Original Paper

Generative AI Adoption Among Swedish Psychologists and Psychology Master's Students: Cross-Sectional Survey

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Abstract

Background: The developments in generative AI (GenAI) are expected to have a substantial impact on the field of mental health, including the delivery of clinical services and the role of psychologists. However, there is limited knowledge about how psychologists use and perceive GenAI, including its potential, risks, and effects on the future role of psychologists and professional practice. This includes the competency levels among psychologists and factors associated with the intention to use GenAI within the psychology profession.

Objective: This study examined the use of GenAI, self-rated digital and GenAI competencies, behavioral intention to use GenAI, and perceptions of its future impact on professional practice among psychology students, internship psychologists, and licensed psychologists in Sweden.

Methods: A national cross-sectional online survey was conducted from January to February 2026 in collaboration with the Swedish Psychological Association. The 36-item survey included closed and open-ended questions, including Likert scale, nominal scale, and multiple-choice items. A total of 1077 respondents, with 64.7% (n=697) being women and with a mean age of 45.5 years (SD 13.7), were included in the analyses. Responses were analyzed using descriptive and inferential statistical methods, including hierarchical multiple linear regression, ANOVA, and correlational analysis.

Results: Approximately 1 in 3 respondents (302/990, 30.5%) reported frequent (daily or weekly) professional use of GenAI, with private and professional use strongly associated (r=.62, P<.001). The most common professional application of GenAI was for information retrieval, knowledge acquisition, and fact-checking. Almost half of the respondents (442/990, 44.6%) reported having patients or clients who were using GenAI for mental health purposes. Responses indicated high levels of general and professional digital competence, whereas lower levels were reported for general and professional GenAI competence. More positive attitudes toward future professional integration of GenAI were associated primarily with current private and professional GenAI use, and ethical challenges had the most negative average score related to the future impact of GenAI. The unified theory of acceptance and use of technology (UTAUT) variables explained 39% of the variance beyond age, gender, and private GenAI use in behavioral intention to use GenAI professionally, with curiosity (β=0.44) and performance expectancy (β=0.32) emerging as the strongest predictors.

Conclusions: Many psychologists and psychology students regularly use general-purpose GenAI tools both personally and professionally. However, more than one-third have never used it in their work, indicating a potential digital divide within the profession. Psychologists' reports that patients use GenAI for mental health purposes, alongside their limited self-rated expertise in using GenAI professionally, highlight the need to develop relevant competencies and examine implications for

psychological practice. Future research should explore the role of curiosity, performance expectancy, and personal experience in relation to GenAI use within the psychology profession.

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Keywords: psychologists; mental health professionals; generative AI; competencies; digital mental health; digital psychology; professional practice; attitudes; technology adoption

Introduction

Background

The use of technology in psychotherapy is not new, and there is a long tradition of digital mental health interventions being delivered by psychologists and psychology students in both research settings and routine care settings, including in Sweden [1-4]. Also, the COVID-19 pandemic accelerated the use of videoconferencing psychotherapy in clinical work for practitioners in Sweden [5] and internationally [6-9]. As direct comparisons between digital and in-person formats have shown similar effects [10,11], the digital provision of psychological treatment by psychologists is warranted. However, the effects of this transition on the professional role of psychologists are yet to be explored [12], and the further digitalization of psychological interventions through the increasing use of generative AI (GenAI) for mental health purposes calls for investigations into how psychologists perceive and relate to the use of this technology [12].

AI refers to computer systems that perform tasks usually associated with human intelligence, such as recognizing patterns, processing language, and making predictions [13]. GenAI is a type of AI that produces new content, such as text, images, or audio, in response to a user's request (a prompt). Large language models (LLMs) are AI models trained on very large amounts of text to process and generate language, and natural language processing is the wider field of computational methods for analyzing and producing human language. New technological developments within AI have put the spotlight on its use within psychology [14] and integration into established therapeutic methods such as cognitive behavioral therapy [15,16]. This includes the forms of provision of psychological support and treatment [17], ethical considerations [18], and how the field of psychology and the work of psychologists can be affected [19]. Since the launch of ChatGPT (OpenAI) in November 2022, the use of GenAI has exploded, and almost half of those using an LLM and having a mental health condition are using it for support, such as anxiety management and mood improvement [20]. Across reports, estimates of the share of AI users who use AI for mental health range from 3% to 70%, and a recent review approximated the share at 27%, while noting that heterogeneous data sources and a lack of standard definitions confound such estimates [21]. In a blinded comparison, ChatGPT-generated advice was perceived as human-like and even significantly more authentic and professional than human-written responses [22]. The use of natural language processing and AI technology is being integrated into electronic health records, clinical note-taking systems, assessment, and decision support for mental health care workers [23]; however, evidence for its use in psychotherapy delivery, treatment monitoring, and prediction of treatment response is still lacking [24]. Also, concerns are being raised about ethics, trust, and the risks of using ChatGPT for mental health provision [25,26], and current models are still suffering from misinformation, biases, "hallucinations," and adversarial prompts [27].

A recent survey in Australia showed that around a third of the general public were using AI for mental health support and advice, and approximately 40% of mental health practitioners were using it for research, administrative, and training tasks in their work [28]. Similar numbers of users have been seen in US surveys, where one-third of American psychologists were using it monthly in their practice [29], and for related occupational groups, such as general practitioners, the same trend is seen [30]. Surveys of clinical psychologists conducted before the increased use of AI have indicated moderate digital mental health knowledge levels, but also a fear that digital technology could replace traditional services, replace work duties, and increase existing inequalities in care [31], partly due to a lower degree of knowledge of digital interventions for marginalized and underserved groups [32]. Other barriers to digital mental health interventions are general negative perceptions of digital tools, lack of confidence in their use, resistance to changes in practice, and insufficient training [33]. In addition, the increased use of GenAI among both patients and psychologists could potentially not only affect the way clinical interventions are provided, but also the professional work of psychologists [34]. This topic was discussed before the broad public launch of LLMs, as the use of new technological solutions has effects on the professional identity of psychologists [35], and leads to specific challenges and opportunities for the psychology profession related to its practice and mandate [36]. The transition to digital formats may, for instance, negatively affect the perception of the therapeutic alliance and the patient-therapist relationship [37,38], and lead to a sense of loss in professional regard and social status [39].

However, with the increasing use and integration of GenAI in both private and professional contexts, this technology has the potential to influence psychologists' daily work and professional practice in ways that differ from earlier generations of digital technologies. AI solutions can enhance clinical decision-making, increase efficiency, and provide new forms of access to care, but come with ethical challenges related to consent, transparency, bias, privacy, accountability, and professional judgment [18]. The rapidly changing landscape calls for guidelines on the use of GenAI among psychologists, including ethical considerations, which have only been developed by a handful of professional psychology organizations across the world [40-42].

Other surveys of psychologists and digital technology have shown that even though there is an acceptance of digital technology, there is at the same time a lack of competencies and confidence in digital mental health provision [43,44], including the use of GenAI for professional work [45]. As challenges related to technological adoption will need to be addressed with the increased use of GenAI, and psychologists are needed in interdisciplinary and strategic discussions, there is also a need for increased digital and GenAI literacy, not only in clinical work [18]. A commonly used model in research studies to predict the behavioral intention to use technology is the unified theory of acceptance and use of technology (UTAUT/UTAUT2) [46,47]. This model has been used in surveys to collect data on technology adoption and usage behavior and assesses key determinants in relation to behavioral intention and actual use. UTAUT has been extensively applied in health and behavioral research to study acceptance of digital interventions [48], and amendments to the model have integrated new predictors, such as curiosity, which has been linked with online adoption [49].

There is currently a lack of scales and frameworks that can define and measure the competencies and professional impact of digital technology and GenAI for psychology students and clinical psychologists. In the medical field, the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) has been developed and validated; however, it does not apply specifically to the work of psychologists and professional identity [50]. For psychologists, the Digital Competencies for Applied Psychological Practitioners scale (DCAPP), which measures digital clinical competencies based on the framework developed in collaboration with the British Psychological Society [51], has been tested and adapted to other national contexts [44,52], including a preliminary validation in Sweden [53]. Scales measuring general attitudes toward AI have been developed and tested [54,55], but instruments measuring how AI affects variables related to professional practice and identity are still scarce.

Objectives

The first objective of this study was to examine private and professional use of GenAI and self-rated competencies in digital technology, digital psychology, and GenAI among psychology students, internship psychologists, and licensed psychologists in Sweden. The second objective was to examine predictors of behavioral intention to use GenAI within the psychologist role and how psychologists perceive their future professional practice will be affected by the use and integration of GenAI.

Methods

Study Design

The study was designed as a national cross-sectional survey of psychology master's students, internship psychologists, and licensed psychologists in Sweden. It examined private and professional use of GenAI, self-rated digital and GenAI competencies, behavioral intention to use GenAI professionally, and perceptions of how the integration of GenAI may affect future professional practice and the psychology profession.

Participants and Procedures

The Checklist for Reporting Results of Internet E-Surveys (CHERRIES) checklist was used for reporting the survey [56]. A full version of the checklist can be found in Checklist 1. The online self-report survey was distributed in January and February 2026 and was open for 41 days. A convenience sampling method was used to collect the survey data. The survey targeted members of the Swedish Psychological Association, consisting of psychology master's students, internship- and licensed psychologists. Information about the study and an invitation to participate were distributed in collaboration with the administrative office of the Swedish Psychological Association. This included emails to registered members who had approved email subscriptions (n=12,603) and social media posts and advertisements in channels targeting psychologists used by the association (n=5900). As these channels targeted largely the same population, substantial overlap between channels was expected. To prevent responses from nonpsychologists, links provided in social media posts directed users to the association's webpage, where access to the survey required e-identification (Swedish BankID), thereby confirming membership and professional status. A total of 3 emails were sent to all members, along with 2 reminders to recipients who had not opened the initial email. In addition, 3 Facebook (Meta Platforms, Inc) posts and 3 Facebook stories were distributed, along with 1 Facebook advertisement and 1 Instagram (Meta Platforms, Inc) advertisement. All recruitment materials included information about the study purpose, data management, and estimated completion time. A detailed description of actual reach per recruitment activity, the study information distributed, and the timeline is provided in Multimedia Appendix 1. Participation in the survey was voluntary, and respondents provided informed consent through the online platform (Multimedia Appendix 2). Informed consent was mandatory to participate in the survey. No incentives were provided for participation.

Survey Development

Survey Design and Content

The main author KV developed an initial version of the survey. A draft of the survey was distributed to topic experts, members of the Swedish Psychological Association secretariat, and coauthors in the study (GA and PC), who provided feedback. The draft was then modified based on this feedback. The survey was divided into 9 sections: respondent characteristics, digital competencies, current experience of GenAI, acceptance and use of technology, GenAI competencies, future professional use of GenAI, opportunities and challenges, the role of the Swedish Psychological Association, and other comments. The last 3 sections consisted of four open-ended questions. These answers were not analyzed in the present study because they were intended to be analyzed using qualitative methods in a separate publication (opportunities and challenges), to serve as the basis for a

future report from the Swedish Psychological Association on its role in relation to psychologists' GenAI use (role of the association), and because they did not contain relevant data for analysis (other comments). A variety of closed and open-ended questions were used, including Likert-scale, nominal scale, and multiple-choice items. The full survey can be found in Multimedia Appendix 3.

Respondent Characteristics

This section included questions on age, gender, professional role (psychology master's student, internship, or licensed), and work setting. Gender categories were based on recommendations from the Swedish Association for Sexuality Education, which had been used in earlier surveys by the research group. Work setting categories were derived from how the Swedish Psychological Association categorizes its members.

Digital Competencies

This section included questions on general digital competencies and competencies in digital psychology. Questions drew upon the 2 subscales in the DCAPP [52], which have been used to measure knowledge and abilities among psychology students in Sweden [53]. Likert-scale alternatives were modified for the survey to increase clarity but were still aligned with the original alternatives.

Experience with GenAI

This section included questions on respondents' private and professional use of GenAI, including which specific solutions were used. For psychology students, the question on professional use referred to its use in their psychology studies. The section also included questions on which specific tasks respondents were using GenAI for in their professional work or studies, if they were using any other form of AI, and whether they had clients who used GenAI for psychological support, advice, or treatment. Scale items were created to measure the frequency of use (daily, weekly, monthly, occasionally, and never). The specific GenAI solutions included were based on statistics from the Swedish Internet Foundation [57].

Acceptance and Use of Technology

As both UTAUT and UTAUT2 exist in a variety of versions [58], the included predictors were selected based on a review of the literature on UTAUT and its constructs, discussions with researchers already using UTAUT scales for research (*Acknowledgements* section), relevance to this study, and a limit on the total number of items in the full survey. In this section, respondents answered questions on specific predictors of the intention to use GenAI as a psychologist, including performance expectancy, effort expectancy, social influence, facilitating conditions, curiosity, and worry. Given the need to balance survey length against the risk of respondent fatigue in a nationally distributed survey, each construct was operationalized with a single face-valid item.

GenAI Competencies

This section included questions on self-rated competencies in the general and professional use of GenAI. Likert-scale alternatives were aligned with those used for questions on digital competencies in the survey.

Attitudes Toward Future Professional Practice

Attitudes toward the effects of GenAI on professional practice and the psychology profession were assessed using 9 items that were designed to capture key internal and external dimensions of professional practice and the psychologist profession in the context of GenAI: meaningfulness of work, professional pride, work satisfaction, public demand for psychologists, professional status, societal view of psychologists, therapeutic relationships, ethical challenges, and professional autonomy. All items were rated on a Likert-type scale assessing respondents' attitudes toward the future impact and integration of GenAI in their professional practice.

The survey included a total of 31 items and five additional items depending on responses in the survey, making it a maximum of 36 items in the full survey. The questionnaire was distributed through the secure online platform Iterapi (Linköping University), a widely used solution in research for online surveys, questionnaires, and internet-based interventions [59], and took approximately 15 minutes to complete. All questions were in Swedish. A detailed description of the Iterapi platform can be found in Multimedia Appendix 4.

Statistical Analysis

All quantitative data were analyzed using descriptive and inferential statistical procedures in SPSS software (version 30.0; IBM Corp). Sample sizes vary across analyses primarily due to respondents discontinuing the survey before reaching later items. Descriptive statistics (frequencies, percentages, means, and SDs) were used to summarize sample characteristics and key study variables and are presented in the text and figures. To examine determinants of behavioral intention to use GenAI within the UTAUT framework, hierarchical multiple regression analyses were conducted. The model (outcome: behavioral intention to use GenAI professionally) entered control variables in block 1 (age, gender, and prior private use of GenAI) and the 6 UTAUT determinants in block 2 (performance expectancy, effort expectancy, social influence, facilitating conditions, curiosity, and worry). Internal consistency of scale items related to GenAI impact on professional practice and the psychologist role was evaluated using Cronbach α, and exploratory factor analysis (principal axis factoring) was used to examine the underlying factor structure. A hierarchical regression analysis in 3 blocks was conducted using the composite score as the outcome. The model entered demographics in block 1 (age and gender), professional role in block 2, and current private and professional GenAI use in block 3. In addition, multiple linear regression analyses were conducted to examine associations between digital and GenAI competencies and demographic variables (age, gender, and professional role). In all regression analyses, respondents who provided responses for the

analysis and reported other gender identities than man and woman (n=14) were excluded due to insufficient subgroup sizes for meaningful statistical comparisons. In the hierarchical regression analysis, respondents providing responses and reporting other or researcher as professional role (n=6) were excluded for the same reason. Differences in competencies among licensed psychologists across work settings were analyzed using one-way ANOVA, and Pearson's correlation coefficients were calculated to assess the association between private and professional use of GenAI. Missing values were handled using pairwise deletion within each analysis, so the effective n is reported for every regression, ANOVA, and correlation. Free-text responses to the question regarding which tasks respondents had primarily used GenAI for in their professional work or studies were categorized to give a descriptive overview of reported tasks, using an AI-assisted approach. Before being entered into ChatGPT Plus (GPT-5 model; OpenAI) with data training disabled, responses were screened for sensitive personal information and identifiable data. ChatGPT was then used to generate codes and group similar responses into categories. The resulting codes and categories were subsequently reviewed by the authors to identify obvious errors and misclassifications. A detailed description of the analytical procedure, including data safety measures, GenAI model and version, and the output, is provided in Multimedia Appendix 5.

Ethical Considerations

Under the Swedish Ethical Review Act (SFS 2003:460), prospective ethical review is mandatory only for research that collects or processes categories of sensitive personal data defined in section 3 (eg, data on health, ethnicity, religious beliefs). The Swedish Ethical Review Authority confirmed that the present survey did not fall within that scope (2025-00064-01), which is analogous to an exempt or minimal-risk determination in institutional review board–based systems. All participants provided informed consent before accessing the survey, and all analyses were conducted on pseudonymized data.

Results

Sample Characteristics

A total of 1130 respondents provided informed consent, of whom 1084 started the survey. After data cleaning and visual inspection, 7 respondents were removed due to duplicate submission (n=3), duplicate/invalid responding (n=1), ineligibility (n=1), and atypical timestamps (n=2), resulting in a final sample of 1077 respondents. The analytical sample sizes varied across analyses, with the smallest subsample consisting of 947 respondents. Information on inspection, data cleaning procedures, sample sizes, and missing data can be found in Multimedia Appendices 6 and 7. The mean age was 45.5 years (SD 13.7). Most of the 1077 respondents were licensed psychologists (83.7%, n=901) and women (64.7%, n=697). Among licensed psychologists, 54.3% (489/901) worked in primary or psychiatric care settings, with a mean time of 14.9 years (SD 10.7) since becoming licensed. All demographic data and respondent characteristics can be found in Table 1.

Table 1. Respondent characteristics (N=1077).

Variable	Values
Age (y), mean (SD), N=1077	45.5 (13.7)
Gender, n (%)	
Women	697 (64.7)
Men	365 (33.9)
Nonbinary	7 (0.6)
Others	1 (0.1)
Unsure	2 (0.2)
Prefer not to answer	5 (0.5)
Psychologist category, n (%)	
Psychology master's student	108 (10.0)
Psychologist internship	56 (5.2)
Licensed psychologists	901 (83.7)
Researcher (no license)	3 (0.3)
Other	9 (0.8)
Years of practice with license, mean (SD), n=896	14.9 (10.7)
Type of practice setting, n (%), n=901	
Somatic setting (children and adolescents)	15 (1.7)
Somatic setting (adults)	39 (4.3)
Psychiatric setting (children and adolescents)	112 (12.4)
Psychiatric setting (adults)	211 (23.4)
Primary care	166 (18.4)

Variable	Values
Habilitation	42 (4.7)
School	101 (11.2)
Occupational health	45 (5.0)
Government setting	35 (3.9)
University	21 (2.3)
Organizational consultant	34 (3.8)
Other	80 (8.9)

Experience and Use of GenAI

Almost half of the respondents (461/990, 46.6%) reported using GenAI daily or weekly for private purposes, whereas 14.2% (141/990) had never used it. Among respondents who reported any prior use of GenAI (849/990, 85.8% of those answering this item), the most common solution was ChatGPT (763/849, 89.9%), followed by Gemini (315/849, 37.1%) and Copilot (259/849, 30.5%). Regarding professional use, 30.5% (302/990) reported using GenAI daily or weekly, and 34.0% (337/990) of respondents reported never using it. The most frequently used solution among those reporting professional use as psychologists was ChatGPT (490/653, 75.0%), followed by Copilot (215/653, 32.9%), and Gemini (150/653, 23.0%). In addition, 10.3% (67/653) reported using GenAI-assisted electronic health records. A small proportion of respondents (51/990, 5.2%) used other AI solutions, the most frequently mentioned being NotebookLM (Google LLC; n=17). The distribution of private and professional use across psychology students, internship psychologists, and licensed psychologists is presented in Table 2.

Table 2. Frequency of private and professional generative AI (GenAI) use by professional role (N=983).[a]

Frequency	Psychology students (n=90)	Internship psychologists (n=48)	Licensed psychologists (n=845)	Total (N=983)
Private GenAI use, n (%)				
Daily	14 (15.6)	15 (31.3)	179 (21.2)	208 (21.2)
Weekly	31 (34.4)	9 (18.8)	209 (24.7)	249 (25.3)
Monthly	11 (12.2)	10 (20.8)	139 (16.4)	160 (16.3)
Occasionally	24 (26.7)	13 (27.1)	189 (22.4)	226 (23.0)
Never	10 (11.1)	1 (2.1)	129 (15.3)	140 (14.2)
Professional GenAI use, n (%)				
Daily	13 (14.4)	4 (8.3)	110 (13.0)	127 (12.9)
Weekly	28 (31.1)	12 (25)	133 (15.7)	173 (17.6)
Monthly	16 (17.8)	6 (12.5)	131 (15.5)	153 (15.6)
Occasionally	21 (23.3)	11 (22.9)	165 (19.5)	197 (20.0)
Never	12 (13.3)	15 (31.3)	306 (36.2)	333 (33.9)

[a]Values are n (%), with percentages calculated within each category. 7 respondents were excluded from this table: researchers without a psychology license (n=3) and respondents classified as other (n=4). Percentages may not sum to 100% due to rounding.

The AI-assisted categorization of free-text responses (n=651) revealed that the most common areas of professional GenAI application were information retrieval, knowledge acquisition, and fact-checking (222/651, 34.1%), summary and condensation of text (213/651, 32.7%), copywriting, drafting, and proofreading (201/651, 30.9%), and brainstorming, idea generation, and reflection (136/651, 20.9%). When comparing use by professional role, students described more frequent use for research, literature, and scholarly work (41/78, 52.6% vs 88/573, 15.4%) and studies, exams, and learning support (21/78, 26.9% vs 13/573, 2.3%), whereas psychologists (licensed and internship) reported more frequent use for treatment, interventions, and psychoeducation (127/573, 22.2% vs 1/78, 1.3%), health record journaling and clinical documentation (121/573, 21.1% vs 0/78, 0%), diagnostics, assessment, and testing (92/573, 16.0% vs 2/78, 2.6%), and patient/client communication and patient-centered materials (80/573, 14.0% vs 5/78, 6.4%). The full list of categories and number of codes per category can be found in Multimedia Appendix 5.

Almost half of the respondents (442/990, 44.6%) reported having had patients or clients who they knew had used GenAI for mental health support, advice, or treatment, 26.1% (258/990) reported that they had not, and 29.3% (290/990) were unsure or did not know. There was a small significant negative correlation between age and professional use (r=–.13, P<.001) and men reported significantly higher private (t_{974}=4.60, P<.001) and professional use (t_{974}=2.39, P=.017) than women. Private use of GenAI was strongly associated with professional use (r=.62, P<.001), explaining approximately 38% of the variance.

Digital and GenAI Competencies

A large proportion of respondents (919/1053, 87.3%) rated their general digital competencies as good or very good. The mean rating for digital competencies was 3.50 (SD

0.72). Ratings were somewhat lower for digital psychology competencies, with 68.5% (721/1053) reporting good or very good competencies, whereas 28.3% (298/1053) rated themselves as beginners or having basic competencies. The mean rating was 2.91 (SD 0.93). The proportion of respondents rating themselves as experts was more than twice as high for general digital competencies (74/1053, 7.0%) compared with digital psychology competencies (34/1053, 3.2%).

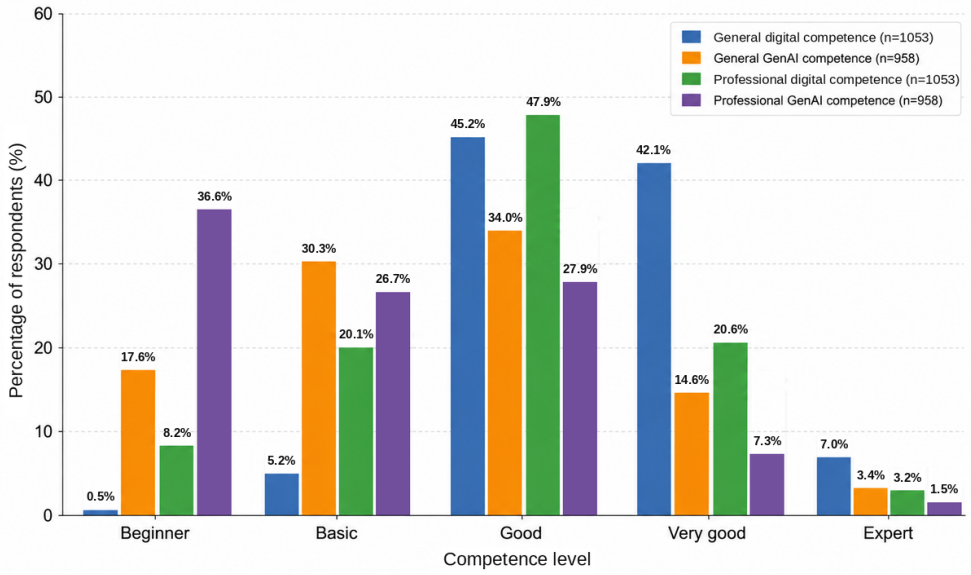
Multiple linear regression analysis showed that age (β=–0.28, P<.001) and gender (β=0.29, P<.001) were significant predictors of general digital competence, with younger individuals and men reporting higher levels. Professional role was not a significant predictor when controlling for these variables. For digital psychology competence, professional role (β=0.32, P<.001), age (β=–0.26, P<.001), and gender (β=0.15, P<.001) were all significant predictors, with being a licensed psychologist emerging as the strongest predictor.

A total of 48.6% (466/958) rated their general GenAI competencies as good or very good, and 47.9% (459/958) rated themselves as beginners or as having basic competencies. The mean rating was 2.56 (SD 1.05). For GenAI use as a psychologist, 35.2% (337/958) rated their competencies as good or very good, and 63.4% (607/958) as beginners or as having basic competencies, with a mean rating of 2.10 (SD 1.03). As for digital competencies, the proportion of respondents rating themselves as experts was twice as high for general GenAI competencies (33/958, 3.4%) compared with professional use (14/958, 1.5%). For a full comparison between digital and GenAI competencies, see Figure 1.

Age (β=–0.23, P<.001) and gender (β=0.25, P<.001) were significant predictors of general AI competence, whereas professional role was not. For GenAI psychologist competence, age (β=–0.19, P<.001), gender (β=0.18, P<.001), and professional role (β=0.12, P<.001) were all significant predictors. The effect of professional role was weaker than its effect on digital psychology competence.

One-way ANOVA indicated no significant differences in digital psychology competence across work settings, $F_{11,874}$=0.97, P=.47, η^2=.012. For GenAI psychologist competence, a small effect of work setting was observed, $F_{11,810}$=1.80, P=.05, η^2=.024. Given the small effect size and the P value at the conventional threshold for statistical significance, this finding should be interpreted with caution.

Figure 1. Self-rated competence levels across 4 areas.



UTAUT Predictors of Behavioral Intention to Use GenAI

Multiple linear regression analysis showed that the overall model was significant, $F_{9,940}$=287.25, P<.001, explaining 73.3% of the variance (R^2=.733, adjusted R^2=.731). The inclusion of UTAUT variables in the second block significantly increased explained variance (ΔR^2=.390, $F_{6,940}$=229.33, P<.001). Among the variables, curiosity emerged as the strongest positive predictor of behavioral intention (β=0.44, P<.001), followed by performance expectancy (β=0.32, P<.001). Smaller but statistically significant positive effects were observed for social influence (β=0.08, P<.001), facilitating conditions (β=0.06, P<.001), and effort expectancy (β=0.04, P=.04). Worry was negatively associated with behavioral intention (β=–0.05, P=.01). Among the control variables, prior private use of GenAI was a significant predictor (β=0.11, P<.001), whereas age and gender were not significantly associated with behavioral intention when included in the model. Full results for the final regression model are presented in Table 3.

Table 3. Multiple regression predictors for behavioral intention to use generative AI (GenAI; final model; N=950).

Variable	B[a]	SE	β[b]	95% CI	*t* test (*df*)	*P* value
Age	0.000	0.002	–0.00	–0.004 to 0.004	–0.07 (940)	.95
Gender	–0.018	0.053	–0.01	–0.123 to 0.087	–0.34 (940)	.74
Private GenAI use	0.113	0.023	0.11	0.068 to 0.159	4.88 (940)	<.001
Performance expectancy	0.355	0.031	0.32	0.294 to 0.416	11.46 (940)	<.001
Effort expectancy	0.057	0.027	0.04	0.004 to 0.110	2.10 (940)	.04
Social influence	0.094	0.023	0.08	0.049 to 0.139	4.12 (940)	<.001
Facilitating conditions	0.070	0.020	0.06	0.030 to 0.109	3.42 (940)	<.001
Worry	–0.057	0.021	–0.05	–0.098 to –0.016	–2.74 (940)	.01
Curiosity	0.449	0.027	0.44	0.397 to 0.501	16.93 (940)	<.001

[a]B: unstandardized regression coefficient.
[b]β: standardized regression coefficient.

Future Professional Practice

Descriptive statistics at the item level indicated that respondents were generally neutral to slightly negative regarding the future impact of GenAI on the psychology profession if integrated into everyday practice. Ethical challenges received the most negative ratings (mean –0.75, SD 0.91), whereas work satisfaction was rated most positively (mean 0.11, SD 1.14). See Table 4 for item-level descriptive statistics.

Table 4. Item-level descriptive statistics for perceived effects of generative AI on future professional practice (N=947).[a]

Item	Mean (SD)
Ethical challenges	–0.75 (0.91)
Public demand for psychologists	–0.53 (0.94)
Professional status	–0.49 (0.97)
Societal view of psychologists	–0.45 (0.93)
Professional pride	–0.44 (1.02)
Therapeutic relationships with clients	–0.26 (0.98)
Meaningfulness of work	–0.07 (1.09)
Professional autonomy	–0.06 (1.14)
Work satisfaction	0.11 (1.14)

[a]5-point Likert scales have scores ranging from –2 (strongly negative impact) to +2 (strongly positive impact).

The 9 items assessing attitudes toward the future integration of GenAI into professional practice and its effects on the psychology profession demonstrated high internal consistency (Cronbach α=0.93) and were therefore combined into a composite measure. Exploratory factor analysis (principal axis factoring) supported a one-factor solution (Kaiser-Meyer-Olkin [KMO]=.92; Bartlett test P<.001), explaining 64.7% of the variance (eigenvalue=5.82). The mean for the 9-item composite score was -0.33 (SD 0.82; n=947), suggesting slightly negative attitudes toward the future integration. A hierarchical multiple regression analysis was conducted to examine the predictors associated with attitudes toward GenAI integration into professional practice. The final model was significant, $F_{5,922}$=76.71, P<.001, explaining 29.4% of the variance (R^2=.294, adjusted R^2=.290). The inclusion of GenAI use variables in the third block resulted in a substantial increase in explained variance (ΔR^2=.282, $F_{2,922}$=184.32, P<.001), indicating that GenAI use accounted for most of the explained variance. The first block, including age and gender, did not significantly predict attitudes toward the future integration of GenAI into professional practice (R^2=.005, P=.10). The addition of professional role in the second block resulted in a small but significant increase in explained variance (ΔR^2=.006, P=.01). In the final model, private GenAI use (β=0.28, P<.001) and professional GenAI use (β=0.32, P<.001) emerged as the strongest predictors of more positive attitudes toward future professional integration. Professional role remained a small but significant predictor (β=0.11, P<.001), whereas age showed a weak positive association (β=0.07, P=.02). Gender was not a significant predictor of future professional integration (β=–0.04, P=.11). Regression coefficients for the final model are presented in Table 5.

Table 5. Multiple regression predicting attitudes toward future professional integration of generative AI (GenAI; final model; N=928).

Variable	B[a]	SE	β[b]	95% CI	*t* test (*df*)	*P* value
Age	0.004	0.002	0.07	0.001 to 0.008	2.40 (922)	.02
Gender	–0.076	0.048	–0.04	–0.171 to 0.018	–1.59 (922)	.11
Professional role	0.262	0.074	0.11	0.118 to 0.407	3.56 (922)	<.001
Private GenAI use	0.166	0.021	0.28	0.124 to 0.207	7.83 (922)	<.001
Professional GenAI use	0.181	0.020	0.32	0.141 to 0.220	8.96 (922)	<.001

[a]B: unstandardized regression coefficient.
[b]β: standardized regression coefficient.

Discussion

Principal Findings

This study provides one of the first large-scale examinations of psychologists' and psychology master's students' use of GenAI, perceived digital competencies, behavioral intention to use GenAI professionally, and attitudes toward its future integration into professional practice and its impact on the psychology profession. The findings indicate that GenAI has already become part of everyday work for a substantial proportion of psychologists, although self-rated competence in using GenAI professionally remains relatively limited. Regular professional use was reported by approximately one-third of respondents, while private use was even more common and strongly associated with professional adoption. ChatGPT dominated both private and professional use, whereas specialized clinical AI solutions were rarely reported. The findings further suggest that experience with GenAI is more strongly associated with intention and attitudes than demographic characteristics. Curiosity and performance expectancy emerged as the strongest predictors of behavioral intention, while attitudes toward future integration were primarily associated with current private and professional use. Together, these findings suggest that exposure to and experience with GenAI are factors associated with both current adoption and future expectations within the psychology profession.

The Current Use of GenAI Among Psychologists

The findings indicate that GenAI is no longer a future issue for the psychology profession but an emerging component of current practice. Adoption rates were broadly comparable to those reported in recent surveys from Australia and the United States [28,60], suggesting that the adoption patterns observed in this sample may be broadly consistent with those reported for psychologists and comparable professional groups in other countries. The strong association between private and professional use suggests that experimentation with technology in personal contexts may be relevant to consider when examining professional adoption [43]. Similar to findings from an Australian survey of health care professionals, including psychologists, in which respondents reported using general AI solutions for literature searches, research tasks, and report writing [28], the most common applications of GenAI tools in our survey were general tasks not specific to the psychology profession, such as information retrieval ("I also sometimes ask questions about things I don't understand or know"), summarizing ("summary of books and research"), and text editing tasks ("rephrasing sentences"). However, the reported applications differed by professional status. Psychology students more frequently described using GenAI for research, academic writing, and study-related tasks ("I use it for school when it's allowed as a study aid"), whereas licensed and internship psychologists more frequently reported clinically oriented applications, including treatment planning ("treatment plans, exposure activities, etc"), psychoeducation ("simplify psychoeducational texts for patients"), clinical documentation ("record-keeping and writing reports"), and diagnostic assessment ("to clarify the distinction between diagnoses that are clinically similar"). These findings suggest that GenAI use reflects the different tasks and responsibilities associated with education and clinical practice. The use of general-purpose tools for clinical tasks also raises important questions regarding data protection, clinical accuracy, and professional accountability [26,61]. This pattern mirrors findings from other health care professions and may reflect both the flexibility of LLMs and the current lack of mature, evidence-based clinical AI tools [23]. Such tools are beginning to emerge in research settings, as in a recent randomized trial comparing AI-delivered cognitive behavioral and psychodynamic therapy for social anxiety disorder, in which both AI conditions produced moderate within-group symptom reductions and maintained a stable therapeutic alliance [62]. However, the lack of GenAI solutions specifically developed for psychological work will most likely increase the risk of unsanctioned tools unsuitable for mental health purposes being used in professional settings. At the same time, more than one-third of respondents reported never using GenAI professionally, revealing a digital divide within the psychology profession. The lack of use may, on the one hand, reflect appropriate caution considering limited evidence, unresolved ethical issues, and uncertainty regarding governance and data security [45,63], and, on the other hand, reflect skepticism within the profession toward the use of digital technology [64].

The Role of Individual and Professional Characteristics

Men respondents reported higher private and professional use of GenAI, and the same gender difference was found for both general digital technology and GenAI competencies. Similar patterns have been observed in studies outside psychology,

where gender differences were explained in part by women's stronger ethical concerns related to GenAI use [65]. Whatever the reasons for these differences, the risk of a gender gap within the profession should be recognized and addressed. Being a licensed psychologist was more strongly associated with digital psychology competencies than with professional GenAI competencies. This may indicate that digital psychology competencies are primarily acquired through professional experience, whereas GenAI remains sufficiently novel that experience is distributed more broadly across students, internship psychologists, and licensed psychologists.

Competencies and the Future Training of Psychologists

Few psychologists perceived themselves as experts in digital psychology, and even fewer as experts in the professional use of GenAI. These findings are consistent with previous surveys indicating that psychologists often hold positive attitudes toward digital technologies while simultaneously reporting limited confidence, training, and competence in their professional application [31,44]. A lack of knowledge and competencies may constitute an important barrier to adoption, innovation, and meaningful involvement in the development of AI-assisted and other technology-supported psychological services [66]. This could consequently lead to GenAI solutions not being developed, adapted, or implemented in accordance with psychologists' needs and opinions, resulting in technology shaping future psychology work rather than clinical considerations and priorities [35]. Also, a lack of awareness and knowledge can lead to the uninformed and naive use of GenAI, creating ethical concerns, an increased risk of bias, and accountability issues [26,61].

Previous studies have pointed to a lack of training in digital psychology, including the use of GenAI, in academic programs for clinical psychology and master's-level students [19,67-69]. The low self-rated professional GenAI competencies found in this survey suggest a need for training for both psychologists and psychology students if specific knowledge and associated skill sets are to be integrated into the psychology profession. The increased integration of AI into educational programs for psychology students, which has been associated with increased understanding and acceptance of AI technology in general [70], could be expanded to include specific AI competencies related to psychologists' tasks and services.

Future Adoption and Impact on the Psychology Profession

The finding that current use of GenAI, both in private and professional contexts, is associated with attitudes toward future integration and intentions builds on findings from earlier studies on digital mental health provision. In a previous survey of 9115 European health care professionals (most of whom were psychologists) during the COVID-19 pandemic outbreak, prepandemic experience with online consultations and training were the strongest predictor related to actual use and level of telepresence [71].

Performance expectancy appeared as a predictor among UTAUT variables, aligning with results that have examined acceptance toward digital mental health interventions and health care workers' adoption of AI-assisted diagnosis and treatment [72,73]. Trusting the utility of new technology is an important factor, as its use needs to improve the everyday work of psychologists, and increased transparency and AI governance in health care systems can facilitate trust among both patients and providers [74]. However, as curiosity was an even stronger predictor, this indicates that having an open mindset toward new technology and a willingness to safely experiment with and explore GenAI could be an important step in creating an interest in what the technology can be used for within the psychology profession. Nevertheless, if psychologists are not well educated about and aware of how data are handled when using and experimenting with unsanctioned AI tools in their professional practice, the risk of ethical concerns and safeguarding problems will increase with their future use and integration.

Previous surveys among psychologists in other European countries have reported somewhat negative attitudes toward the integration of technology into psychological practice [64] and concerns regarding its impact on professional status [39,75]. Our findings extend these findings to the context of GenAI, as respondents rated the future impact of GenAI integration as slightly negative in relation to ethical challenges, public demand for psychologists, professional status, professional pride, and the societal view of the psychology profession. Such concerns may partly reflect the rapid expansion of LLM-based mental health services and AI-generated psychological advice [20,76]. Unlike previous digital technologies, which primarily functioned as tools supporting psychologists' work, GenAI has the potential to perform tasks traditionally associated with professional expertise. The adoption of GenAI may therefore raise questions not only about clinical practice but also about professional identity and the future role of psychologists, which highlights the importance of continued professional discussion, education, and structured guidance regarding the integration of GenAI into psychological services [45].

Finally, the integration of GenAI into the everyday lives of psychologists is also affected by the organizational and technical context. Regulations and reimbursement systems have a marked impact on whether, and how, AI solutions are implemented. Process models of access and service use in technology-enhanced mental health care can help examine where GenAI fits across informal support and formal services, and how it interacts with the organization and allocation of care [77]. Its use relates to the system for GenAI and other digital commercial products, as regulations, referral pathways, and reimbursement systems vary between countries, affecting the role of psychologists in the provision of GenAI-supported solutions [36,78,79].

Strengths and Limitations

A major strength of the study is the large national sample and the inclusion of psychologists at different stages of professional development (psychology master's students,

internship psychologists, and licensed psychologists). The demographic distribution of respondents was similar with respect to age and gender compared to data on licensed psychologists in Sweden [80,81]. The study also examined both current use and future-oriented attitudes, providing a broader understanding of GenAI adoption within the profession. Several limitations should nevertheless be acknowledged. The UTAUT constructs were measured using single items, limiting psychometric precision and potentially affecting construct validity and reliability, as multi-item latent measurement approaches permit stronger psychometric testing and single-item measures are less able to capture the full breadth and internal consistency of complex constructs. Validated multi-item instruments for the acceptance of AI and digital technology in mental health have recently become available, such as the UTAUT-AI-DMHI [82], which future surveys in this area could adopt to strengthen measurement. Also, a recently developed UTAUT2 screener with single items showed acceptable psychometric robustness [83]. However, as its item set differs from the one used in this study, it does not establish the validity of the items used here. Furthermore, the composite measure of attitudes toward future professional integration was supported by internal consistency analyses and exploratory factor analysis in the same sample but was not validated through confirmatory factor analysis in an independent sample. Another limitation of the study is the use of a cross-sectional rather than a longitudinal design, which would have better captured rapid changes over time related to psychologists' views, competencies, attitudes, and use of GenAI. To minimize the risk of findings being outdated, data analyses and drafting of the manuscript were conducted in close to data collection to reduce the time from data collection to publication. The free-text answers on professional use were categorized with the help of ChatGPT, and the categories may have differed under a fully researcher-led analysis. No categories or codes were modified from the original output. As GenAI can support qualitative analysis, but interpretation remains the researcher's responsibility [84], the categorization of free-text answers should therefore be read as a descriptive overview.

Conclusions and Future Directions

As research on GenAI in psychology and psychological treatment is rapidly advancing, these findings suggest that GenAI is already part of the everyday work of psychologists, although substantial variation remains in both competence and use. Across analyses, current use of GenAI, curiosity about using it in the future, and expectations of its usefulness consistently emerged as more important than demographic characteristics or professional role. As respondents, on average, rated the future impact of GenAI on their role and professional practice as slightly negative, these results highlight the importance of creating opportunities for psychologists to develop informed, critical, and practical experience with GenAI. Future research should examine longitudinal changes in attitudes and use, evaluate competency frameworks and measures specific to psychologists, and investigate how psychologists' GenAI integration influences professional practice and development over time.

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Generative AI Use

Generative AI was used to assist with language editing and to improve the readability of the manuscript. ChatGPT (OpenAI) was used to assist in categorizing free-text answers from the survey and to create a figure used in Multimedia Appendix 7. All scientific content, interpretations, analyses, and conclusions were reviewed and verified by the authors, who take full responsibility for the final manuscript.

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Data Availability

Data and other materials not included in the manuscript or its appendices, including all relevant raw data, will be freely available to researchers for noncommercial purposes upon request.

Authors' Contributions

Conceptualization: KV, PC, GA
Data curation: KV
Formal analysis: KV
Investigation: KV
Methodology: KV, PC, GA
Project administration: KV
Resources: PC, GA
Validation: PC, GA
Writing – original draft: KV

Writing – review & editing: KV, PC, GA

Conflicts of Interest

PC has received honoraria from OpenAI within the past three years. Other authors do not have conflicts to report.

Multimedia Appendix 1

Reach and recruitment timeline.
[DOCX File (Microsoft Word File), 24 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Informed consent (original and translated).
[DOCX File (Microsoft Word File), 38 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Full survey (original and translated).
[DOCX File (Microsoft Word File), 38 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Description of the online survey platform (Iterapi).
[DOCX File (Microsoft Word File), 18 KB-Multimedia Appendix 4]

Multimedia Appendix 5

Professional use of generative AI (categories and procedure).
[DOCX File (Microsoft Word File), 30 KB-Multimedia Appendix 5]

Multimedia Appendix 6

Data inspection and cleaning.
[DOCX File (Microsoft Word File), 18 KB-Multimedia Appendix 6]

Multimedia Appendix 7

Sample sizes and missing data (figure).
[PNG File (Portable Network Graphics File), 1578 KB-Multimedia Appendix 7]

Checklist 1

CHERRIES checklist.
[DOCX File (Microsoft Word File), 30 KB-Checklist 1]

References

1. Zale A, Lasecke M, Baeza-Hernandez K, et al. Technology and psychotherapeutic interventions: bibliometric analysis of the past four decades. Internet Interv. 2021;25:100425. [doi: 10.1016/j.invent.2021.100425] [Medline: 34401384]
2. Vernmark K, Buhrman M, Carlbring P, Hedman-Lagerlöf E, Kaldo V, Andersson G. From research to routine care: a historical review of internet-based cognitive behavioral therapy for adult mental health problems in Sweden. Digit Health. 2024;10:20552076241287059. [doi: 10.1177/20552076241287059] [Medline: 39381804]
3. Andersson G, Carlbring P. Internet interventions in clinical psychology. In: Asmundson GJG, editor. Comprehensive Clinical Psychology. 2nd ed. Elsevier; 2022:194-205. [doi: 10.1016/B978-0-12-818697-8.00211-9]
4. Andersson G. Internet-Delivered CBT: Distinctive Features. Routledge; 2025. [doi: 10.4324/9781003453444]
5. Vernmark K, Norlin M, Andersson G. Clinicians' attitudes towards videoconferencing cognitive behavioural therapy: an exploratory survey. Cogn Behav Ther. 2026;19:e13. [doi: 10.1017/S1754470X26100567]
6. Van Kessel K, Kura C, du Preez E, Coomber T. Delivering videocall therapy during COVID-19: counselling psychologists' experience. N Z J Psychol. 2024;53(1). [doi: 10.63146/001c.129239]
7. Feijt M, de Kort Y, Westerink J, Bierbooms J, Bongers I, IJsselsteijn W. Integrating technology in mental healthcare practice: a repeated cross-sectional survey study on professionals' adoption of digital mental health before and during COVID-19. Front Psychiatry. 2022;13:1040023. [doi: 10.3389/fpsyt.2022.1040023] [Medline: 36874171]
8. Hall SB, Bartley AG, Wenk J, Connor A, Dugger SM, Casazza K. Rapid transition from in-person to videoconferencing psychotherapy in a counselor training clinic: a safety and feasibility study during the COVID-19 pandemic. J Couns Dev. May 18, 2022;101(1):84-95. [doi: 10.1002/jcad.12439] [Medline: 35942200]

9. De Witte NAJ, Carlbring P, Etzelmueller A, et al. Online consultations in mental healthcare during the COVID-19 outbreak: an international survey study on professionals' motivations and perceived barriers. Internet Interv. 2021;25:100405. [doi: 10.1016/j.invent.2021.100405] [Medline: 34401365]
10. Hedman-Lagerlöf E, Carlbring P, Svärdman F, Riper H, Cuijpers P, Andersson G. Therapist-supported Internet-based cognitive behaviour therapy yields similar effects as face-to-face therapy for psychiatric and somatic disorders: an updated systematic review and meta-analysis. World Psychiatry. Jun 2023;22(2):305-314. [doi: 10.1002/wps.21088] [Medline: 37159350]
11. Fernandez E, Woldgabreal Y, Day A, Pham T, Gleich B, Aboujaoude E. Live psychotherapy by video versus in-person: a meta-analysis of efficacy and its relationship to types and targets of treatment. Clin Psychol Psychother. Nov 2021;28(6):1535-1549. [doi: 10.1002/cpp.2594] [Medline: 33826190]
12. Stein OA, Prost A. Exploring the societal implications of digital mental health technologies: a critical review. SSM Ment Health. Dec 2024;6:100373. [doi: 10.1016/j.ssmmh.2024.100373]
13. Banh L, Strobel G. Generative artificial intelligence. Electron Mark. Dec 2023;33(1):1-17. [doi: 10.1007/s12525-023-00680-1]
14. O'Toole AJ, Ludvig EA. The use of AI in psychology: a historical perspective. Br J Psychol. May 2026;117(2):433-443. [doi: 10.1111/bjop.70061] [Medline: 41588571]
15. Shafran R, Bond L, Carlbring P, et al. From innovation to implementation: artificial intelligence in cognitive behaviour therapy training and supervision. Behav Res Ther. Feb 2026;197:104945. [doi: 10.1016/j.brat.2025.104945] [Medline: 41512419]
16. Vanhée L, Andersson G, Garcia D, Sikström S. The rise of artificial intelligence for cognitive behavioral therapy: a bibliometric overview. Appl Psychol Health Well Being. May 2025;17(2):e70033. [doi: 10.1111/aphw.70033] [Medline: 40274359]
17. Carlbring P, Hadjistavropoulos H, Kleiboer A, Andersson G. A new era in internet interventions: the advent of Chat-GPT and AI-assisted therapist guidance. Internet Interv. Apr 2023;32:100621. [doi: 10.1016/j.invent.2023.100621] [Medline: 37273936]
18. Ethical guidance for AI in the professional practice of health service psychology. American Psychological Association; Jul 2025. URL: https://www.apa.org/topics/artificial-intelligence-machine-learning/ethical-guidance-professional-practice.pdf [Accessed 2026-04-29]
19. Åhs F, Mozelius P, Espvall M. Preparing psychologists and social workers for the daily use of AI. Proc 4th Eur Conf Impact Artif Intell Robot. 2022;4(1):1-5. [doi: 10.34190/icair.4.1.771]
20. Rousmaniere T, Zhang Y, Li X, Shah S. Large language models as mental health resources: patterns of use in the United States. Pract Innov. 2026;11(2):139-155. [doi: 10.1037/pri0000292]
21. Bodner R, Lim K, Siddals S, Goldberg S, Torous J. Barriers to understanding how many people use AI for mental health support: an estimate and narrative review. npj Digit Public Health. 2026;1(1):21. [doi: 10.1038/s44482-026-00025-7]
22. Lopes E, Jain G, Carlbring P, Pareek S. Talking mental health: a battle of wits between humans and AI. J Technol Behav Sci. 2023;9(4):628-638. [doi: 10.1007/s41347-023-00359-6]
23. Laricheva M, Liu Y, Shi E, Wu A. Scoping review on natural language processing applications in counselling and psychotherapy. Br J Psychol. May 2026;117(2):677-701. [doi: 10.1111/bjop.12721] [Medline: 39095975]
24. Gutierrez G, Stephenson C, Eadie J, Asadpour K, Alavi N. Examining the role of AI technology in online mental healthcare: opportunities, challenges, and implications, a mixed-methods review. Front Psychiatry. 2024;15:1356773. [doi: 10.3389/fpsyt.2024.1356773] [Medline: 38774435]
25. Kalam KT, Rahman JM, Islam MR, Dewan SMR. ChatGPT and mental health: friends or foes? Health Sci Rep. Feb 2024;7(2):e1912. [doi: 10.1002/hsr2.1912] [Medline: 38361805]
26. Svensson E, Osika W, Carlbring P. Commentary: trustworthy and ethical AI in digital mental healthcare - wishful thinking or tangible goal? Internet Interv. 2025;41:100844. [doi: 10.1016/j.invent.2025.100844] [Medline: 40574943]
27. Camilleri MA. Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. Technol Forecast Soc Change. Apr 2024;201:123247. [doi: 10.1016/j.techfore.2024.123247]
28. Cross S, Bell I, Nicholas J, et al. Use of AI in mental health care: community and mental health professionals survey. JMIR Ment Health. Oct 11, 2024;11:e60589. [doi: 10.2196/60589] [Medline: 39392869]
29. AI in the therapists' office: uptake increases, caution persists. American Psychological Association. Mar 1, 2026. URL: https://www.apa.org/monitor/2026/03/ai-reshaping-therapy [Accessed 2026-05-26]
30. Blease CR, Locher C, Gaab J, Hägglund M, Mandl KD. Generative artificial intelligence in primary care: an online survey of UK general practitioners. BMJ Health Care Inform. Sep 17, 2024;31(1):e101102. [doi: 10.1136/bmjhci-2024-101102] [Medline: 39288998]

31. Rawnsley C, Stasiak K. Unlocking the digital toolbox — a mixed methods survey of New Zealand mental health clinicians' knowledge, use and attitudes towards digital mental health interventions. J Technol Behav Sci. 2024;9(4):875-885. [doi: 10.1007/s41347-024-00403-z]
32. Vernmark K, Geranmayeh A, Topooco N, Andersson G, Shahnavaz S. Understanding psychologists' usage, knowledge, and attitudes toward digital mental health solutions for refugees and migrants: exploratory cross-sectional survey in Sweden. JMIR Hum Factors. Mar 3, 2026;13:e75263. [doi: 10.2196/75263] [Medline: 41774913]
33. Torous J, Linardon J, Goldberg SB, et al. The evolving field of digital mental health: current evidence and implementation issues for smartphone apps, generative artificial intelligence, and virtual reality. World Psychiatry. Jun 2025;24(2):156-174. [doi: 10.1002/wps.21299] [Medline: 40371757]
34. Schubert S, Buus N, Monrouxe LV, Hunt C. The development of professional identity in clinical psychologists: a scoping review. Med Educ. Jul 2023;57(7):612-626. [doi: 10.1111/medu.15082] [Medline: 36922739]
35. Gambirasio M, Ivaldi S, Scaratti G. How platformisation transforms the psychological profession: reflections from a proposal of indicators for the classification of psychological platforms. J Community Appl Soc Psychol. Jul 2024;34(4):e2861. [doi: 10.1002/casp.2861]
36. Carl JR, Jones DJ, Lindhiem OJ, et al. Regulating digital therapeutics for mental health: opportunities, challenges, and the essential role of psychologists. Br J Clin Psychol. Jan 2022;61 Suppl 1:130-135. [doi: 10.1111/bjc.12286] [Medline: 33650131]
37. Weineland S, Ribbegårdh R, Kivi M, et al. Transitioning from face-to-face treatment to iCBT for youths in primary care - therapists' attitudes and experiences. Internet Interv. Dec 2020;22:100356. [doi: 10.1016/j.invent.2020.100356] [Medline: 33318951]
38. Lagetto G, Teti A, Fortunato L, et al. The therapeutic relationship in videoconferencing psychotherapy: a qualitative study of therapists' experiences. Clin Neuropsychiatry. Oct 2024;21(5):418-435. [doi: 10.36131/cnfioritieditore20240506] [Medline: 39540073]
39. Nævdal R, Vis C, Kenter RMF. Therapist characteristics and acceptance of internet-delivered cognitive behavioral therapy: a national cross-sectional survey using the technology acceptance model after ten years of iCBT in Norway. Internet Interv. 2025;42:100881. [doi: 10.1016/j.invent.2025.100881] [Medline: 41141287]
40. Artificial intelligence and psychology. Canadian Psychological Association (CPA); 2024. URL: https://cpa.ca/docs/File/CPD/Artificial%20Intelligence%20and%20Psychology%20EN%202024.pdf [Accessed 2026-05-26]
41. Updated guidelines on use of AI in psychology. New Zealand Psychologist Board. 2026. URL: https://psychologistsboard.org.nz/updated-guidelines-on-use-of-ai-in-psychology/ [Accessed 2026-05-26]
42. Using AI in psychological practice: how the new APS practice guidelines help psychologists. Australian Psychological Society. 2026. URL: https://psychology.org.au/insights/use-ai-in-practice-new-aps-practice-guidelines [Accessed 2026-05-26]
43. Van Kessel K. Clinical psychologists' attitudes towards using technology in therapy: a survey. J N Z Coll Clin Psychol. 2021;31(1):3-9. URL: https://ndhadeliver.natlib.govt.nz/delivery/DeliveryManagerServlet?dps_pid=IE79226270 [Accessed 2026-11-12]
44. Dobson R, Variava R, Douglas M, Reynolds LM. Digital competency of psychologists in Aotearoa New Zealand: a cross-sectional survey. Front Digit Health. 2022;4:951366. [doi: 10.3389/fdgth.2022.951366] [Medline: 36158995]
45. Löchner J, Carlbring P, Schuller B, Torous J, Sander LB. Digital interventions in mental health: an overview and future perspectives. Internet Interv. Jun 2025;40:100824. [doi: 10.1016/j.invent.2025.100824] [Medline: 40330743]
46. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q. Sep 1, 2003;27(3):425-478. [doi: 10.2307/30036540]
47. Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. Mar 1, 2012;36(1):157-178. [doi: 10.2307/41410412]
48. Rouidi M, Elouadi AE, Hamdoune A, Choujtani K, Chati A. TAM-UTAUT and the acceptance of remote healthcare technologies by healthcare professionals: a systematic review. Inform Med Unlocked. 2022;32:101008. [doi: 10.1016/j.imu.2022.101008]
49. Mustafa S, Zhang W, Anwar S, Jamil K, Rana S. An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. Sci Rep. Nov 21, 2022;12(1):20056. [doi: 10.1038/s41598-022-24532-8] [Medline: 36414788]
50. Karaca O, Çalışkan SA, Demir K. Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) - development, validity and reliability study. BMC Med Educ. Feb 18, 2021;21(1):112. [doi: 10.1186/s12909-021-02546-6] [Medline: 33602196]
51. Pote H, Moulton-Perkins A, Rides G. Digital competencies for psychological practitioners in IAPT services. Royal Holloway, University of London; 2020. URL: https://ora.ox.ac.uk/objects/uuid:efd776f9-d538-4558-a72f-d1d3e155e74c/files/sms35tc05v [Accessed 2026-01-15]

52. Pote H, Moulton-Perkins A, Rides G, Lai S. Development of the digital competencies for applied psychological practitioners (DCAPP) scale. OSF. 2024. URL: https://osf.io/z9dre/overview [Accessed 2026-11-12]
53. Vernmark K, Lai S, Moulton-Perkins A, Pote H. AI-assisted adaptation of the Swedish version of the Digital Competencies for Applied Psychological Practitioners Scale: preliminary psychometric evaluation. JMIR Form Res. Sep 8, 2026;10:e92332. [doi: 10.2196/92332] [Medline: 42709962]
54. Cicero L, Russo A, Di Stefano G, Zammitti A. The general attitudes towards artificial intelligence scale (GAAIS): validation and psychometric properties analysis in the Italian context. BMC Psychol. Jul 1, 2025;13(1):641. [doi: 10.1186/s40359-025-02935-2] [Medline: 40597372]
55. Grassini S. Development and validation of the AI attitude scale (AIAS-4): a brief measure of general attitude toward artificial intelligence. Front Psychol. 2023;14:1191628. [doi: 10.3389/fpsyg.2023.1191628] [Medline: 37554139]
56. Eysenbach G. Improving the quality of Web surveys: the Checklist for Reporting Results of Internet E-Surveys (CHERRIES). J Med Internet Res. Sep 29, 2004;6(3):e34. [doi: 10.2196/jmir.6.3.e34] [Medline: 15471760]
57. AI – artificiell intelligens [Article in Swedish]. Svenskarna och internet. URL: https://svenskarnaochinternet.se/rapporter/svenskarna-och-internet-2025/ai-artificiell-intelligens/ [Accessed 2026-05-26]
58. Hakimi TI, Jaafar JA, Mohamad MA, Omar M. Unified theory of acceptance and use of technology (UTAUT) applied in higher education research: a systematic literature review and bibliometric analysis. Multidiscip Rev. 2024;7(12). [doi: 10.31893/multirev.2024303]
59. Vlaescu G, Carlbring P, Andersson G. Features and functionality of the Iterapi platform for internet-based psychological treatments: an update. Internet Interv. 2026;45:100955. [doi: 10.1016/j.invent.2026.100955] [Medline: 42237994]
60. As AI use surges among psychologists, so do concerns about risks. American Psychological Association. 2026. URL: https://www.apa.org/monitor/2026/04-05/ai-psychologists-experience-concerns [Accessed 2026-05-26]
61. Hutnyan M, Gottlieb MC. Artificial intelligence in psychological practice: applications, ethical considerations, and recommendations. Prof Psychol Res Pr. 2025;56(5):343-352. [doi: 10.1037/pro0000631]
62. Hlynsson JI, Mechler J, Lindqvist K, Andersson G, Carlbring P. Anna vs. Judith: a randomized comparison of AI-delivered psychodynamic and cognitive behavioral therapies for social anxiety disorder. Internet Interv. 2026;45:100960. [doi: 10.1016/j.invent.2026.100960] [Medline: 42358455]
63. Feng Y, Hang Y, Wu W, et al. Effectiveness of AI-driven conversational agents in improving mental health among young people: systematic review and meta-analysis. J Med Internet Res. May 14, 2025;27:e69639. [doi: 10.2196/69639] [Medline: 40367506]
64. Mendes-Santos C, Weiderpass E, Santana R, Andersson G. Portuguese psychologists' attitudes toward internet interventions: exploratory cross-sectional study. JMIR Ment Health. Apr 6, 2020;7(4):e16817. [doi: 10.2196/16817] [Medline: 32250273]
65. Stöhr C, Ou AW, Malmström H. Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. Comput Educ: Artif Intell. Dec 2024;7:100259. [doi: 10.1016/j.caeai.2024.100259]
66. Scott S, Knott V, Finlay-Jones AL, Mancini VO. Australian psychologists experiences with digital mental health: a qualitative investigation. J Technol Behav Sci. 2023;8(4):341-351. [doi: 10.1007/s41347-022-00271-5]
67. Rawnsley C, Stasiak K. Training the digital clinician by evaluating health education and curriculum integration New Zealand psychology and psychiatry programs: mixed methods study. JMIR Med Educ. Dec 31, 2025;11:e72777. [doi: 10.2196/72777] [Medline: 41474868]
68. Pote H, Rees A, Holloway-Biddle C, Griffith E. Workforce challenges in digital health implementation: how are clinical psychology training programmes developing digital competences? Digit Health. 2021;7:2055207620985396. [doi: 10.1177/2055207620985396] [Medline: 33628457]
69. Blease C, Kharko A, Annoni M, Gaab J, Locher C. Machine learning in clinical psychology and psychotherapy education: a mixed methods pilot survey of postgraduate students at a Swiss university. Front Public Health. 2021;9:623088. [doi: 10.3389/fpubh.2021.623088] [Medline: 33898374]
70. Gado S, Kempen R, Lingelbach K, Bipp T. Artificial intelligence in psychology: how can we enable psychology students to accept and use artificial intelligence? Psychol Learn Teach. 2022;21(1):37-56. [doi: 10.1177/14757257211037149]
71. Van Daele T, Mathiasen K, Carlbring P, et al. Online consultations in mental healthcare: modelling determinants of use and experience based on an international survey study at the onset of the pandemic. Internet Interv. 2022;30:100571. [doi: 10.1016/j.invent.2022.100571] [Medline: 36105006]
72. Cheng M, Li X, Xu J. Promoting healthcare workers' adoption intention of artificial-intelligence-assisted diagnosis and treatment: the chain mediation of social influence and human-computer trust. Int J Environ Res Public Health. Oct 15, 2022;19(20):13311. [doi: 10.3390/ijerph192013311] [Medline: 36293889]

73. Philippi P, Baumeister H, Apolinário-Hagen J, et al. Acceptance towards digital health interventions - model validation and further development of the unified theory of acceptance and use of technology. Internet Interv. Dec 2021;26:100459. [doi: 10.1016/j.invent.2021.100459] [Medline: 34603973]
74. Dobson R, Stowell M, Whittaker R. Maintaining patient trust as artificial intelligence's role in healthcare grows. N Z Med J. Feb 13, 2026;139(1629):94-101. [doi: 10.26635/6965.7122] [Medline: 41678762]
75. Sokół-Szawłowska M. Change in the form of work of psychologists after the outbreak of the COVID-19 pandemic in Poland, and the subjective mental state of this professional group. Int J Occup Saf Ergon. Dec 2023;29(4):1552-1557. [doi: 10.1080/10803548.2023.2254600] [Medline: 37661633]
76. Franke Föyen L, Zapel E, Lekander M, Hedman-Lagerlöf E, Lindsäter E. Artificial intelligence vs. human expert: licensed mental health clinicians' blinded evaluation of AI-generated and expert psychological advice on quality, empathy, and perceived authorship. Internet Interv. 2025;41:100841. [doi: 10.1016/j.invent.2025.100841] [Medline: 40525210]
77. De Witte NAJ, Best P, Torous J, et al. Comprehensive model for mental health access and service use (CoMMA): a process model for technology-enhanced mental healthcare. Internet Interv. 2026;44:100927. [doi: 10.1016/j.invent.2026.100927] [Medline: 41909247]
78. Essén A, Stern AD, Haase CB, et al. Health app policy: international comparison of nine countries' approaches. NPJ Digit Med. Mar 18, 2022;5(1):31. [doi: 10.1038/s41746-022-00573-1] [Medline: 35304561]
79. Castro O, Salamanca-Sanabria A, Alattas A, et al. Top-funded companies offering digital health interventions for the prevention and treatment of depression: a systematic market analysis. Arch Public Health. Nov 4, 2024;82(1):200. [doi: 10.1186/s13690-024-01424-z] [Medline: 39497184]
80. Socialstyrelsen. Bilaga 1 resultat av tillgång och efterfrågan på de 22 legitimationsyrkena 2017 [internet]. Socialstyrelsen. Sep 2019. URL: https://www.socialstyrelsen.se/globalassets/sharepoint-dokument/artikelkatalog/ovrigt/2022-2-7759-bilaga1.pdf [Accessed 2025-10-08]
81. Statistik om hälso- och sjukvårdspersonal [Article in Swedish]. Socialstyrelsen. 2019. URL: https://www.socialstyrelsen.se/statistik-och-data/statistik/alla-statistikamnen/halso-och-sjukvardspersonal/ [Accessed 2025-10-15]
82. Békés V, Bőthe B, Aafjes-van Doorn K. Acceptance of using artificial intelligence and digital technology for mental health interventions: the development and initial validation of the UTAUT-AI-DMHI. Clin Psychol Psychother. 2025;32(3):e70085. [doi: 10.1002/cpp.70085] [Medline: 40448409]
83. De Witte NAJ, Buelens F, Grassini S, Van Daele T. Acceptance of digital health and well-being: the development of the UTAUT2-Screener. J Technol Behav Sci. 2026:1-12. [doi: 10.1007/s41347-026-00683-7]
84. Nguyen-Trung K, Friese S. Towards a methodologically congruent framework for GenAI use in nonpositivist qualitative research. Int J Soc Res Methodol. 2026:1-22. [doi: 10.1080/13645579.2026.2703248]

Abbreviations

CHERRIES: Checklist for Reporting Results of Internet E-Surveys
DCAPP: Digital Competencies for Applied Psychological Practitioners
GenAI: generative AI
KMO: Kaiser-Meyer-Olkin
LLM: large language model
MAIRS-MS: Medical Artificial Intelligence Readiness Scale for Medical Students
UTAUT: unified theory of acceptance and use of technology

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