conclusion and Recommendations

The research focused on AI and data literacy of 317 undergraduates at the University of Sargodha. The self-assessed proficiency among women was high as compared to men. In the analysis provided, there was no gender difference in objective knowledge or perceptions and exposure. The means of the science students were a bit higher in comparison to the Social Science students; however, none of the disciplinary differences was significant. The data does not, however, indicate an existing disciplinary divide. The more serious issue is the one that is shared between groups. Students had an interest in AI and were mostly confident, but objective knowledge was uneven. The reaction by universities must be to a shared AI and data literacy base for all undergraduates. It should provide a critical examination of underlying mechanisms, data quality, algorithmic bias, fairness, privacy, verification procedures, and principles of responsible disclosure. Short workshops are a good thing, but not sufficient. These concepts must be reflected in classes, homework, and exams. Discipline-specific teaching should then take place. Students of science may try models and check the quality of data. Social Science students could check the workings of algorithms, observe social implications, or analyze AI-generated assertions. The area of faculty development is crucial in both aspects. The instrument must be validated in future research; stronger objective items need to be used; confidence intervals and effect sizes need to be reported on all tests, and departments in multiple universities should be compared. Longitudinal studies are needed on whether structured teaching is better in imparting knowledge and the reduction of the gap between confidence and performance.

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