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TRANSFORMING PROFESSIONAL PRACTICE WITH CHATGPT: LEARNING AND INFORMATION PROCESSING

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Purpose: The main objective of the present study was to identify differences in how employed and non-employed students evaluate ChatGPT's dual functions – information processing and tutoring.
Design/methodology/approach: A Computer-Assisted Self-Interview (CASI) survey was conducted in the second quarter of 2024. After excluding non-users of ChatGPT, 449 valid responses were analyzed. Instrument reliability and factorability were verified. To assess the intensity of selected variables, a five-point Likert-type scale was applied. Because variables departed from normality, non-parametric tests (Mann-Whitney U) compared evaluations between employed and non-employed respondents.
Findings: Respondents in both groups evaluated ChatGPT positively as a substitute for a traditional search engine, with no notable differences between employed and non-employed students. In contrast, non-employed students assessed ChatGPT's tutoring role more favorably, which may reflect their greater reliance on digital tools for academic support. Overall, evaluations tended to be positive, although the variability in responses suggests differing levels of familiarity with or expectations toward the technology.
Research limitations/implications: This study reflects one point in time, so future research should examine changes over longer periods. The analysis focused only on two main functions of ChatGPT – information processing and tutoring and on general use rather than specific academic tasks. Because the sample consisted solely of Polish students, the findings may not be fully applicable in other cultural contexts. Future studies should therefore involve more diverse populations and explore additional functions and learning situations.
Practical implications: For students and early-career knowledge workers, conversational search with summarized answers can serve as the standard approach. Tutoring and guided support may be especially useful for those with more time for structured learning, such as non-employed students. Universities and organizations should combine AI use with basic training in how to check information, create effective prompts, and evaluate results, while also providing clear source information to ensure that human judgment remains central.
Social implications: Adjusting AI support to students' time and workload can help reduce inequalities in learning. Teaching habits of verification – such as citing sources and signaling uncertainty – can lower the risks of overreliance, bias, and weakened critical thinking, while still allowing users to benefit from productivity gains.

Originality/value: Introduces a two-function framework (interactive retrieval/processing vs. tutoring) linking HCIR-style information work with AI-supported learning, and provides empirical evidence that employment status does not shape evaluations of the search-substitution function but does differentiate evaluations of the tutoring function in a large sample of active users.
Keywords: ChatGPT; conversational search; Human-Computer Information Retrieval (HCIR), AI tutoring.
Category of the paper: Research paper.

1. Introduction

Generative conversational systems like ChatGPT are transforming the way individuals engage with information in their daily work. By leveraging advancements in Natural Language Processing (NLP), these systems can understand and generate human-like text, making interactions more intuitive and efficient (Bansal et al., 2024; Fui-Hoon Nah, 2023; Stock, 2000). As a result, users can retrieve information more naturally through dialogue, enhancing the information retrieval process (Agrawal, 2025; Segeda, 2025; McTear, 2022). Furthermore, the integration of knowledge graphs allows these systems to access and synthesize vast amounts of interconnected data, improving their ability to provide relevant responses (Liu et al., 2019). Chatbots, as a subtype of these systems, are increasingly utilized in various sectors, including customer service, where they automate tasks traditionally performed by humans (Almansor et al., 2019; Io, Lee, 2017; Thorne, 2017). This rapid diffusion of conversational AI is not only reshaping how people find and make sense of information but also revolutionizing learning processes in professional environments. Consistent with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), evaluations of conversational tools are driven primarily by perceived usefulness (performance expectancy) and perceived ease of use (effort expectancy), which, in turn, predict behavioral intention and use behavior (Venkatesh, Thong, Xu, 2012; Venkatesh et al., 2003; Davis, 1989). From a human–computer information retrieval (HCIR) perspective, dialog-based search and iterative synthesis reduce cognitive load and increase decision accuracy, thereby providing a mechanism that links the information-processing function to work outcomes (Hauff et al., 2021; White et al., 2013; Marchionini, 2006).

Beyond narrowly defined "writing aid" uses, two functions have become especially salient for knowledge-intensive tasks:

1. Interactive information retrieval and processing, where conversational search and synthesis replace multi-tab keyword querying.
2. On-demand tutoring, where the system explains concepts, scaffolds problem solving, and offers step-by-step guidance.

In theoretical terms, the interactive information-retrieval and processing function operates primarily by increasing performance expectancy and reducing perceived effort (effort expectancy) – thereby lowering cognitive costs within the HCIR framework – whereas the tutoring function depends more strongly on perceived ease of use (effort expectancy) and facilitating conditions (e.g., time and resources), consistent with the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology.

Together, these capabilities promise time savings, reduced cognitive load, and faster movement from raw inputs to actionable judgments – while also raising concerns about bias, overreliance, and the erosion of critical appraisal skills.

A growing body of research highlights both the benefits and limitations of LLM-supported tutoring with respect to learning outcomes and the associated improvement in workplace performance. Reviews and experimental studies indicate that such tutoring can enhance motivation, foster higher-order thinking, and improve task performance, even with minimal guidance (Guo et al., 2025; Giannakos et al., 2024; Steinert et al., 2024). In parallel, studies of Human–Computer Information Retrieval (HCIR) and conversational search highlight how iterative dialogue, clarification questions, and retrieval augmentation can improve practical precision and recall relative to traditional search flows (Wang, Ai, 2022; Hauff et al., 2021; Salle et al., 2022). Yet, despite this momentum, we know less about how these two functions jointly structure users' day-to-day work and which user characteristics systematically shape their evaluations of ChatGPT in each role. Thus, this area reveals a research gap, the exploration of which may constitute a valuable contribution to the development of disciplines such as management sciences, sociology, and pedagogy. This gap matters for organizations and higher-education institutions alike. Many students are already part-time employees or interns and act as "junior knowledge workers" whose tool choices spill over into professional practice. Previous studies indicate that perceptions and adoption vary depending on user characteristics, including age, familiarity with large language models (LLMs), context of use, and other factors (Acosta-Enriquez et al., 2024; Camilleri, 2024; Raman et al., 2024). Employment status, in particular, may shape both time availability and task portfolios, potentially shifting preferences toward rapid information triage (interactive retrieval from LLMs such as ChatGPT) rather than extended, lesson-oriented interactions (tutoring). At the same time, responsible-use frameworks emphasize keeping human judgment central, pairing AI support with provenance cues and light training in verification (Saenz et al., 2024; Marzouk et al., 2023; Dastani, Yazdanpanah, 2023).

Against this backdrop, this paper investigates how professional work is being transformed by ChatGPT, focusing on users' evaluations of its two primary functions that directly support knowledge work: interactive information retrieval and processing, and tutoring for learning and upskilling. Drawing on a large sample of higher education students in Poland – many of whom are employed alongside their studies – we pose the following research question:

RQ1: How do users evaluate ChatGPT as an interactive tool for information retrieval and processing?

RQ2: How do users evaluate ChatGPT as a tutor that provides explanations and structures learning?

The remainder proceeds as follows. Section 2 reviews related literature and develops hypotheses – building on prior evidence, theoretical frameworks, and the aforementioned research questions, we propose two hypotheses regarding the effects of employment status-one for each function discussed in Section 2.2. To test these hypotheses, we conducted a computer-assisted self-administered interview (CASI) during the second quarter of 2024, yielding 449 valid responses from active ChatGPT users. Section 3 details the methodology. Following assessments of reliability and the data's suitability for factor analysis, we employed non-parametric tests to compare evaluations based on employment status. Section 4 presents the results, including descriptive statistics and statistical tests. Section 5 presents a discussion of the results, their interpretation, and the practical implications for educational and professional contexts. Section 6 concludes with limitations and directions for future research.

2. Conceptual background

2.1. Literature review

Among the most frequently used functions of ChatGPT are its role as an interactive tool for information retrieval and processing, and its role as a traditional tutor supporting educational tasks. Both of these dimensions substantially transform the work performed by contemporary individuals. Consequently, to move beyond descriptive accounts, this review is anchored in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Predictions about the evaluation and adoption of ChatGPT follow from performance expectancy, effort expectancy, and facilitating conditions, moderated by user characteristics. By offloading routine search and synthesis, users can redirect attention to higher-order reasoning and creative problem-solving (León-Domínguez, 2024).

Empirical and review studies characterize ChatGPT as an effective and scalable tutor that provides instant explanations, writing support, guidance, and structuring of the learning process, which is highly beneficial for everyday work and for enhancing professional qualifications (Park, Kim, 2025; Sirisathitkul, Jaroonchokanan, 2025; Pardos, Bhandari, 2024). As a tutor in the workplace, ChatGPT explains complex issues in simple language, provides step-by-step guidance, and offers suggestions for improving texts, code, or analyses. This facilitates faster professional onboarding and the systematic development of skills. It can also simulate typical situations (e.g., a client conversation or a discussion of results) and propose short exercises (Afzal et al., 2024; Yang et al., 2024). ChatGPT also yields positive effects by reducing the time required for learning, thereby enabling more efficient task performance and minimizing errors (Huesca et al., 2024; Reid, 2024). ChatGPT is also applied as a workplace tutor in cybersecurity and artificial intelligence training contexts (Cong-Lem et al., 2025) Research shows that when employees perceive ChatGPT as an intelligent, self-learning system, they acquire information and knowledge more readily. Consequently, they assess its usefulness more favorably and report a greater willingness to use it – and this willingness is the strongest predictor of actual adoption (Jo, Park, 2023). This, in turn, points to another important function of ChatGPT, namely its role as a tool for information retrieval and processing.

In the workplace and in the performance of everyday tasks, ChatGPT has facilitated a shift from keyword-based queries to conversational search interfaces. This transition is enabled by ChatGPT's natural language capabilities, which enhance user interaction and information retrieval. The conversational approach not only supports more intuitive and efficient searches but also reduces cognitive load, making it a preferred method for information seeking. This shift is observable across various sectors, where ChatGPT is employed for tasks ranging from brainstorming to drafting and proofreading, thereby transforming how information is accessed and applied in professional contexts (Retkowsky et al., 2024; Jo, Park, 2023). At the same time, this reconfiguration of workplace search reshapes information literacy: users increasingly depend on iterative, multi-turn exchanges that allow clarification and domain adaptation (e.g., through retrieval augmentation), thereby improving practical precision and recall (Zou et al., 2023; Kiesel et al., 2021; Liu, 2021). Consequently, the integration of techniques such as retrieval augmentation and interactive classification systems is pivotal in this transformation. These systems support a dynamic search process in which users refine queries and receive feedback that is both contextually relevant and precise. Such iterative processes offered by ChatGPT are particularly important for professionals who require high-quality, task-specific information, often under strict time constraints (Vishwakarma, Kumar, 2024; Al Naqbi et al., 2024; Zeng et al., 2022). Moreover, Human-Computer Information Retrieval (HCIR) enhances cognitive engagement. HCIR systems foster fluid, iterative user interaction and enable users to actively explore and refine search tasks – an ability that is crucial in time-sensitive professional contexts (White et al., 2013). However, in enumerating these benefits, it is essential not to overlook the attendant risks. Overreliance on conversational systems may inadvertently diminish critical-thinking skills, as users may accept AI-generated responses without adequate verification (Glickman, Sharot, 2024; Zhai et al., 2024). Moreover, concerns about bias, misinformation, and data security underscore the need to balance efficiency with responsible use, ensuring that human judgment remains central to information practices (Fecher et al., 2025; Buchanan, Hickman, 2024; Polyportis, Pahos, 2024). In particular, the human-computer information retrieval (HCIR) literature treats the user as an active partner in iterative search, and features such as explainability, source traceability, and opportunities for clarification serve as mechanisms to reduce cognitive load, thereby strengthening perceived usefulness and effort expectancy (Hauff et al., 2021). Nonetheless, there is no indication that these risks will impede progress in the use of AI as an interactive tool for the acquisition and processing of information. On the contrary, recent studies indicate that, when embedded in HCIR-informed workflows and paired with retrieval augmentation, source attribution, and uncertainty cues, conversational systems can both accelerate sense-making and improve decision quality (Poddar et al., 2022). The strongest gains appear when tools nudge verification (e.g., cite-and-trace, side-by-side evidence views) and users receive light training in prompt and evaluation strategies – positioning AI as a high-leverage partner in knowledge work, under clear provenance, organizational guardrails, and human oversight (Farber, 2025; Järvelä et al., 2025; Robertson et al., 2024; Adam, Benlian, 2023).

2.2. Formulating hypotheses

A growing body of evidence indicates that students increasingly use ChatGPT in their everyday information-seeking activities – such as generating ideas, extracting key points, and identifying scholarly sources – treating it as an interactive interface for information retrieval rather than merely a writing aid (Ravšelj et al., 2025). Patterns of preference between Google and ChatGPT vary depending on user characteristics (e.g., familiarity with large language models, age), suggesting that group-specific attributes – including employment status – may shape how learners assess ChatGPT's capabilities in information processing (Zhang, Yang, 2025). Researchers also describe LLMs as tools that accelerate access to and filtering of information, while emphasizing that both benefits and risks depend on their design and the surrounding context (Kasneci et al., 2023). Reviews concerning student engagement demonstrate heterogeneous outcomes across different environments and learner profiles, reinforcing the nondeterministic expectation that employment status influences perceptions of ChatGPT as a tool for information retrieval and processing (Lo et al., 2024). According to the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), evaluations of ChatGPT's information-processing role increase with performance expectancy and effort expectancy. Within the HCIR paradigm, this effect is mediated by reductions in cognitive costs during dialog-based search. Because employment status shapes available time and task portfolios, we anticipate differences in the strength of these mechanisms across groups. Accordingly, we state Hypothesis 1 (H1) as follows:

H1: Employment status differentiates students' evaluations of ChatGPT as an interactive tool for information retrieval and processing (a substitute for a traditional search engine).

Research shows that LLM-supported tutoring, particularly when accompanied by explicit guidance or feedback, enhances learning outcomes. A review of multiple experiments revealed improvements in instructional performance, higher motivation, development of higher-order thinking, and reduced cognitive load (Deng et al., 2024). A randomized controlled trial further demonstrated that a guidance mechanism in working with ChatGPT-encouraging learners to attempt a solution independently before receiving hints – promotes self-regulated learning, higher-order thinking, and knowledge construction more effectively than typical instructional tools (Lee et al., 2024). At the same time, student employment may reduce the time available for activities requiring greater time investment, such as extended study sessions (Darolia, 2014), and meta-analytic evidence shows that effective time management is moderately positively associated with academic achievement (Aeon et al., 2021). Taken together, these mechanisms motivate the expectation that employment status differentiates students' evaluations of ChatGPT's role as a tutor. Therefore, H2 is formulated as follows:

H2: Employment status differentiates students' evaluations of ChatGPT's role as a tutor (a learning support tool).

Considered jointly, H1 and H2 specify two complementary mechanisms – information retrieval and tutoring – by which employment status may influence students' evaluations of ChatGPT.

3. Research methodology

The study employed the CASI (Computer-Assisted Self-Interviewing) methodology. Participants accessed the questionnaire via a QR code or a link to the Webankieta platform. Responses were submitted using mobile phones, computers, or other internet-enabled devices. The collected data were subsequently exported to Microsoft Excel and IBM SPSS Statistics 29 for analysis. The survey was conducted in the second quarter of 2024.

Respondents were recruited from a variety of educational institutions across Poland and thus represented individuals enrolled in higher education. They covered a broad spectrum of academic disciplines, including the social sciences, humanities, natural sciences, and technical fields. Faculty and administrative staff at educational institutions assisted in facilitating student participation (in addition, social media campaigns were used to collect responses from individuals).

For further analysis, questionnaires from respondents who reported not using ChatGPT were excluded. Thus, only those who declared employing ChatGPT in their daily lives were retained. In total, 449 valid questionnaires from ChatGPT users were included in the dataset.

The survey instrument consisted primarily of closed-ended questions. To assess the intensity of selected variables, a five-point Likert-type scale was applied: −2 = "Certainly not," −1 = "Preferably not," 0 = "Uncertain," 1 = "Preferably yes," 2 = "Certainly yes".

Following data collection, a series of statistical tests – including Cronbach's alpha, the Kaiser-Meyer-Olkin (KMO) measure, and Bartlett's test of sphericity – were performed (see Table 1). These results confirmed the reliability of the survey instrument and its appropriateness for factor analysis.

Table 1.
Chat GPT as an information processing and learning tool – basic descriptive statistics

Cronbach's alpha	Kaiser-Mayer-Olkin tests	Bartlett's test of sphericity
0.872	0.850	Approx. Chi-Square 3461.510 df 378 Sig. < 0.001

Source: own elaboration.

The Kolmogorov-Smirnov test was originally utilized to examine the distributional characteristics of the variables, indicating substantial departures from the normal distribution. As a result, non-parametric statistical methods were subsequently employed. In particular, Mann-Whitney U tests were conducted to assess the disparities among the variables.

4. Results

Table 2 presents basic descriptive statistics on the use of ChatGPT for interactive information acquisition and processing – as a substitute for a traditional search engine – and for its role as a conventional tutor that provides lessons and explains complex course topics. Evaluations of both functions are disaggregated by respondents' employment status (employed vs. not employed). In the search-engine-substitution function, assessments are clearly positive and very similar among students who are not employed and those who are employed (arithmetic mean 1.08 vs. 1.09). By contrast, the traditional tutoring role is stronger among students who are not employed (arithmetic mean 0.93) than among employed students (arithmetic mean 0.64), even though in both groups the median equals one. Additionally, standard deviations exceeding one indicate substantial variability in respondents' individual experiences.

The distributions also exhibit negative skewness across groups (ranging from -0.781 to -1.717), indicating that positive evaluations of ChatGPT were more frequent than negative ones. At the same time, the kurtosis values highlight differences in the shape of the distributions: positive kurtosis in most groups indicates "heavier tails", whereas the negative kurtosis for employed students in the tutoring role (-0.371) suggests a flatter and more dispersed response pattern. Taken together, these statistics confirm that while central tendencies are broadly similar, the underlying variation in experiences and intensity of use is noteworthy.

Table 2.
Chat GPT as an information processing and learning tool – basic descriptive statistics

Specification	Information processing – ChatGPT as a Search engine		Learning – Chat GPT as a Tutor	
	Not employed N = 88	Employed N = 361	Not employed N = 88	Employed N = 361
Mean	1.08	1.09	0.93	0.64
Standard error of the mean	0.117	0.054	0.108	0.059
Median	1.00	1.00	1.00	1.00
Mode	1	1	1	1
Standard deviation	1.096	1.018	1.015	1.117
Variance	1.200	1.037	1.030	1.248
Skewness	-1.717	-1.465	-1.347	-0.781
Standard error of skewness	0.257	0.128	0.257	0.128
Kurtosis	2.688	1.745	1.712	-0.371
Standard error of kurtosis	0.508	0.256	0.508	0.256
Min	-2	-2	-2	-2
Max	2	2	2	2

Source: own elaboration.

In order to assess the disparities among the distinct groups, non-parametric tests were employed (as mentioned the distribution was not normal). The Mann-Whitney U tests concerning employed respondents (as opposed to those not employed) and their information processing capabilities do not reveal any significant differences in the contemporary perception of ChatGPT ($U = 15824.500$; $Z = -0.060$, $p = 0.952$). The circumstances concerning the role of the tutor are delineated differently.

The Mann-Whitney U tests, when comparing employed participants (as opposed to those not employed) and their learning experiences, reveal notable disparities in their current perceptions of ChatGPT ($U = 13621.000$; $Z = -2.256$, $p = 0.024$). Consequently, it is possible to dismiss hypothesis 1, whereas hypothesis 2 can be substantiated.

In summary, the findings show that while ChatGPT's role as an information-processing tool is widely recognized, its tutoring function is more sensitive to contextual factors such as time availability and workload. The observed variability further suggests that individual characteristics beyond employment status may play a significant role in shaping adoption and evaluation patterns.

5. Discussion

The findings suggest that students (regardless of employment status – accordingly, hypothesis 1 can be rejected) converge in using ChatGPT as a fast, interactive substitute for traditional search, with virtually identical central tendencies (median = 1; mean ≈ 1.08-1.09) and pronounced negative skewness indicating generally positive evaluations. Consistent with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of

Technology (UTAUT), this pattern implies that when performance expectancy is high and cognitive costs in dialog-based search (HCIR) are low, evaluations converge across employment groups. This aligns with recent evidence that many undergraduates frequently choose conversational tools for academic help-seeking, with preferences varying by user characteristics (e.g., LLM fluency, age) (Zhang, Yang, 2025; Ravšelj et al., 2025).

By contrast, ChatGPT's role as a classic tutor appears more salient among non-working students (mean = 0.93 vs. 0.64), and the Mann–Whitney test confirms this difference ($p = .024$), supporting hypothesis 2. The advantage observed among nonworking students aligns with UTAUT: effort expectancy and facilitating conditions (e.g., time and support) enhance evaluations of the tutoring role, whereas time constraints among employed students attenuate this effect. This pattern is consistent with experimental and review evidence showing that LLM-based tutoring can improve learning when students have time and when guidance is provided (Deng et al., 2024; Lee et al., 2024). A plausible interpretation is that employed students have less time for guided, lesson-like interactions or rely on alternative learning resources at work, whereas non-working students may seek more structured explanations and step-by-step support. At the same time, standard deviations exceeding 1 (on a −2 to 2 scale) and positive kurtosis in three groups – with negative kurtosis in one – indicate heterogeneous distributional shapes, with heavier tails (and a higher chance of extreme responses) in the positively kurtotic groups and a flatter profile in the negatively kurtotic group, mirroring broader literature that finds mixed engagement effects and emphasizes the importance of instructional design and safeguards (Kasneci et al., 2023; Lo et al., 2024).Practically, these results imply that universities could emphasize search-facilitating features for all students, while tailoring tutoring-style scaffolds – especially scaffolded, hint-based use – for those not working, in line with human-centered policy guidance on GenAI in education (UNESCO, 2023).

From a practical perspective, the results point to two distinct modes of using ChatGPT. The first involves quick conversational search, which may serve as the standard approach. The second entails more structured tutoring, which is most appropriate when deeper learning or the acquisition of new skills is required. For working students, brief and targeted support – such as concise hints, short checklists, or rapid feedback – may better align with limited time resources. However, it should be noted that greater time constraints among working students compared to non-working peers represent only one possible explanation; identifying the precise reasons for these differences requires further in-depth research. In contrast, non-working students often have the opportunity to engage in extended, step-by-step learning sessions. In both cases, it is essential to incorporate features that encourage verification of answers, such as source attribution or indicators of uncertainty, alongside basic training in evaluation skills.

More broadly, the findings raise important implications for educational and workplace settings. Institutions could integrate ChatGPT into teaching and training programs in ways that complement, rather than replace, critical thinking and expert knowledge.

The observed differences between employed and non-employed students suggest that support should be adapted to users' time constraints and needs. By tailoring these approaches, institutions can enhance the benefits of ChatGPT while mitigating risks of misuse or unequal access.

6. Conclusions

The findings of this study underscore the dual role of ChatGPT in reshaping professional activities, functioning both as an interactive tool for information retrieval and as a tutor supporting structured learning. Notably, the results indicate that employment status affects evaluations of ChatGPT's tutoring function but not its information-processing role, suggesting the need for differentiated approaches in educational and workplace contexts.

This study has several limitations. First, its static temporal horizon captures only a snapshot of reality at a specific point in time; longitudinal research could offer deeper insights into the evolution of attitudes and usage practices. Second, the analysis focuses on ChatGPT as an information retrieval and processing tool and as an on-demand tutor, functions that are highly relevant but not exhaustive of its capabilities. Third, the study examines only general usage patterns without considering specific application contexts, which may have revealed more nuanced findings. Finally, the exclusive focus on Polish students limits the generalizability of the results; broader cross-cultural and cross-system studies could provide a more diverse and comprehensive understanding of ChatGPT use. These conclusions are consistent with predictions from TAM and UTAUT and with HCIR mechanisms: rapid, dialog-based information processing depends on high performance expectancy under conditions of low cognitive cost, whereas the tutoring function is more sensitive to effort expectancy and facilitating conditions.

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