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The Impact of Generative Artificial Intelligence on Decision-Making, Employment Perceptions and Future Skill Readiness: A Comparative Study of Students and Working Professionals

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Abstract - *Generative artificial intelligence (GenAI) tools have become part of everyday study and work, yet little is known about how users themselves judge their effect on decision-making, employment prospects and readiness for an AI-shaped workplace. This study reports a questionnaire survey of 145 respondents (85 students, 40 working professionals and 20 who were both), all of whom had used GenAI. Responses were analysed with descriptive statistics, composite scales for decision-making (α = 0.69), employment outlook (α = 0.84) and skill readiness (α = 0.90), non-parametric group comparisons with Holm correction, rank correlations, regression checks and thematic analysis of open-ended answers. Respondents reported that GenAI speeds up decisions (84.1% agreed) and that combining it with human judgment improves them (97.9%); 87.6% said they verify AI output before important decisions. Employment views were mixed rather than polarised: 69.7% held that GenAI both creates and replaces jobs, and 95.2% expected workers in their field to need new skills. Readiness was moderate (mean 3.41 of 5), and only 4.1% agreed that their institution or workplace provides adequate AI training. Professionals reported more verification and less uncritical acceptance of AI output than students, but most of these gaps weakened or disappeared after adjusting for duration of AI use and field of study, which were stronger correlates of readiness. The findings point to structured AI-literacy training, routine verification practices and field-sensitive upskilling. Because the sample is non-probability and cross-sectional, the results are associations rather than causal effects.*

Key Words: Generative Artificial Intelligence, Decision-Making, Employment Perceptions, Skill Readiness, Students, Working Professionals, AI Literacy, Survey Research.

1. INTRODUCTION

Generative artificial intelligence refers to models that produce text, code, images or other content in response to a prompt. Large language models built on the transformer architecture have made this capability widely accessible through chat-style tools [1]. Adoption has been unusually fast: nationally representative survey evidence from the United States shows generative AI reaching a large share of the working-age population within two years of public release [2]. Students use these tools to study and research, while professionals use them to write, analyse data and write code.

Experimental and field evidence suggests that the tools can raise productivity on well-defined tasks. In an online experiment on professional writing tasks, access to ChatGPT reduced completion time and raised rated quality [3]. In a customer-support setting, access to an AI assistant raised the number of issues resolved per hour, with the largest gains among less experienced workers [4]. A field experiment with consultants, however, found that performance improved inside the boundary of what the model could do well and deteriorated for a task placed just outside it [5]. How people decide when to trust AI output therefore matters as much as access to the tools.

Two further concerns frame this study. First, generative models can produce fluent but incorrect statements [6], and human users are known to over-rely on automated advice [7], [8]. Second, analyses of task exposure suggest that a substantial share of occupations contain tasks that language models could perform or speed up [9], [10], which has made employment and skills a central question for people entering or already in the workforce. Much of the evidence above comes from experiments or economic datasets. Fewer studies ask users in education and in employment, side by side, how they perceive the effect of GenAI on their own decisions, their field and their preparedness.

This paper addresses that gap with a survey of 145 GenAI users who were students, working professionals or both. It examines (i) how respondents use GenAI, (ii) how they describe its effect on their decision-making, (iii) how they view its effect on employment, and (iv) how ready they feel and what they want to learn, and it compares students with working professionals while accounting for differences in field and experience.

2. LITERATURE REVIEW

2.1 GenAI and Decision-Making

Studies of algorithmic advice show two opposite tendencies. People may discount an algorithm after seeing it err [11], yet in other settings they prefer algorithmic advice to advice from other people [12]. The automation-bias literature documents omission and commission errors when users follow automated cues without checking them, and identifies system design and user training as mitigating factors [7], [8]. For generative models the risk is sharpened by hallucination, where output is fluent but unsupported by the source or by fact [6]. The practical question is whether users build verification habits that match the strength of their reliance.

2.2 GenAI and Employment

Early estimates of computerisation risk assigned a large share of occupations to high-probability categories [13], while task-based accounts stress that technology both displaces tasks and creates new ones [14], [15]. For language models specifically, exposure estimates indicate that higher-wage and higher-education occupations are not shielded [9], [10]. Employer surveys likewise anticipate substantial change in the skills that jobs require [16]. These sources describe exposure and expectations; they do not tell us how workers and students perceive the trade-off between displacement and opportunity.

2.3 Skills, Education and Training

Reviews of AI in higher education point to opportunities for personalised support alongside risks to assessment integrity and over-reliance, and they call for educators to be involved in how tools are adopted [17], [18]. If institutions do not provide structured guidance, learners and employees are left to build AI skills informally, and the quality of that learning becomes uneven.

2.4 Research Gap

Existing work rarely measures decision-making behaviour, employment perceptions and skill readiness in the same instrument, and it seldom compares students with working professionals. This study does so, and reports how far apparent group differences are explained by field and by how long respondents have used GenAI.

3. PROBLEM STATEMENT

GenAI is being adopted faster than formal training and policy can follow. It is not clear how users judge their own decisions when AI is involved, whether they expect jobs to be created or replaced, how prepared they feel, and whether students and working professionals differ. This research asks how GenAI users describe the effect of these tools on decision-making, employment and skill readiness, and which respondent characteristics are associated with those views.

4. OBJECTIVES

- To describe how students and working professionals use generative AI tools.
- To assess self-reported effects of GenAI on the speed, quality and verification of decisions.
- To examine perceptions of GenAI's effect on jobs, career prospects and required skills.
- To measure self-rated skill readiness and perceived adequacy of AI training.
- To compare students and working professionals, and to test whether differences persist after accounting for field of study and duration of GenAI use.
- To identify the preparation strategies respondents recommend for an AI-driven future.

5. RESEARCH METHODOLOGY

5.1 Research Design

The study is a cross-sectional, descriptive and comparative questionnaire survey. The workflow is shown in Figure 1: questionnaire design, respondent data, cleaning and coding, descriptive analysis, construct scoring and reliability, group comparison, association and field analysis, and thematic analysis of the open-ended answers.

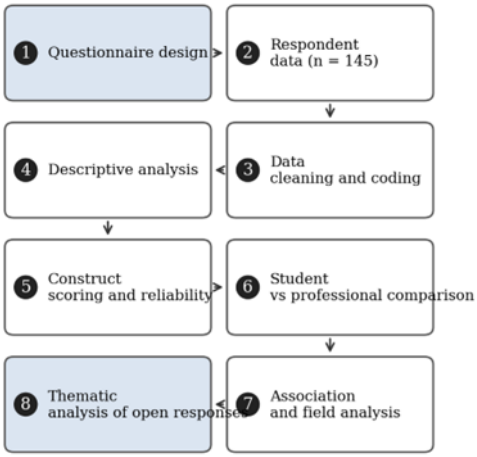


Figure 1. Research workflow

5.2 Questionnaire

The questionnaire opened with a consent item (18 years or older, study information read, participation voluntary). It then collected current status (student, working professional or both), age group, gender (optional), highest qualification and field of study or work; GenAI use (ever used, tools, frequency, purposes and duration); sixteen five-point Likert

statements (1 = strongly disagree to 5 = strongly agree); three single-choice questions (AI skill most wanted, view of AI and employment, biggest concern); and one optional open-ended question on how students and professionals can prepare for an AI-driven future. The sixteen statements form three constructs (Table 1). The item on accepting recommendations without evaluation was reverse-scored when computing the decision-making composite. Item wording is given in Table 3.

Table 1. Constructs and internal consistency

Construct	Items	Cronbach's α	Mean (SD)
Decision-making (DM1–DM6)	6	0.69	3.90 (0.37)
Employment outlook (EO1–EO5)	5	0.84	3.86 (0.47)
Skill readiness (SR1–SR5)	5	0.90	3.41 (0.54)

DM4 reverse-scored in the composite. Alpha for decision-making is moderate; its composite is treated as indicative.

5.3 Respondents and Data

The analysed dataset holds 145 complete records with no missing values on any item; all 145 respondents answered the optional open-ended question. All respondents affirmed the consent statement and all reported having used GenAI, so the results describe GenAI users only. The dataset analysed contains no names or contact details. Respondents were not drawn from a probability sampling frame, so the sample is treated as a non-probability sample and the results are not generalised to a wider population.

5.4 Data Analysis

Analyses were run in Python (pandas, SciPy, statsmodels). Likert items were treated as ordinal [19], [20], [21]: item results are reported as the share agreeing (rating 4 or 5) with Wilson 95% confidence intervals [22], with means and standard deviations given for comparability. Internal consistency was estimated with Cronbach's α [23]. Students and working professionals were compared with the Mann–Whitney U test [24], with Cliff's δ as the effect size [25] and Holm correction across the sixteen items [26]; the 20 respondents who were both students and professionals are reported descriptively and included in Kruskal–Wallis tests [27]. Because several contingency tables had small expected counts, chi-square statistics were assessed with Monte Carlo permutation p-values (5,000 permutations) and reported with Cramér's V. Spearman rank correlations described associations. Ordinary least squares models with heteroscedasticity-robust (HC3) errors served as a sensitivity check for group differences. Bootstrap 95% confidence intervals (5,000 resamples) were computed for composite means. Open-ended answers were read in full and each was assigned to one dominant theme in a six-category codebook developed from the responses, following the general approach of thematic analysis [28].

6. RESPONDENT PROFILE

Table 2. Profile of respondents (N = 145)

Characteristic	n	%
Current status		
Student	85	58.6
Working professional	40	27.6
Both	20	13.8
Age group (years)		
18–21	24	16.6
22–25	81	55.9
26–30	22	15.2
31–40	18	12.4
Gender (optional)		
Male	79	54.5
Female	58	40.0
Prefer not to say	8	5.5
Highest qualification		
Undergraduate	43	29.7
Postgraduate	96	66.2
Doctorate / PhD	6	4.1
Field of study / work		
IT / Computer Science	73	50.3
Business / Management	20	13.8
Engineering	15	10.3
Healthcare / Life Sciences	14	9.7
Finance / Accounting	13	9.0
Social Sciences / Humanities	10	6.9

Percentages may not sum to 100 because of rounding.

The profile is summarised in Table 2. Students formed the largest group (58.6%), followed by working professionals (27.6%) and respondents who were both (13.8%). Status and age were closely aligned: all working professionals were aged 26–40, all respondents who were both were aged 22–25, and all students were aged 18–25. Two-thirds held a postgraduate qualification (66.2%) and half studied or worked in IT or Computer Science (50.3%). The groups differed in composition. IT/CS accounted for 55 of 85 students (64.7%) but only 9 of 40 professionals (22.5%). Professionals also had used GenAI for longer: 24 of 40 (60.0%) had used it for more than two years, compared with

24 of 85 students (28.2%), and none of the professionals but 19 students (22.4%) had used it for less than a year. These differences are taken into account in Section 7.5.

7. RESULTS AND ANALYSIS

7.1 Patterns of GenAI Use

Use was frequent: 72 respondents (49.7%) used GenAI daily, 60 (41.4%) several times a week and 13 (9.0%) weekly. Most had used it for one to two years (46.9%) or longer (38.6%); 14.5% had used it for three to twelve months. ChatGPT had been used by 144 respondents (99.3%), followed by Claude (44.8%), Copilot (44.1%), Gemini (33.1%) and Perplexity (33.1%) (Figure 2a). Research (63.4%) and study (62.1%) were the most common purposes, followed by coding (46.9%), work productivity (44.8%) and writing (43.4%); career planning (7.6%) and personal use (6.2%) were rare (Figure 2b).

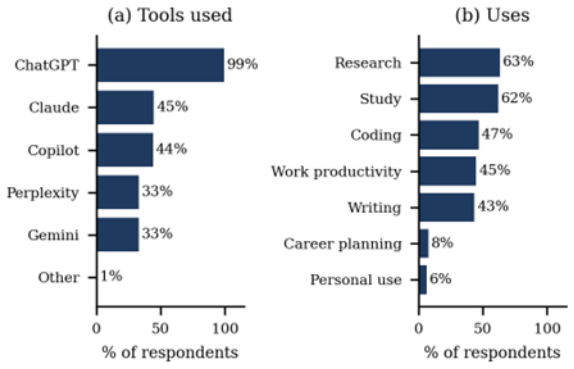


Figure 2. (a) Tools used and (b) purposes of use (multiple responses allowed)

Purposes reflected status. Study was named by 80 of 85 students (94.1%) and by no professional, whereas work productivity was named by 29 of 40 professionals (72.5%) against 25 of 85 students (29.4%), and writing by 55.0% against 36.5%. Gemini had been used by 47.1% of students but 5.0% of professionals. Students reported more distinct purposes on average than professionals (2.88 vs 2.28; Kruskal–Wallis across the three groups, $p < .001$).

7.2 Decision-Making

Respondents were more positive about speed than about quality (Table 3, Figure 3). A total of 122 (84.1%; 95% CI 77.3–89.2) agreed that AI helps them decide faster, but fewer, 94 (64.8%; 56.8–72.1), agreed that it improves decision quality. Verification was reported as a norm: 127 respondents (87.6%; 81.2–92.0) agreed that they verify AI-generated information before important decisions, and only 10 (6.9%; 3.8–12.2) agreed that they sometimes accept recommendations without independent evaluation. Almost all (142; 97.9%; 94.1–99.3) agreed that combining AI assistance with human judgment improves their decisions, and 62.1% felt confident deciding without AI. No respondent rated the speed, quality, verification or human-plus-AI statements below 3.

Table 3. Item statistics (N = 145)

Code	Statement	Mean (SD)	% agree
DM1	AI helps me make decisions faster.	4.10 (0.64)	84.1
DM2	AI improves the quality of my decisions.	3.68 (0.54)	64.8
DM3	I verify AI-generated information before important decisions.	4.09 (0.58)	87.6
DM4	I sometimes accept AI recommendations without independently evaluating them.	2.35 (0.75)	6.9
DM5	I feel confident making decisions without AI.	3.60 (0.53)	62.1
DM6	Combining AI assistance with human judgment improves my decisions.	4.28 (0.50)	97.9
EO1	AI could automate some tasks in my current or intended occupation.	3.88 (0.63)	73.1
EO2	I am concerned that AI may reduce opportunities in my field.	3.36 (0.62)	39.3
EO3	AI can create new career opportunities.	3.92 (0.60)	77.9
EO4	Workers in my field will need to update their skills due to AI.	4.30 (0.55)	95.2
EO5	AI will significantly change my career prospects in the next five years.	3.86 (0.59)	74.5
SR1	I understand the basic capabilities and limitations of generative AI.	3.66 (0.56)	61.4
SR2	I can assess whether AI-generated information is reliable.	3.45 (0.55)	44.8
SR3	I am actively developing AI-related skills.	3.79 (0.76)	64.1
SR4	I feel prepared to use AI in my current or future occupation.	3.63 (0.71)	55.2
SR5	My institution or workplace provides adequate AI-related training.	2.55 (0.61)	4.1

% agree = ratings 4–5. DM4 is shown un-reversed.

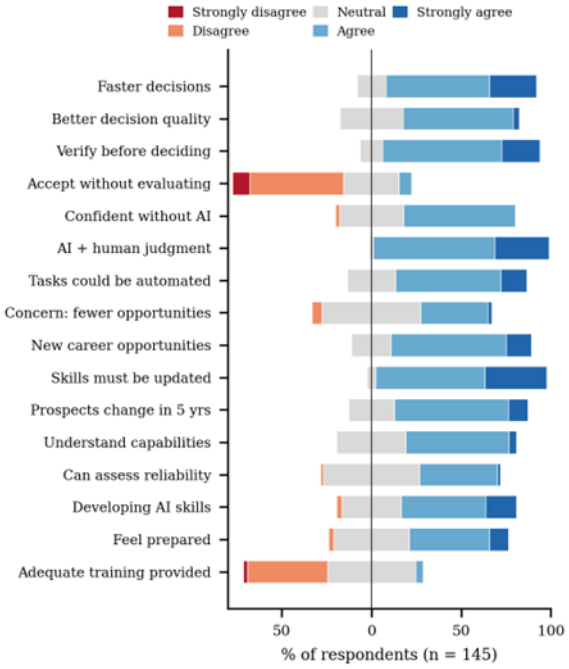


Figure 3. Distribution of responses to the 16 Likert statements

7.3 Employment Perceptions

Respondents saw both exposure and opportunity. Most agreed that AI could automate some tasks in their current or intended occupation (106; 73.1%) and that it can create new career opportunities (113; 77.9%). Concern about reduced opportunities in their own field was less common: 57 respondents (39.3%; 31.7–47.4) agreed, 80 were neutral and 8 disagreed. Nearly all (138; 95.2%) expected workers in their field to need new skills, and 108 (74.5%) expected AI to change their career prospects significantly within five years. On the summary question, 101 respondents (69.7%) chose "both creates and replaces jobs", 25 (17.2%) "mainly creates opportunities", 11 (7.6%) "mainly replaces jobs", 6 (4.1%) "little impact" and 2 (1.4%) "unsure". When asked for their biggest concern, respondents named overdependence most often (45; 31.0%), ahead of job displacement (32; 22.1%), privacy (27; 18.6%), inaccurate information (20; 13.8%), lack of accountability (11; 7.6%) and bias or discrimination (10; 6.9%).

7.4 Skill Readiness

Readiness was moderate (composite mean 3.41 of 5; 95% bootstrap CI 3.33–3.50). Some 89 respondents (61.4%) said they understand the basic capabilities and limitations of GenAI, 93 (64.1%) were actively developing AI skills and 80 (55.2%; 47.0–63.0) felt prepared for their current or future occupation. Fewer, 65 (44.8%), said they can assess whether AI-generated information is reliable. Respondents therefore verify (87.6%) more often than they feel able to judge reliability (44.8%). Training was the weakest point: only 6 respondents (4.1%; 1.9–8.7) agreed that their institution or workplace provides adequate AI training, while 68 (46.9%) disagreed. The skill most wanted was AI-assisted data analysis (49; 33.8%), followed by programming with AI (36; 24.8%), prompting (21; 14.5%), productivity automation (21; 14.5%) and AI ethics (18; 12.4%).

7.5 Students and Working Professionals

Composite scores are shown in Figure 4 and item-level tests in Table 4. Working professionals scored higher than students on the decision-making composite (4.07 vs 3.79; U = 990, p < .001, δ = −0.42). The employment-outlook composite was somewhat higher for students (3.90 vs 3.73; p = .046, δ = 0.22), a difference that is small and was not corrected for multiple testing. Skill readiness did not differ (3.37 vs 3.42; p = .83). The two groups also agreed that training is inadequate (2.52 vs 2.53; p = .86).

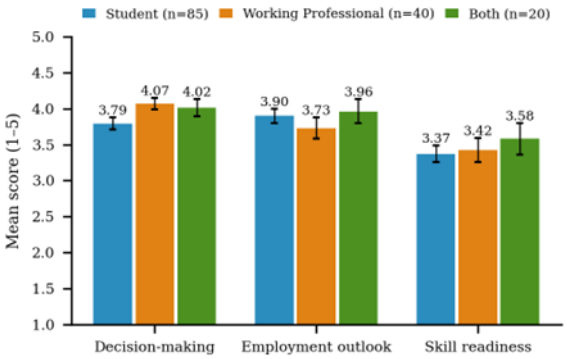


Figure 4. Composite scores by status (means with 95% bootstrap CIs)

Table 4. Students vs working professionals (item level)

Item	Student	Prof.	p	p (Holm)	Cliff's δ
DM1 Faster decisions	4.09	4.08	.856	1.000	0.02
DM2 Decision quality	3.61	3.78	.091	.996	−0.16
DM3 Verify AI output	3.95	4.32	<.001	.013	−0.31
DM4 Accept unevaluated	2.61	1.88	<.001	<.001	0.52
DM5 Confident without AI	3.49	3.75	.016	.191	−0.23

Item	Student	Prof.	p	p (Holm)	Cliff's δ
DM6 AI + human judgment	4.22	4.38	.126	1.000	−0.14
EO1 Tasks automatable	3.84	3.88	.669	1.000	−0.04
EO2 Concern: opportunities	3.52	3.00	<.001	<.001	0.42
EO3 New opportunities	3.95	3.80	.171	1.000	0.13
EO4 Skills must update	4.32	4.22	.349	1.000	0.09
EO5 Prospects change	3.87	3.75	.281	1.000	0.10
SR1 Understand AI	3.56	3.75	.104	1.000	−0.16
SR2 Assess reliability	3.33	3.65	.003	.036	−0.29
SR3 Developing skills	3.82	3.65	.146	1.000	0.15
SR4 Feel prepared	3.61	3.55	.750	1.000	0.03
SR5 Training adequate	2.52	2.52	.863	1.000	−0.02
Decision-making (composite)	3.79	4.07	<.001	–	−0.42
Employment outlook (composite)	3.90	3.73	.046	–	0.22
Skill readiness (composite)	3.37	3.42	.831	–	−0.02

Means shown; Student n = 85, Working professional n = 40. Positive δ: students higher. Holm correction applied across the 16 items only.

After Holm correction four items differed. Professionals reported more verification (4.32 vs 3.95; adjusted p = .013) and less uncritical acceptance (1.88 vs 2.61; p < .001), and rated their ability to assess reliability higher (3.65 vs 3.33; p = .036). Students were more concerned about reduced opportunities in their field (3.52 vs 3.00; p < .001). Confidence in deciding without AI (adjusted p = .19) and perceived decision quality (p ≈ 1.0) did not differ after correction.

Categorical answers are shown in Table 5. The skill respondents most wanted differed by status ($\chi^2(4) = 14.22$, permutation p = .005, V = 0.34): students favoured AI-assisted data analysis (35.3%), programming with AI (28.2%) and prompting (20.0%), whereas professionals spread their choices across data analysis, productivity automation (each 25.0%) and AI ethics (22.5%). The view of AI and employment differed modestly (students vs professionals: $\chi^2(4) = 9.68$, p = .040, V = 0.28; exploratory, given small cells): 11.8% of students but none of the professionals chose "mainly replaces jobs", while 27.5% of professionals chose "mainly creates opportunities" against 11.8% of students. The main concern did not differ significantly between students and professionals (p = .092), although 12 of the 20 respondents who were both (60.0%) named overdependence.

Table 5. Categorical responses by status (n)

Response	Student	Prof.	Both	All
AI skill most wanted				
AI-assisted data analysis	30	10	9	49
Programming with AI	24	8	4	36
Prompting	17	3	1	21
Productivity automation	7	10	4	21
AI ethics	7	9	2	18
View of AI and employment				
Both creates and replaces jobs	59	27	15	101
Mainly creates opportunities	10	11	4	25
Mainly replaces jobs	10	0	1	11
Little impact	4	2	0	6
Unsure	2	0	0	2
Biggest concern				
Overdependence	19	14	12	45
Job displacement	25	5	2	32
Privacy	17	7	3	27
Inaccurate information	12	6	2	20
Lack of accountability	4	6	1	11
Bias / discrimination	8	2	0	10

Column totals: Student 85, Working professional 40, Both 20, All 145.

Because status is entangled with field and experience, a sensitivity analysis regressed each outcome on status (professional vs student), IT/CS vs other fields, duration of use and frequency of use (students and professionals only, n = 125). Once these were included, the professional–student difference in the decision-making composite fell to +0.05

points (p = .33), and differences in employment outlook (−0.09; p = .20), readiness (−0.06; p = .37) and verification (+0.06; p = .64) were negligible. Less uncritical acceptance among professionals remained (−0.29; p = .045), and lower concern about reduced opportunities was borderline (−0.24; p = .081). Duration of use carried most of the association with decision-making (+0.39 per category; p < .001), verification (+0.40; p < .001) and readiness (+0.48; p < .001). The gaps in Table 4 are therefore better read as differences in experience and field mix than as effects of student or professional status itself.

7.6 Experience, Field and Readiness

Readiness rose with experience (Figure 5a). Mean readiness was 2.82 for respondents with three to twelve months of use, 3.19 for one to two years and 3.91 for more than two years (Spearman ρ = .77, p < .001); frequency of use was also associated with readiness (ρ = .67) and with employment outlook (ρ = .76). The association with duration held within students (ρ = .81) and within professionals (ρ = .82). Composite scores were strongly related for decision-making and readiness (ρ = .71) and for employment outlook and readiness (ρ = .67), but only weakly for decision-making and employment outlook (ρ = .25). Perceived adequacy of training was strongly related to feeling prepared (ρ = .77) and to developing AI skills (ρ = .67), so respondents who rate training more favourably also feel more prepared and more active in building skills.

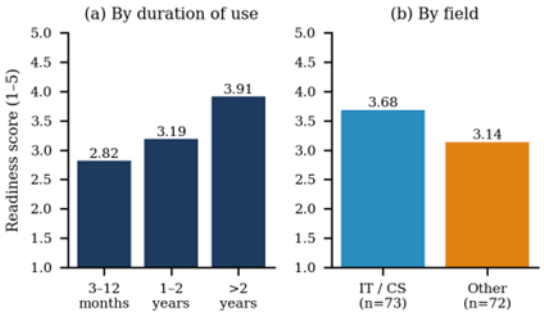


Figure 5. Mean skill-readiness score by (a) duration of GenAI use and (b) field

Frequency of use was linked to checking habits. More frequent users reported less verification (ρ = −.22, p = .007) and more acceptance without evaluation (ρ = .25, p = .002); daily users scored 3.96 on verification and 2.54 on acceptance, against 4.23 and 1.92 for weekly users. This is a cross-sectional association and does not show that frequent use causes lower vigilance, but it is the pattern that automation-bias research would lead one to watch [7], [8].

Field mattered. Respondents in IT/CS (n = 73) scored higher than other respondents (n = 72) on employment outlook (4.13 vs 3.59; p < .001, δ = 0.67) and readiness (3.68 vs 3.14; p < .001, δ = 0.59), but not on decision-making (3.93 vs 3.87; p = .14). They were also more concerned about reduced opportunities (3.62 vs 3.10) and more likely to accept recommendations without evaluation (2.71 vs 1.99; both p < .001). Across the six fields, readiness differed strongly (Kruskal–Wallis H(5) = 55.1, p < .001; ε^2 = 0.38), with the lowest means in Social Sciences/Humanities (2.60, n = 10) and Healthcare/Life Sciences (3.04, n = 14); these two groups are small and should be read cautiously.

7.7 Preparing for an AI-Driven Future: Open-Ended Responses

All 145 respondents answered the open question. Six themes emerged (Figure 6, Table 6). The largest, verification and critical evaluation of outputs (26.2%), covered cross-checking against authoritative sources, testing generated code, and treating AI output as a draft. Domain expertise and human-centred skills (18.6%) and AI-technical, automation and systems skills (17.2%) came next, followed by privacy, security and organisational compliance (15.9%), foundational competence kept independent of AI (13.8%) and ethics, bias and accountability (8.3%).

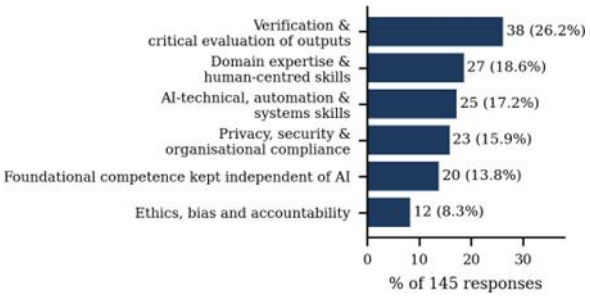


Figure 6. Themes in open-ended responses (one dominant theme per response)

Table 6. Themes and illustrative responses

Theme	n (%)	Illustrative response (verbatim)
Verification and critical evaluation	38 (26.2)	Treat AI outputs as drafts and enforce strict quality verification standards.
Domain expertise and human-centred skills	27 (18.6)	Combine quantitative data analysis with empathetic client relationship skills.
AI-technical, automation and systems skills	25 (17.2)	Focus on system architecture and cloud automation rather than syntax typing.
Privacy, security and compliance	23 (15.9)	Never paste confidential organizational or personal data into public generative platforms.

Theme	n (%)	Illustrative response (verbatim)
Foundational competence independent of AI	20 (13.8)	Practice independent whiteboard coding to retain algorithmic intuition.
Ethics, bias and accountability	12 (8.3)	Study algorithmic bias and promote diverse perspective representation in AI training.

The theme assigned reflects the dominant emphasis; some responses touch more than one theme.

Themes varied by field more than by status. Foundational competence was the dominant theme for 19 of 73 IT/CS respondents (26.0%) but 1 of 72 others (1.4%); AI-technical and systems skills for 30.1% against 4.2%; and domain expertise and human-centred skills for 6.8% against 30.6% (permutation $p < .001$, $V = 0.57$). Differences between students and professionals were not significant ($p = .058$).

8. DISCUSSION

Four findings stand out. First, respondents credit GenAI more for speed than for quality. This is consistent with experimental evidence that the tools shorten task time [3], [4], but the present data are self-reports, and the gap between 84.1% and 64.8% suggests users are cautious about claiming better decisions. Second, a human-in-the-loop view is close to universal (97.9%). Verification is the stated norm (87.6%), yet only 44.8% feel able to judge reliability, so the habit may be stronger than the skill behind it. The negative association between frequency of use and verification is a signal worth monitoring in light of automation-bias findings [7], [8] and the hallucination literature [6].

Third, employment views are ambivalent rather than alarmed. Most respondents expect both job creation and replacement (69.7%), almost all expect to need new skills (95.2%), and overdependence ranked above job displacement as the main concern. This fits task-based accounts in which technology changes the content of work as well as its quantity [14], [15], and it indicates that respondents frame the challenge as one of adaptation. Fourth, the student–professional contrasts are mostly contrasts of experience and field. Professionals appear more careful and more settled about employment, but once duration and frequency of use and field are held constant most gaps shrink, and duration of use is the strongest correlate of both decision-making scores and readiness. The very low rating of institutional training (4.1%) is shared by both groups, and respondents with more experience appear to be building their skills informally.

The field gradient adds a caution. IT/CS respondents were the most ready and the most optimistic about opportunities, yet also more worried about reduced opportunities and more likely to accept recommendations without evaluation. Readiness was lowest in the small Social Sciences/Humanities and Healthcare/Life Sciences groups. The open-ended answers show that respondents themselves place verification, data protection and retained fundamentals at the centre of preparation, which mirrors the quantitative emphasis on checking and on training gaps.

9. IMPLICATIONS

- Institutions and employers should provide structured AI-literacy training; only 4.1% of respondents rated current provision as adequate.
- Training should teach verification as a skill, not only as a habit: how to test code, check citations and figures, and judge when output is unreliable.
- Clear rules on what data may be entered into public tools address the privacy concern raised by 18.6% of respondents and by 15.9% of the open-ended answers.
- Upskilling should be field-specific. Demand centres on AI-assisted data analysis, but non-IT fields reported lower readiness.
- Programmes should preserve foundational competence so that learners can evaluate what AI produces.

10. LIMITATIONS

- The design is cross-sectional and based on self-report, so associations cannot be read as causal, and claims about verification may be affected by social desirability.
- The sample is a non-probability sample of GenAI users, with half from IT/CS and two-thirds with postgraduate qualifications; results should not be generalised.
- Status is entangled with age, qualification, field and experience, and the “both” group is small ($n = 20$). The regression check is limited by the coarse coding of duration and frequency.
- Nine of the sixteen statements received no ratings of 1 or 2, so responses were compressed towards agreement and variance was limited.
- The decision-making composite has moderate reliability ($\alpha = 0.69$), and many tests were run; only item-level tests were corrected for multiplicity.
- The open-ended responses were assigned to a single dominant theme in one pass, without an independent second coder or an agreement statistic.

11. FUTURE SCOPE

- Repeating the survey with a probability or quota sample across fields, institutions and regions.
- Longitudinal follow-up to see whether verification habits and readiness change as experience grows.

- Behavioural tasks that measure verification and error detection rather than relying on self-report.
- Evaluating the effect of structured AI-literacy training on readiness and verification.
- Field-specific studies, particularly in healthcare, finance and the humanities, with larger subsamples.

12. CONCLUSION

Among 145 GenAI users, the tools were seen as faster rather than clearly better for decisions, and combining them with human judgment was almost universally endorsed. Employment views were balanced between opportunity and replacement, and the main worry was overdependence rather than job loss. Readiness was moderate and training provision was rated very low. Professionals and students differed in verification and concern, but those differences were largely accounted for by experience with the tools and by field. The results support investment in AI-literacy programmes that teach verification, data protection and field-relevant skills, and they invite tests on broader and more representative samples.

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