



PERCEIVED COGNITIVE SKILLS AND THEIR RELATIONSHIP TO THE USE OF ARTIFICIAL INTELLIGENCE TOOLS IN RESEARCH AND SCHOLARLY ACTIVITY AMONG TEACHER-RESEARCHERS IN THE SALAH AL-DIN DIRECTORATE OF EDUCATION

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Abstract. The study was aimed at determining the status and level of use and development of modern digital tools in agricultural extension in the Nineveh Governorate, such as agricultural extension content, digital interaction and participation, digital extension, modern communication technologies, smartphones and agricultural applications, multimedia, and agricultural videos. It also explored the link between current use and development of modern tools and selected variables at personal and professional level. It was administered using two questionnaires. The first section gathered personal and professional information, and the second section had 60 items in six sections, each containing 10 items. The questionnaire had a Cronbach alpha reliability coefficient of 0.95 and showed face validity. The study was carried out on 256 extension workers in the Nineveh Agriculture Directorate and its agricultural divisions (32). A random sample of 200 extension workers (about 78% of the population) was drawn. Data were analysed in SPSS. The findings showed moderate general level of development and modern tools used in agricultural extension work, leaning towards high. The use of modern communication tools was high, while the use of smartphones and agricultural applications was moderate, tending toward high. Digital platforms and the use of multimedia was moderate and tending to low, while digital interaction and participation was high. Digital extension content development was moderate, leaning to high. There was no significant relationship with education level, specialization, years of service or participation in training courses relating to digital technologies. Age and years of service in agricultural extension were found to be significantly correlated at 0.05 level and Internet use frequency at 0.01 level, while owning a smart phone and the most frequently used digital tool were significantly correlated at 0.05 level. The study suggests aligning digital tools and resources to farmers' needs and capacities, and building partnerships between the Nineveh Agriculture Directorate, universities, and research centers to create relevant digital platforms and tools. Extension workers' perspectives regarding barriers to the utilization of modern digital technologies in agricultural extension should be explored for further research.

Keywords: Development Reality, Modern Methods, Guidance Work, Nineveh Governorate.

1. Introduction

Artificial intelligence is no longer a technological promise waiting to be fulfilled. It has become part of a researcher's ordinary working day: it reads sources alongside them, offers alternative wordings, and cuts weeks of manual data handling down to hours. This did not happen overnight. It is the result of rapid, cumulative progress in large language models and their research applications, to the point where it is now hard to imagine a contemporary research project untouched by these tools (Dwivedi et al., 2023).

Once generative chat models spread widely, the question people were asking changed. It used to be whether researchers would take up these tools at all; now it is why they take them up so unevenly. Why do some researchers adopt them enthusiastically while others keep a cautious distance? A study of 150 academic researchers from a range of disciplines found that familiarity with AI-assisted writing tools, and their actual use, varied considerably both between individuals and between fields. Some had never used them; others relied on them every day (Al-Bukhrani et al., 2025).

Most of the explanations offered by these studies, however, have stayed within the familiar territory of attitudes, subjective norms and perceived barriers. What they tend to overlook is something closer to the researcher's own cognitive make-up: the ability to pick out relevant information from what the tools generate, to divide attention across several sources and tasks, to grasp and evaluate the meaning of the output, to retain and retrieve it, to fold it into existing knowledge, and to use it in solving research problems. The present study starts from exactly this gap.

2. Statement of the Problem

The problem addressed here is a gap in knowledge. On one side there is a large and growing literature on what drives the adoption of AI tools in academic settings; on the other, very little attention has been paid to the researcher's cognitive skills as a predictor in their own right. As the literature review will show, earlier studies have focused mainly on attitudes toward the tool, subjective norms and technological self-efficacy. The cognitive processes a researcher actually performs when working with the output of these tools (selective and divided attention, perception, memory, knowledge management, and thinking and problem solving) have remained largely in the background. This is somewhat paradoxical, since from the standpoint of cognitive psychology and its educational applications, these processes are the very foundation on which a person's response to any new technology that demands dense, continuous information processing is built.

The gap is even more visible in the Iraqi context. A growing number of teachers with postgraduate degrees working in directorates of education now carry out regular research for promotion and publication, yet this group has received far less research attention on AI use than university students and faculty members. The research problem can therefore be stated as the following main question: What is the relationship between perceived cognitive skills and the use of AI tools in research and scholarly activity among teacher-researchers, and to what extent do these skills predict the level of that use? This main question gives rise to the following sub-questions:

1. What is the level of perceived cognitive skills among teacher-researchers?
2. What is their level of AI tool use in research and scholarly activity, and what level of challenges and obstacles do they perceive in doing so?
3. Does the level of each variable differ by gender, specialization, academic rank and years of research experience?
4. Which dimensions of cognitive skills are most closely related to AI tool use and contribute most to predicting it?

3. Significance of the Study

3.1 Theoretical significance

Theoretically, the study tries to connect two fields that have not met often enough, in either the Arabic or the international literature: cognitive psychology and information-processing models on the one hand, and technology adoption research on the other. It does so in a specific setting that has been neglected compared with student populations, namely that of the practising teacher-researcher. It also offers two locally developed instruments whose factor structure is tested through confirmatory factor analysis, so that they can be used in later studies.

3.2 Practical significance

In practical terms, the findings are expected to give directorates of education, universities and research centres an evidence base for designing training programmes that target specific cognitive skills alongside direct technical training on the tools, provided the results show that these skills make a meaningful contribution to use. The study also gives a descriptive picture of the main challenges teacher-researchers face in using these tools, which is information decision-makers need when planning in-service training.

4. Objectives

The study aims to identify:

1. The level of perceived cognitive skills among teacher-researchers, as a total score and across its six dimensions.
2. The level of teacher-researchers' use of AI tools in research and scholarly activity, as a total score and across its four dimensions.
3. The level of challenges and obstacles teacher-researchers perceive in using these tools, and the tools they use most.
4. The correlation between perceived cognitive skills and AI tool use, at the level of the total score and of each dimension.
5. The extent to which perceived cognitive skills predict the level of AI tool use.
6. The significance of differences in both variables by gender, specialization, academic rank and years of research experience.

5. Hypotheses

Objectives 4 to 6 were formulated as the following null hypotheses, all tested at the 0.05 level of significance:

1. There is no statistically significant correlation between the total score of

perceived cognitive skills and the total score of AI tool use in research and scholarly activity.

2. There are no statistically significant differences in perceived cognitive skills by gender, specialization, academic rank or years of research experience.
3. There are no statistically significant differences in AI tool use by gender, specialization, academic rank or years of research experience.
4. Perceived cognitive skills, as a total score and by dimension, do not make a statistically significant contribution to predicting the level of AI tool use.
5. There is no statistically significant correlation between each dimension of perceived cognitive skills and the total score of AI tool use.

Objectives 1 to 3 are descriptive. They are answered by the first and second sub-questions and do not require hypotheses.

6. Scope and Delimitations

1. Participants: teachers holding postgraduate degrees who are active in research and use AI tools in that work.
2. Place: the Al-Shirqat and Ashur education departments of the Salah al-Din General Directorate of Education, Republic of Iraq.
3. Time: 7 to 9 September 2026, the period during which the instruments were administered.
4. Subject: perceived cognitive skills in six dimensions (selective attention, divided attention, perception, memory, knowledge management, and thinking and problem solving); AI tool use in four dimensions (extent and frequency of use, academic purposes of use, cognitive skills supported by the tools, and mindful and ethical use); and challenges and obstacles, treated as a separate descriptive variable. "AI tools" here means generative tools and AI-supported search tools such as ChatGPT, Claude, Gemini and Google Scholar, and similar applications.

7. Definition of Terms

7.1 Cognitive skills

Conceptual definition: the mental processes through which a person receives, selects, transforms, stores, retrieves and uses information in acquiring knowledge and solving problems (Neisser, 1967). The study adopts this definition, which rests on the information-processing perspective.

Operational definition: the total score a respondent obtains on the 29-item Perceived Cognitive Skills Scale developed for this study. The score reflects the respondent's own appraisal of how well their cognitive processes work when they use AI tools in research. Because the scale relies on self-report, what it measures is the skill as the researcher perceives it rather than actual performance, which is why the title refers to perceived skills.

Each dimension is defined operationally by the score on its items. Selective attention (items 1–5): focusing on information relevant to the research topic in the tool's output and ignoring the rest. Divided attention (6–10): keeping track of more than one source, tool or task at the same time without a drop in performance. Perception (11–15): understanding what the output means, interpreting it in the context of one's research, and recognising the tool's limits. Memory (16–20): retaining

information, prompts and sources and recalling them when needed. Knowledge management (21–25): integrating what has been learned into one's existing knowledge, and evaluating, documenting, updating and sharing it. Thinking and problem solving (26–29): analysing the output critically and using it to address research problems.

7.2 Use of AI tools in research and scholarly activity

Conceptual definition: the researcher's use of AI-based applications at the various stages of research work, from searching for information and reviewing and summarising the literature to help with writing, translation, data analysis and idea generation (Zawacki-Richter et al., 2019; Dwivedi et al., 2023).

Operational definition: the total score a respondent obtains on the items of the first four dimensions of the AI Tool Use Scale (items 1–23).

7.3 Perceived challenges and obstacles

Operational definition: the score a respondent obtains on items 24–29 of the use scale. A higher score indicates more perceived difficulty in using the tools. The score is treated as a separate descriptive variable and is not added to the total use score, for conceptual and statistical reasons explained in the Method section.

7.4 Teacher-researcher

Operational definition: a teacher working in the Al-Shirqat or Ashur education department who holds a postgraduate degree (master's or doctorate), carries out regular research (promotion research, journal publication or conference participation), and uses at least one AI tool in that work.

8. Theoretical Framework

8.1 The concept of cognitive skills

In the higher education literature, the term cognitive skills refers to a set of general intellectual competencies regarded as among the main outcomes of a university education, even when they are not tied to any particular course or discipline. These skills have gone by several names over the years, from critical thinking to reflective judgement to cognitive development, but the labels share a common core (Kim et al., 2015, p. 527).

A broad review of the cognitive psychology literature concluded that problem solving is the most researched of these skills with respect to transfer across learning contexts, and that transfer depends on the setting in which a skill is acquired and the way it is learned, not only on the nature of the skill itself (Billing, 2007, p. 483). This has a direct bearing on the present study. A researcher who has mastered an AI tool for one research task will not necessarily carry that competence over to other tasks unless the underlying cognitive skill has been developed in a way that allows it to generalise.

In defining cognitive skills, the study adopts the information-processing perspective, which views the human mind as a system that receives stimuli, selects some of them for processing, and then transforms, stores, retrieves and uses them (Neisser, 1967; Atkinson & Shiffrin, 1968). Two things justify this choice. Working with AI tools is, at heart, working with a dense flow of machine-generated information that calls for constant selection and evaluation. And the perspective allows a researcher's cognitive performance to be broken down into measurable processes. The study

does not ignore higher-order regulatory components either. Metacognition, a person's awareness of their own cognitive processes and ability to monitor and control them (Flavell, 1979, p. 906), and self-regulated learning, the ability to plan, monitor and evaluate one's performance without outside direction (Zimmerman, 2000, p. 13), both show up in the knowledge management and thinking and problem-solving dimensions, when the researcher judges how credible the output is and decides what to keep.

8.2 Dimensions of cognitive skills in light of the information-processing model

a. Selective attention

Selective attention is the ability to direct cognitive resources toward particular stimuli while holding them back from others. Broadbent (1958) described attention as a filter that lets some information pass on to further processing and blocks the rest because the processing channel has limited capacity. This dimension matters a great deal when working with AI tools, which tend to give long answers in which accurate and inaccurate information, and relevant and peripheral content, are mixed together. Picking out what serves the purpose of the research becomes a precondition for getting any value from them.

b. Divided attention

Divided attention refers to the ability to spread cognitive resources across more than one task or source at once. Kahneman (1973) saw attention as a limited capacity that is allocated to concurrent tasks according to their demands, and multiple resource theory adds that performance on concurrent tasks depends on how far they compete for the same resources (Wickens, 2008). Today's researcher meets this situation whenever they move between an AI tool, a database, a word processor and original sources within a single working session.

c. Perception

Perception is the process by which a person gives meaning to incoming information on the basis of prior knowledge and the context of the situation (Neisser, 1967). In this study it shows in the researcher's grasp of the precise meaning of the tool's output, in interpreting it in line with the aims of the study, in noticing patterns and relationships among the sources the tool suggests, and in recognising where the tool falls short.

d. Memory

The multi-store model describes memory as a series of sensory, short-term and long-term stores, with information passing between them through rehearsal, encoding and retrieval (Atkinson & Shiffrin, 1968). Baddeley later developed the concept of working memory as an active system that holds information temporarily while processing it, and added a component that links current information to stored knowledge (Baddeley, 2000). Using AI tools calls for remembering prompts that worked, retrieving information and sources gathered at earlier stages of a project, and keeping track of changes made to generated text.

e. Knowledge management

The term knowledge management has been used mostly in economics and organisational management, where it is defined as the set of efforts made to carry out four functions: acquiring knowledge, distributing and communicating it,

interpreting it, and putting it to use (Al-Kubaisi, 2005). The present study, however, treats the concept at the individual level, as what is known as personal knowledge management: the practices through which a person organises, evaluates, updates and shares their knowledge (Pauleen & Gorman, 2011). This dimension is closely tied to metacognition, because integrating knowledge drawn from a tool into one's existing knowledge, and judging its credibility before relying on it, are essentially monitoring processes.

f. Thinking and problem solving

Problem solving is defined as cognitive activity aimed at turning a given situation into a desired one when the way to get there is not obvious to the person. It involves representing the problem, planning a solution, carrying it out and monitoring it (Mayer & Wittrock, 2006). In research work it appears when the researcher analyses the tool's output critically, writes complex prompts that draw out deeper answers, and uses the tool to test early ideas before developing them further.

8.3 AI tools in research and scholarly activity

AI tools serve many functions in research work, including summarising papers, suggesting wording, correcting errors, answering questions, helping with citation and supporting peer review (Al-Bukhrani et al., 2025). For the purposes of this study these functions can be grouped into four categories: tools that help with academic writing and phrasing, tools that help with reviewing the literature and summarising sources, tools that carry out data analysis, and tools that support verification and documentation. This range of functions is itself a methodological complication that unidimensional measures often miss, since a researcher may use one tool heavily at the writing stage while having nothing to do with statistical analysis tools. For this reason the use scale in this study was built on several dimensions.

8.4 Cognitive processing theories and tool use

Cognitive load theory offers one way to understand the link between cognitive skills and the use of smart tools. Its starting point is that working memory has limited capacity and that a task exceeding this capacity creates a load that hampers performance and learning (Sweller, 1988, p. 257). From this angle, AI tools can be seen as a way of reducing extraneous load on the researcher by handing routine tasks over to them, such as drafting first versions of sentences or formatting reference lists, which frees up capacity for higher-level analytical work where human judgement is indispensable.

This view connects with the idea of cognitive offloading, which describes people's tendency to use external tools to lighten the demands on their internal cognitive processes (Risko & Gilbert, 2016, p. 676). The idea cuts both ways. It helps explain why these tools appeal to people with strong cognitive skills, who use them strategically while keeping control over the output. At the same time it raises a legitimate question: could heavy reliance on the tools gradually erode the very skills involved? The current literature has not settled this.

8.5 Technology adoption models

The theory of reasoned action was an early basis for explaining technology adoption. It traced a person's intention to perform a given behaviour to two factors: their attitude toward that behaviour, and the subjective norms they perceive in their social and professional surroundings (Fishbein & Ajzen, 1975). The technology

acceptance model then developed this idea within information systems research, identifying two variables that mediate the adoption decision: perceived usefulness and perceived ease of use (Davis, 1989, p. 319). It is worth noting that many studies based on this model have taken these two variables as given, when in fact they do not arise from nowhere; they are shaped in part by the person's cognitive abilities.

The unified theory of acceptance and use of technology followed the same line and added further factors such as social influence and facilitating conditions (Venkatesh et al., 2003, p. 425). Even so, the purely cognitive side of the adopter has remained fairly marginal in most applications of the theory, and this is what the present study tries to address within its limits.

8.6 Conceptual model

Based on the above, the study proposes that perceived cognitive skills (the independent variable) are related to and predict AI tool use (the dependent variable), that both variables may differ by gender, specialization, academic rank and years of research experience, and that challenges and obstacles can be recorded as a separate descriptive variable. It should be noted that the items of the cognitive skills scale were written in the context of working with AI tools, and that two of them (27 and 29) refer explicitly to using the tool. This overlap in content between the two measures could inflate the correlation between them, so its effect is examined through a sensitivity analysis in which the correlation is recalculated without these items (see Statistical Analysis).

9. Previous Studies

A number of studies have looked at aspects of the relationship between people's cognitive and psychological characteristics and their adoption of AI tools, although they differ in how closely they approach cognitive skills as a focus of analysis in their own right. The most relevant are reviewed critically below.

Al-Bukhrani et al. (2025) examined what determines academic researchers' adoption of AI-based writing tools, drawing on the theory of reasoned action, with a sample of 150 researchers from several disciplines. They found that a positive attitude toward the tool and subjective norms had a significant effect on intention to use, while perceived barriers had no significant effect. This is telling: it suggests that a researcher's decision is governed less by the difficulties of the tool than by their own internal attitudes, which is close to the reasoning behind the present study, even though cognitive skills were not measured in that work.

In a qualitative study framed by an extended technology acceptance model, El Hosayny et al. (2025) explored how 15 doctoral students perceived the benefits and challenges of AI tools in supporting critical thinking in academic research, using semi-structured interviews and thematic analysis. Participants saw the tools as highly useful and easy to use and felt they stimulated critical and reflective thinking, though they might hinder creativity; there were also concerns about over-reliance and breaches of academic integrity. The study shares with the present one the assumption that a cognitive skill is connected to the use of smart tools, but it differs in its qualitative approach, its small sample, and its focus on perceived usefulness rather than on measuring the skill itself.

Kleine et al. (2023) studied the attitudes of 206 psychology students and trainee psychotherapists toward adopting two AI-based tools in mental health care, using

the unified theory of acceptance and use of technology. They found a significant positive relationship between cognitive technology readiness and intention to use one of the tools, and a negative relationship between AI anxiety and intention to use both. The study is valuable because it is one of the few to include an explicitly cognitive dimension in a technology adoption model, although its applied context is quite different from that of the present study.

In an educational setting closer to the present one, Şimşek et al. (2025) extended the technology acceptance model by adding metacognitive self-regulation, subjective norms, learning motivation and learning agility, and tested it with 748 pre-service teachers from 12 Turkish universities. Metacognitive self-regulation and learning motivation had significant effects on the perceived usefulness and perceived ease of use of generative AI tools, and the model explained 51% of the variance in intention to use. This supports a central assumption of the present study, that cognitive variables play an explanatory rather than a marginal role in adoption, although the sample consisted of teachers in training rather than practising researchers (Şimşek et al., 2025, p. 20913).

In the region, El-Ashry et al. (2025) investigated how attitudes toward and acceptance of AI affected critical thinking motivation among 390 nursing students at three Saudi universities. They reported positive attitudes toward AI and positive but weak correlations between AI-related variables and critical thinking motivation (r between 0.20 and 0.40). The study is close to the present one in its attention to the Arab academic setting, but it dealt with critical thinking motivation rather than cognitive skills and was limited to students in one health discipline.

Among doctoral students, Uludağ et al. (2025) extended the technology acceptance model with five factors (social influence, perceived enjoyment, AI self-efficacy, AI sociotechnical blindness and perceived ethics) and applied it to 361 science doctoral students at 35 universities. All of the added factors had a significant effect on intention to use ChatGPT for learning. The study is close to the present one in targeting a group adjacent to researchers and in including self-efficacy, but it focused on use for learning rather than for research output.

In the Arab context, Al-Badawi Balla and Al-Mustafa (2025) carried out a field study at the University of Al-Butana in Sudan with 57 faculty members, aiming to identify their attitudes toward using AI applications in research and the obstacles that limit this use. They found a generally positive attitude accompanied by considerable obstacles, with significantly higher scores for faculty of higher academic rank and longer experience. This study stands out for targeting a group similar to that of the present study in an Arab setting, but it stopped at describing attitudes and did not treat cognitive skills as a predictor (Al-Badawi Balla & Al-Mustafa, 2025, p. 25).

Comments on previous studies

Taken together, these studies agree that some cognitive or metacognitive factor affects the adoption of AI tools, whether it is described as critical thinking, self-regulation, cognitive readiness or self-efficacy. This agreement gives the cognitive skills variable clear theoretical legitimacy. Where the studies part ways is in how they measure it. Some measured only perceived cognitive benefit rather than the skill itself, one used a qualitative design with a small sample, others targeted groups adjacent to researchers such as doctoral students and pre-service teachers, and most stayed within teaching and learning rather than research production. The present study differs from them in bringing together three elements: measuring the

researcher's cognitive processes along dimensions taken from the information-processing model, targeting practising teacher-researchers in an Iraqi setting, and using a predictive correlational design that takes gender, specialization, academic rank and years of experience into account. The previous studies informed the construction of the instruments, the choice of demographic variables and the interpretation of the results.

10. Method and Procedures

10.1 Research design

A descriptive correlational design was used, as it best suits the nature and aims of the problem. It makes it possible to describe the levels of perceived cognitive skills and of AI tool use, and then to determine the relationship between the two variables and how far the first predicts the second, without any experimental intervention in either.

10.2 Population

The original population consisted of 177 teachers holding postgraduate degrees and active in research in the Al-Shirqat and Ashur education departments. Because the items of the cognitive skills scale were written in the context of working with AI tools, only people who actually use these tools can answer them. Actual experience with the tools was therefore set as an inclusion criterion, and 30 teachers who answered no to a screening question ("Do you use AI tools in writing research and in scholarly activities?") were excluded, leaving an eligible population of 147. One consequence of this exclusion is a restricted range in both variables, since non-users are absent from the study; this is taken into account when interpreting the size of the correlation.

10.3 Participants

Given the small size of the eligible population, a census approach was used: the two instruments were sent electronically via Google Forms to all of its members, and 124 teachers returned responses that were valid for statistical analysis, a response rate of 84.35% of the eligible population. Table 1 summarises these figures.

Table 1. Research population and participants

Description	n	Percentage
Original population	177	100%
Excluded (do not use AI tools)	30	16.95%
Eligible population	147	83.05%
Respondents (relative to the original population)	124	70.06%
Valid responses for analysis	124	84.35% of the eligible population

10.4 Instruments

Since no existing scales suited the nature, population and variables of the study in the Iraqi context, the researcher developed two instruments. The first is the Perceived Cognitive Skills Scale, with 29 items across six dimensions. The second is the Scale of AI Tool Use in Research and Scholarly Activity, with 23 items across four dimensions, followed by a six-item challenges and obstacles dimension. Both instruments were preceded by a demographic section (gender, specialization, academic rank and years of research experience) and an open question asking which AI tools the respondent uses most. Table 2 shows the structure of the instruments,

and the full item lists are given in Appendices 1 and 2.

Table 2. Structure of the instruments

Scale	Dimension	Item numbers	No. of items
Perceived cognitive skills	Selective attention	1 – 5	5
	Divided attention	6 – 10	5
	Perception	11 – 15	5
	Memory	16 – 20	5
	Knowledge management	21 – 25	5
	Thinking and problem solving	26 – 29	4
AI tool use	Extent and frequency of use	1 – 6	6
	Academic purposes of use	7 – 12	6
	Cognitive skills supported by the tools	13 – 17	5
	Mindful and ethical use	18 – 23	6
Separate descriptive variable	Challenges and obstacles	24 – 29	6

10.5 Instrument development

The instruments were developed in a series of steps: defining the purpose and dimensions of each instrument in light of the theoretical framework, reviewing the relevant literature and existing measures, writing items suited to the target group, submitting the instruments to expert reviewers, piloting them to check the clarity of instructions and items, examining their psychometric properties on the study participants, and finally preparing the final versions.

10.6 Scoring

Both instruments used a five-point frequency scale (always, often, sometimes, rarely, never), scored 5, 4, 3, 2 and 1 respectively, and all items are positively worded. Total scores range from 29 to 145 on the cognitive skills scale (hypothetical mean 87) and from 23 to 115 on the use scale (hypothetical mean 69). On the challenges and obstacles items (24–29), a higher score means more perceived obstacles. These items are scored separately, with a range of 6 to 30, and are neither reverse-scored nor added to the total use score, for two reasons. The first is conceptual: perceiving obstacles is neither the opposite of use nor one of its components, and it may well increase as experience with the tool grows. The second is statistical: reverse-scoring a dimension that correlates positively with the other dimensions produces negative item-total correlations, reduces the variance and reliability of the total score, and distorts any correlations computed from it.

To make dimensions of different lengths comparable, means are reported at the item level on a 1–5 range, and response levels are judged using a class-width criterion: $(5 - 1) \div 5 = 0.80$, as shown in Table 3.

Table 3. Criterion for judging response levels

Item mean range	Relative weight	Level
1.00 – 1.80	20% – 36%	Very low
1.81 – 2.60	36.2% – 52%	Low
2.61 – 3.40	52.2% – 68%	Moderate
3.41 – 4.20	68.2% – 84%	High
4.21 – 5.00	84.2% – 100%	Very high

10.7 Face validity

The items of both scales were reviewed by eight experts in educational psychology, teaching methods, and measurement and evaluation, who judged whether each item belonged to its dimension, whether it was clearly worded, and whether it fitted the aims of the study. An agreement rate of 80% or higher was set as the criterion for keeping an item; all items met it and were retained.

10.8 Pilot administration

The instruments were piloted with 20 teachers from a similar population to check the clarity of instructions and items and to estimate completion time, which ranged from 15 to 20 minutes. Because of its small size, this pilot group was not used to compute psychometric properties; these were computed on all study participants ($n = 124$), as described below.

10.9 Item discrimination and item-total correlations

Item discrimination was computed on the study participants ($n = 124$) using the extreme-groups method: total scores on each scale were ranked in descending order and the top and bottom 27% were taken, giving 33 respondents in each group. The difference between the two group means on each item was then tested with an independent-samples t -test. Corrected item-total correlations (with the item itself removed from the total) were also computed. An item was accepted if its t value was significant and positive and its corrected correlation was 0.30 or above. For the challenges and obstacles items, these indices were computed against the score of that dimension only. On the cognitive skills scale, t values ranged from 5.26 to 10.13 and corrected correlations from 0.45 to 0.78, except for item 30, which did not discriminate at all ($t = 0.15$, $p = 0.883$, $r = -0.06$). On the use scale, t values ranged from 2.97 to 7.83 and corrected correlations from 0.17 to 0.67, with item 16 the only one below the acceptance criterion ($r = 0.17$). For the challenges and obstacles items, t values ranged from 7.40 to 12.37 and correlations with the dimension score from 0.44 to 0.66. The two weak items were therefore removed, leaving 29 items on the cognitive skills scale and 23 items on the use scale (renumbered), and all subsequent analyses were carried out on the final versions.

10.10 Construct validity

Face validity and internal consistency were not considered sufficient, since they say nothing about whether the dimensions are distinct from one another. Confirmatory factor analysis was therefore carried out using maximum likelihood estimation with the *semopy* package in Python (Igolkina & Meshcheryakov, 2020). For each scale, two models were compared: a one-factor model in which all items load on a single general factor, and a multi-factor model matching the proposed dimensions (six factors for cognitive skills and four for use), with a second-order hierarchical model where needed. Conventional fit criteria were used: CFI and TLI ≥ 0.90 , RMSEA ≤ 0.08 and SRMR ≤ 0.08 (Hu & Bentler, 1999), and models were compared using the chi-square difference and AIC. Because the number of participants (124) is modest relative to the number of items, the results are read with caution and judgements rest on the indices as a whole rather than on any single one.

Discriminant validity between dimensions was examined with the heterotrait-monotrait ratio (HTMT), where a value below 0.85 indicates that two dimensions are distinct (Henseler et al., 2015). If the dimensions were not sufficiently distinct, the total score was taken as the basis of the analysis and dimension-level results were

treated as secondary. Table 4 presents the fit indices, which show that all models met the fit criteria. For the cognitive skills scale, the six-factor model fitted significantly better than the one-factor model ($\Delta\chi^2 = 64.53$, $df = 15$, $p < 0.001$; CFI = 0.951, RMSEA = 0.043). However, HTMT values between its dimensions ranged from 0.82 to 1.02 and exceeded 0.85 for 13 of the 15 pairs. The dimensions can thus be told apart in the measurement model, but they are close enough in content for the total score to serve as the basis of the analysis. For the use scale, the four-factor model did not fit better than the one-factor model ($\Delta\chi^2 = 5.41$, $df = 6$, $p = 0.492$), and HTMT values ranged from 0.92 to 1.03. In practice, then, the use scale is unidimensional: its total score is used, and its four dimensions are reported for descriptive purposes only.

Table 4. Fit indices for the confirmatory factor analysis models

Scale	Model	χ^2	df	CFI	TLI	RMSEA	SRMR	AIC
Cognitive skills	One factor	514.87	377	0.924	0.918	0.055	0.053	630.87
	Six factors	450.34	362	0.951	0.946	0.045	0.050	596.34
	Hierarchical (second order)	470.35	371	0.945	0.940	0.047	0.051	598.35
AI tool use	One factor	279.78	230	0.944	0.938	0.042	0.059	371.78
	Four factors	274.37	224	0.943	0.936	0.043	0.058	378.37

Fit criteria: CFI and TLI ≥ 0.90 ; RMSEA and SRMR ≤ 0.08 . AIC is computed as $\chi^2 + 2q$, where q is the number of free parameters.

10.11 Reliability

Reliability was estimated with Cronbach's alpha, McDonald's omega (which does not assume equal item loadings; McDonald, 1999) and the Spearman–Brown corrected split-half method, for the total scores and for each dimension, as shown in Table 5. Alpha was 0.955 for the total cognitive skills score, 0.917 for the total use score and 0.817 for the challenges and obstacles dimension, and ranged from 0.656 to 0.860 across the subscales. Omega values were almost identical to alpha. Two dimensions, divided attention and cognitive skills supported by the tools (0.656 each), fell below the conventional threshold of 0.70, so results for them should be read with caution.

Table 5. Reliability coefficients of the instruments

Scale / dimension	No. of items	Cronbach's alpha	McDonald's omega	Corrected split-half
Selective attention	5	0.820	0.823	0.821
Divided attention	5	0.656	0.657	0.671
Perception	5	0.818	0.819	0.814
Memory	5	0.844	0.845	0.874
Knowledge management	5	0.860	0.861	0.860
Thinking and problem solving	4	0.814	0.816	0.849
Total cognitive skills score	29	0.955	0.956	0.960
Extent and frequency of use	6	0.773	0.774	0.769
Academic purposes of use	6	0.733	0.738	0.749
Cognitive skills supported by the tools	5	0.656	0.662	0.597
Mindful and ethical use	6	0.776	0.779	0.780
Total use score	23	0.917	0.919	0.911
Challenges and obstacles (separate)	6	0.817	0.820	0.827

10.12 Final administration and data screening

The final versions of the scales were administered to participants between 7 and 9 September 2026. Respondents were first told the purpose of the study and how to answer, and were assured that their data would be kept confidential and used only for research, and that they were free to take part or withdraw. Before analysis the data were screened. Responses were checked for completeness, and no values were missing. Straight-lining, where a respondent chooses the same option for every item on a scale, was checked for, and no cases were found. Multivariate outliers were identified using Mahalanobis distance at the 0.001 level; one case was found and retained, since removing it did not change the results ($r = 0.242$ instead of 0.246). Responses to the two scales were matched for each respondent using the shared serial number, and the demographic data matched for every participant. Category labels in the demographic variables were standardised (for example, spelling variants of "Lecturer"). No responses were excluded as a result of this screening.

10.13 Statistical analysis

Data were analysed using SPSS (version 27), and Python (semopy package) for the confirmatory factor analysis and HTMT, with the following procedures:

1. Frequencies and percentages to describe the participants and the most frequently used tools.
2. Means, standard deviations and relative weights, and one-sample t-tests comparing item means with the hypothetical mean (3), with effect sizes (d).
3. Skewness and kurtosis to check normality, and Levene's test for homogeneity of variance.
4. Pearson's correlation with a 95% confidence interval, and Spearman's correlation as a check where the data departed from normality.
5. Independent-samples t-tests (with Welch's correction where variances were unequal) and one-way ANOVA, with effect sizes d and η^2 , and Mann–Whitney and Kruskal–Wallis tests where groups were small.
6. Simple linear regression on the total score, and multiple linear regression on the dimensions with variance inflation factors (VIF) to diagnose multicollinearity.
7. Harman's single-factor test for common method bias, since both variables were measured by self-report at the same time (Podsakoff et al., 2003).
8. A sensitivity analysis in which the correlation and regression were recalculated after removing the cognitive skills items that refer explicitly to using the tool (27 and 29), to check that the relationship was not due to content overlap between the two scales.
9. Confirmatory factor analysis, Cronbach's alpha, McDonald's omega, split-half reliability and HTMT.

Exact p values are reported; values below 0.001 are written as $p < 0.001$.

11. Results

This section presents the results in the order of the research questions and hypotheses. The analysis was based on the responses of 124 teachers who met the

inclusion criteria and answered every item on both scales.

11.1 Participant characteristics

Table 6. Distribution of participants by demographic variables (n = 124)

Variable	Category	Frequency	Percentage
Gender	Male	114	91.94%
	Female	10	8.06%
Specialization	Scientific	45	36.29%
	Humanities	79	63.71%
Academic rank	Assistant Professor	8	6.45%
	Lecturer	18	14.52%
	Assistant Lecturer	98	79.03%
Years of research experience	Less than five years	77	62.10%
	Five to ten years	23	18.55%
	Ten to fifteen years	24	19.35%

As the table shows, most participants were male (91.94%), most were in the humanities (63.71%), and 79.03% held the rank of Assistant Lecturer, while 62.10% had less than five years of research experience. The female group (10) and the Assistant Professor group (8) each had fewer than fifteen members, which weakens the statistical power to detect differences by gender and academic rank, so these results should be read with caution.

11.2 Level of perceived cognitive skills

Table 7. Means and standard deviations for the dimensions of the Perceived Cognitive Skills Scale (n = 124)

Dimension	Mean	SD	Relative weight	t	p	Level	Rank
Selective attention	3.229	0.796	64.58%	3.20	0.002	Moderate	6
Divided attention	4.003	0.699	80.06%	15.98	< 0.001	High	1
Perception	3.274	0.748	65.48%	4.08	< 0.001	Moderate	5
Memory	3.295	0.797	65.90%	4.13	< 0.001	Moderate	3
Knowledge management	3.342	0.869	66.84%	4.38	< 0.001	Moderate	2
Thinking and problem solving	3.288	0.823	65.77%	3.90	< 0.001	Moderate	4
Total score	3.409	0.693	68.19%	6.58	< 0.001	High	---

Means are at the item level on a 1–5 range; t compares each mean with the hypothetical mean of 3.

The mean total score for perceived cognitive skills was 3.409 (relative weight 68.19%), right at the boundary between the moderate and high levels, and significantly above the hypothetical mean ($t = 6.58$, $p < 0.001$, $d = 0.59$). Divided attention ranked first and was the only dimension at the high level ($M = 4.003$). The other five dimensions were at the moderate level, with close means (3.229–3.342); knowledge management was highest among them and selective attention lowest. Notably, divided attention stood more than six tenths of a point above all the other dimensions.

11.3 Level of AI tool use and of challenges and obstacles

Table 8. Means and standard deviations for the dimensions of the AI Tool Use Scale, in descending order (n = 124)

Dimension	Mean	SD	Relative weight	t	p	Level	Rank
Cognitive skills supported by the tools	3.568	0.665	71.35%	9.51	< 0.001	High	1
Extent and frequency of use	3.469	0.652	69.38%	8.01	< 0.001	High	2
Academic purposes of use	3.460	0.600	69.19%	8.53	< 0.001	High	3
Mindful and ethical use	3.450	0.654	69.01%	7.66	< 0.001	High	4
Total score	3.483	0.572	69.66%	9.41	< 0.001	High	---

The mean total score for AI tool use was 3.483 (relative weight 69.66%), a high level significantly above the hypothetical mean ($t = 9.41$, $p < 0.001$, $d = 0.84$). All four dimensions were at the high level with similar means (3.450–3.568). Cognitive skills supported by the tools ranked first, followed by extent and frequency of use, academic purposes, and finally mindful and ethical use.

Table 9. Means and standard deviations for the challenges and obstacles items, in descending order

Item	Mean	SD	Level	Rank
24. I find it difficult to assess the reliability of the information AI tools provide in my research context.	3.548	0.982	High	1
27. Restrictions on these tools (such as knowledge cut-off dates or paid subscriptions) prevent me from using them effectively in my research.	3.419	1.005	High	2
29. The lack of institutional or academic training on these tools limits my use of them in my scholarly work.	3.395	0.953	Moderate	3
28. I worry that using them may harm my own research, analytical and writing skills.	3.379	1.200	Moderate	4
25. I lack awareness of ways to use AI tools in scientific research.	3.355	1.076	Moderate	5
26. I find it difficult to write prompts that produce accurate research results.	3.347	0.996	Moderate	6
Total dimension score	3.407	0.751	High	---

A higher score indicates more perceived obstacles.

The mean score for the challenges and obstacles dimension was 3.407, at the lower edge of the high level. The obstacle rated highest was difficulty assessing the reliability of the information the tools provide ($M = 3.548$), followed by restrictions on the tools ($M = 3.419$) and the lack of institutional training ($M = 3.395$), while difficulty writing prompts came last ($M = 3.347$). Scores on this dimension correlated strongly and positively with total use ($r = 0.710$, $p < 0.001$) but not significantly with total cognitive skills ($r = 0.152$, $p = 0.093$). This supports the decision to treat the dimension as a separate variable without reverse-scoring it: those who use the tools most are also the most aware of their obstacles.

11.4 Most frequently used AI tools

Table 10. AI tools participants reported using most

Tool	Frequency	Percentage of participants
ChatGPT	95	76.61%
Gemini	29	23.39%

Meta	10	8.06%
Claude	7	5.65%
DeepSeek	7	5.65%

Respondents could name more than one tool, so the percentages do not necessarily add up to 100%.

11.5 Hypothesis 1

Table 11. Pearson correlation between total cognitive skills and total AI tool use

Analysis	n	r	95% CI	r ²	p	Decision
Main correlation	124	0.246	[0.07, 0.40]	0.061	0.006	Significant; weak relationship
Spearman (check)	124	0.235	—	—	0.008	Significant
Sensitivity analysis (items 27 and 29 removed)	124	0.248	[0.07, 0.41]	0.061	0.006	Significant

The table shows a statistically significant positive correlation between total perceived cognitive skills and total AI tool use ($r = 0.246$, $p = 0.006$, 95% CI 0.07–0.40), so the first null hypothesis is rejected. By Cohen's benchmarks, however, the relationship is weak: each variable accounts for only 6.1% of the variance in the other. Spearman's coefficient confirmed the result ($\rho = 0.235$, $p = 0.008$). The correlation did not change when the two items that refer explicitly to using the tool (27 and 29) were removed ($r = 0.248$), nor when the exclusion was widened to items 16, 24, 25 and 28 as well ($r = 0.254$), so the relationship is not an artefact of content overlap between the scales. In Harman's test the first factor accounted for 27.5% of the total variance, well under 50%, which does not point to serious common method bias. Skewness and kurtosis for both variables were within acceptable limits (skewness -0.59 and -0.99 ; kurtosis 0.20 and 1.19).

11.6 Hypotheses 2 and 3

Table 12. Differences in perceived cognitive skills by demographic variables

Variable	Category	n	Mean	SD	Test value	p	Effect size
Gender	Male	114	3.430	0.663	$t = 1.10$	0.275	$d = 0.36$
	Female	10	3.179	0.986			
Specialization	Scientific	45	3.313	0.807	$t = -1.08$ (Welch)	0.282	$d = -0.22$
	Humanities	79	3.464	0.617			
Academic rank	Assistant Lecturer	98	3.373	0.687	$F = 1.10$	0.337	$\eta^2 = 0.018$
	Lecturer	18	3.632	0.637			
	Assistant Professor	8	3.349	0.865			
Research experience	Less than five	77	3.363	0.715	$F = 0.59$	0.557	$\eta^2 = 0.010$
	Five to ten	23	3.540	0.486			
	Ten to fifteen	24	3.432	0.791			

Independent-samples t (Welch where variances were unequal) with d for gender and specialization; F with η^2 for rank and experience.

The table shows no statistically significant differences in perceived cognitive skills by

gender ($p = 0.275$), specialization ($p = 0.282$), academic rank ($p = 0.337$) or years of research experience ($p = 0.557$), and all effect sizes were small ($\eta^2 \leq 0.018$, $|d| \leq 0.36$). The second null hypothesis is therefore retained, with the caveat that the female group (10) and the Assistant Professor group (8) were small. Non-parametric tests (Mann–Whitney and Kruskal–Wallis) gave the same result.

Table 13. Differences in AI tool use by demographic variables

Variable	Category	n	Mean	SD	Test value	p	Effect size
Gender	Male	114	3.483	0.564	$t = 0.00$	0.997	$d = 0.00$
	Female	10	3.483	0.688			
Specialization	Scientific	45	3.694	0.316	$t = 3.81$ (Welch)	< 0.001	$d = 0.60$
	Humanities	79	3.363	0.648			
Academic rank	Assistant	98	3.404	0.576	$F = 9.78$	< 0.001	$\eta^2 = 0.139$
	Lecturer						
	Lecturer	18	3.995	0.242			
Research experience	Assistant Professor	8	3.299	0.456	$F = 2.57$ (Welch)	0.086	$\eta^2 = 0.024$
	Less than five	77	3.416	0.614			
	Five to ten	23	3.622	0.278			
	Ten to fifteen	24	3.567	0.622			

The table shows a statistically significant difference in AI tool use by specialization, in favour of the scientific disciplines ($M = 3.694$ vs. 3.363 , Welch's $t = 3.81$, $p < 0.001$), with a medium effect size ($d = 0.60$). There was also a significant difference by academic rank ($F = 9.78$, $p < 0.001$) with a large effect size ($\eta^2 = 0.139$). Games–Howell post hoc comparisons showed that Lecturers ($M = 3.995$) scored higher than both Assistant Lecturers ($M = 3.404$, $p < 0.001$) and Assistant Professors ($M = 3.299$, $p = 0.007$), with no significant difference between the latter two. No significant differences were found by gender ($p = 0.997$) or years of research experience (Welch's $F = 2.57$, $p = 0.086$). The third null hypothesis is therefore partly rejected, for specialization and academic rank.

11.7 Hypothesis 4

Table 14. Linear regression predicting AI tool use from perceived cognitive skills

Model / predictor	B	SE	β	t	p	VIF
Model 1: simple regression						
Constant	2.790	0.252	---	11.07	< 0.001	---
Total cognitive skills score	0.203	0.072	0.246	2.80	0.006	---
Model 2: multiple regression						
Constant	2.674	0.294	---	9.08	< 0.001	---
Selective attention	−0.176	0.127	−0.245	−1.39	0.168	4.11
Divided attention	0.050	0.105	0.061	0.48	0.633	2.16
Perception	0.287	0.121	0.376	2.37	0.020	3.34
Memory	0.126	0.147	0.175	0.86	0.394	5.56
Knowledge management	−0.090	0.107	−0.137	−0.84	0.402	3.49
Thinking and problem	0.037	0.105	0.053	0.35	0.727	3.01

Model 1: $R = 0.246$, $R^2 = 0.061$, $F(1, 122) = 7.86$, $p = 0.006$.

Model 2: $R = 0.341$, $R^2 = 0.116$, adjusted $R^2 = 0.071$, $F(6, 117) = 2.56$, $p = 0.023$.

Model 1 shows that total perceived cognitive skills significantly predict AI tool use ($B = 0.203$, $\beta = 0.246$, $p = 0.006$), although they explain only 6.1% of its variance. Model 2 was significant overall and explained 11.6% of the variance (adjusted 7.1%), but perception was the only one of the six dimensions to be a significant predictor on its own ($\beta = 0.376$, $p = 0.020$). Selective attention and knowledge management had negative, non-significant coefficients even though their simple correlations with use were positive. This is a well-known consequence of high intercorrelations among predictors (here between 0.62 and 0.85, with VIF values from 2.16 to 5.56), so these coefficients should not be interpreted in isolation from one another. The fourth null hypothesis is therefore rejected.

11.8 Hypothesis 5

Table 15. Pearson correlations between the cognitive skills dimensions and total AI tool use

Dimension	r	95% CI	p	Decision
Selective attention	0.173	[-0.00, 0.34]	0.055	Not significant
Divided attention	0.206	[0.03, 0.37]	0.022	Significant at 0.05 only
Perception	0.308	[0.14, 0.46]	< 0.001	Significant
Memory	0.248	[0.08, 0.41]	0.006	Significant
Knowledge management	0.174	[-0.00, 0.34]	0.053	Not significant
Thinking and problem solving	0.195	[0.02, 0.36]	0.030	Significant at 0.05 only

Because six tests were run, a Bonferroni-adjusted significance level was used ($0.05 \div 6 = 0.0083$); "Significant" in the decision column means significant after correction.

All six dimensions correlated positively with total use, with coefficients between 0.173 and 0.308, that is, weak to moderate by Cohen's benchmarks. After Bonferroni correction, only the correlations for perception ($r = 0.308$, $p < 0.001$) and memory ($r = 0.248$, $p = 0.006$) remained significant; the correlations for divided attention and for thinking and problem solving were significant at the 0.05 level only before correction. The fifth null hypothesis is therefore partly rejected, for perception and memory.

12. Discussion

The results are discussed below in light of the theoretical framework and previous studies, following the order of the research questions.

12.1 Levels of the two variables

The level of AI tool use was high ($M = 3.483$), and the level of perceived cognitive skills sat at the boundary between moderate and high ($M = 3.409$). The high level of use makes sense given how the eligible population was defined: it was limited to people who already use the tools, after non-users had been excluded, so one would expect their level of use to lean toward the high end. This fits with Al-Bukhrani et al. (2025), who found that these tools are widespread among researchers but used to very different depths. The cognitive skills dimensions clustered around the moderate level, apart from divided attention, which stood out ($M = 4.003$). This may reflect a

tendency to overestimate one's ability to handle several tasks at once, whereas models of attention hold that the resources available for concurrent tasks are limited (Kahneman, 1973; Wickens, 2008). These levels are, after all, self-assessments, and social desirability may have pushed them upward, particularly since most participants were early in their research careers (62.10% with less than five years of experience).

12.2 The relationship between cognitive skills and tool use

The study found a significant positive relationship between perceived cognitive skills and AI tool use ($r = 0.246$). The direction of this result agrees with the assumption the study started from, and with studies that have included a cognitive variable in adoption models. Şimşek et al. (2025) found a significant effect of metacognitive self-regulation on perceived usefulness and ease of use; Kleine et al. (2023) reported a positive relationship between cognitive technology readiness and intention to use; and Uludağ et al. (2025) found a significant effect of self-efficacy on intention to use. Cognitive load theory offers one explanation: a researcher needs a certain level of cognitive competence to decide what to hand over to the tool and what to keep for human judgement (Sweller, 1988). The idea of strategic cognitive offloading offers another, describing how people draw on an external tool without giving up control over its output (Risko & Gilbert, 2016).

The relationship is weak, however. Cognitive skills explain only 6.1% of the variance in use. This is close to what El-Ashry et al. (2025) found, namely positive but weak correlations between AI-related variables and critical thinking motivation, and it means that most of the variation in use is driven by other factors that adoption models have highlighted: attitudes and subjective norms (Fishbein & Ajzen, 1975; Al-Bukhrani et al., 2025), perceived usefulness and ease of use (Davis, 1989), and social influence and facilitating conditions (Venkatesh et al., 2003). The size of the relationship was probably also reduced by the restricted range that resulted from excluding non-users, since this narrows the variance in use and lowers any correlation computed on it.

The relationship cannot be put down to content overlap between the scales, because it did not change when the items referring to tool use were removed ($r = 0.248$ and 0.254). Nor can common method variance account for it on its own, since the general factor in Harman's test explained only 27.5% of the variance. At the dimension level, only perception and memory remained significant after Bonferroni correction. This fits the nature of working with AI tools, which depends on understanding what the output means and recognising the tool's limits (perception), and on retaining and recalling effective prompts and extracted information across successive stages of a project (memory), as the information-processing perspective would predict (Neisser, 1967; Baddeley, 2000).

12.3 Differences by demographic variables

No differences in perceived cognitive skills emerged for any demographic variable, which is consistent with treating these skills as general intellectual competencies that are not tied to a particular discipline or rank (Kim et al., 2015). Tool use, on the other hand, differed by specialization in favour of the scientific disciplines, with a medium effect ($d = 0.60$). One likely reason is the nature of research tasks in the sciences, which often involve data analysis and reviewing literature in foreign languages, two of the main functions these tools serve (Al-Bukhrani et al., 2025). Use also differed by academic rank, with Lecturers scoring higher than the other two

groups. This partly agrees with Al-Badawi Balla and Al-Mustafa (2025), who found higher scores among faculty of higher rank, but differs from it in that Assistant Professors did not score higher than Assistant Lecturers. Not too much should be made of this difference, however, since the Assistant Professor group had only eight members and the Lecturer group was unusually homogeneous. No differences in use were found by gender or years of experience, bearing in mind the small number of women in the sample (10).

12.4 Regression results and the distinctness of the dimensions

The multiple regression model was significant overall and explained 11.6% of the variance, but perception was the only dimension with a significant unique contribution. This reflects the weak separation between the dimensions: HTMT values between the cognitive skills dimensions exceeded 0.85 for most pairs, and intercorrelations reached 0.85. As measured in this study, then, cognitive skills behave more like a general construct than a set of independent dimensions. This is in line with Billing's (2007) conclusion that cognitive skills overlap and that their transfer depends on the setting in which they are acquired. It suggests that training aimed at the cognitive structure as a whole is likely to be more useful than training focused on a single dimension, with particular attention to perception and the evaluation of output. The lack of separation was even clearer on the use scale, which turned out to be essentially unidimensional.

12.5 What the challenges and obstacles dimension tells us

Perceived obstacles correlated strongly and positively with use ($r = 0.710$), not negatively as one might expect. In other words, perceiving obstacles is a sign of experience with the tools rather than of turning away from them: those who use the tools more run into their limits more often and become more aware of how hard it is to verify their output, which was the highest-rated obstacle in this study. This finding may help explain why perceived barriers had no significant effect on intention to use in Al-Bukhrani et al. (2025), and it echoes the concerns about over-reliance and output accuracy voiced by the doctoral students in El Hosayny et al. (2025).

12.6 Limitations

Several methodological limitations should be kept in mind. First, the design is correlational and does not allow conclusions about the direction of causality. Second, both variables were measured by self-report at the same time, so what was measured is the researchers' perception of their own skills and use rather than their actual performance, which leaves the results open to common method bias and social desirability. Third, the cognitive skills items were written in the context of tool use, so there is some content overlap with the use scale. Fourth, the study was limited to tool users in two departments of a single directorate, so its findings should be generalised to non-users or other settings only with caution. Fifth, the sample was unbalanced in gender (10 women out of 124) and academic rank (8 Assistant Professors), which reduces the power to detect differences on these variables.

13. Conclusions, Recommendations and Suggestions for Further Research

13.1 Conclusions

The researcher draws the following conclusions from the results. First, perceived cognitive skills are positively but weakly related to AI tool use; they facilitate use but are not its main determinant. Second, the cognitive effect operates through a general cognitive structure, within which perception stands out. Third, tool use is

shaped by the academic context (specialization and academic rank), whereas cognitive skills are not. Fourth, awareness of obstacles goes hand in hand with intensive use of the tools rather than standing in its way.

13.2 Recommendations

In light of the results, the researcher recommends building the development of perception and output-evaluation skills into in-service training on AI tools, without relying on these skills alone given their modest contribution to explaining use, and giving particular attention in such programmes to teacher-researchers in the humanities and to those holding the rank of Assistant Lecturer. In addition, the researcher recommends:

1. Setting clear published rules in directorates of education for the use of AI tools in preparing promotion research and other scholarly work, including disclosure of their use and verification of their output, to guard against excessive reliance on them.
2. Addressing the main obstacles identified in this study, chiefly the difficulty of judging the reliability of output, restrictions on the tools and the lack of institutional training, by including practical training units on writing research prompts and on evaluating and verifying tool output.

13.3 Suggestions for further research

1. Rewording the cognitive skills items that refer explicitly to tool use so that they measure the cognitive skill itself in a general research context, and then testing the factor structure of the scale on a larger sample.
2. Using performance-based measures of cognitive skills (such as attention and working-memory tasks, or the researcher's evaluation of actual tool output) alongside self-report.
3. Conducting a similar study with a larger sample that is better balanced in gender and academic rank and includes university faculty, postgraduate students and non-users of the tools.
4. Conducting an experimental or quasi-experimental study of the effect of a training programme on cognitive skills and its impact on AI tool use, which would allow the causal conclusions that a correlational design cannot support.
5. Conducting a longitudinal study that follows the direction of the relationship over time, to distinguish between cognitive skills facilitating use and intensive use strengthening or weakening those skills.
6. Building an extended predictive model that combines cognitive skills with the variables of adoption models (attitudes, perceived usefulness, AI anxiety and self-efficacy) to estimate the relative contribution of each.
7. Conducting a qualitative study using in-depth interviews to explore how researchers use these tools at different stages of their work.

Declarations

Research ethics: Participants were informed of the purpose of the study and told that participation was voluntary and that they could withdraw at any time. No identifying information was collected, and the data were used for research purposes only.

Use of AI tools: The researcher used the AI tool Claude (Anthropic) to carry out some of the statistical analyses, for language and methodological review, for drafting parts of the presentation and discussion of the results, and for translating the paper into English. The researcher reviewed and verified all of this output and takes full responsibility for the content of the paper.

Data availability: The raw data on which the study is based are available from the researcher on reasonable request.

Conflict of interest: The researcher declares no conflict of interest.

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References

References follow the American Psychological Association (APA) style, 7th edition.

Arabic-language sources

1. Al-Badawi Balla, A. A., & Al-Mustafa, M. M. A. (2025). Faculty members' attitudes toward using artificial intelligence applications in scientific research: A field study at the University of Al-Butana, Sudan [in Arabic]. *Al-Butana Journal of Educational Sciences*, (18), 25–54.

2. Al-Kubaisi, S. (2005). Knowledge management [in Arabic]. Arab Administrative Development Organization.

3. English-language sources

4. Al-Bukhrani, M. A., Alrefaee, Y. M. H., & Tawfik, M. (2025). Adoption of AI writing tools among academic researchers: A Theory of Reasoned Action approach. *PLOS ONE*, 20(1), e0313837. <https://doi.org/10.1371/journal.pone.0313837>
5. Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. In K. W. Spence & J. T. Spence (Eds.), *The psychology of learning and motivation* (Vol. 2, pp. 89–195). Academic Press.
6. Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, 4(11), 417–423. [https://doi.org/10.1016/S1364-6613\(00\)01538-2](https://doi.org/10.1016/S1364-6613(00)01538-2)
7. Billing, D. (2007). Teaching for transfer of core/key skills in higher education: Cognitive skills. *Higher Education*, 53(4), 483–516. <https://doi.org/10.1007/s10734-005-5628-5>
8. Broadbent, D. E. (1958). *Perception and communication*. Pergamon Press.
9. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
10. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., ... Wright, R. (2023).

"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>

11. El-Ashry, A. M., Al Saleh, N. S., AlOtaibi, N. G., Almutairi, T. Z., Sallam, L. A., Alnassar, M. M., Alshehri, K. A., Al-Ghareeb, S. A., Al-Otaibi, R. A., Almutairi, W. M., Alkubati, S. A., & El-Sayed, M. M. (2025). The impact of artificial intelligence attitudes and acceptance on critical thinking motivation among nursing students in Saudi Arabia. *SAGE Open Nursing*, 11. <https://doi.org/10.1177/23779608251369564>
12. El Hosayny, O., Razkane, H., & Yeou, M. (2025). Extended TAM-based acceptance of AI for supporting critical thinking in academic research: An examination of perceived benefits and challenges. *Discover Artificial Intelligence*, 5, 167. <https://doi.org/10.1007/s44163-025-00390-x>
13. Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.
14. Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American Psychologist*, 34(10), 906–911. <https://doi.org/10.1037/0003-066X.34.10.906>
15. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
16. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
17. Igolkina, A. A., & Meshcheryakov, G. (2020). semopy: A Python package for structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 27(6), 952–963. <https://doi.org/10.1080/10705511.2019.1704289>
18. Kahneman, D. (1973). *Attention and effort*. Prentice-Hall.
19. Kim, Y. K., Edens, D., Iorio, M. F., Curtis, C. J., & Romero, E. (2015). Cognitive skills development among international students at research universities in the United States. *Journal of International Students*, 5(4), 526–540. <https://doi.org/10.32674/jis.v5i4.413>
20. Kleine, A.-K., Kokje, E., Lerner, E., & Gaube, S. (2023). Attitudes toward the adoption of 2 artificial intelligence-enabled mental health tools among prospective psychotherapists: Cross-sectional study. *JMIR Human Factors*, 10, e46859. <https://doi.org/10.2196/46859>
21. Mayer, R. E., & Wittrock, M. C. (2006). Problem solving. In P. A. Alexander & P. H. Winne (Eds.), *Handbook of educational psychology* (2nd ed., pp. 287–303). Lawrence Erlbaum Associates.
22. McDonald, R. P. (1999). *Test theory: A unified treatment*. Lawrence Erlbaum

Associates.

23. Neisser, U. (1967). *Cognitive psychology*. Appleton-Century-Crofts.
24. Pauleen, D. J., & Gorman, G. E. (Eds.). (2011). *Personal knowledge management: Individual, organizational and social perspectives*. Gower.
25. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
26. Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences*, 20(9), 676–688. <https://doi.org/10.1016/j.tics.2016.07.002>
27. Şimşek, A., Tepetaş Cengiz, G. Ş., & Bal, M. (2025). Extending the TAM framework: Exploring learning motivation and agility in educational adoption of generative AI. *Education and Information Technologies*, 30(15), 20913–20942. <https://doi.org/10.1007/s10639-025-13591-9>
28. Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4
29. Uludağ, F., Kılıç, E., & Çelik, H. E. (2025). Artificial intelligence, social influence, and AI anxiety: Analyzing the intentions of science doctoral students to use ChatGPT with PLS-SEM. *Humanities and Social Sciences Communications*, 12, 1308. <https://doi.org/10.1057/s41599-025-05641-x>
30. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
31. Wickens, C. D. (2008). Multiple resources and mental workload. *Human Factors*, 50(3), 449–455. <https://doi.org/10.1518/001872008X288394>
32. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, 16, 39. <https://doi.org/10.1186/s41239-019-0171-0>
33. Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. <https://doi.org/10.1016/B978-012109890-2/50031-7>