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ORIGINAL RESEARCH ARTICLE

The quality traits of artificial intelligence operations in predicting mental healthcare professionals' perceptions: A case study in the psychotherapy division

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ABSTRACT

As advancements in healthcare technologies continue to emerge, the integration of AI-Technology has brought about significant transformations in various healthcare sectors. While substantial advancements have been made in applying AI to enhance physical health, its implementation in the field of mental health is still in its early stages. This descriptive study aims to address this gap by exploring the perspectives of mental health professionals (MHPs) on the acceptance and utilization of AI technology. Unified Theory of Acceptance and Use of Technology (UTAUT) was utilized to assess MHPs' attitudes and beliefs towards AI implementation in psychotherapeutic practices. The sample was compromised of 349 MHPs. The findings reveal the task characteristic (TC) domain as the most influential domain, followed by Performance expectancy (PE), Behavioural intentions (BI), Personal innovativeness in IT (PT), Social influence (SI), Effort expectancy (EE), Perceived substitution crisis (PSC), Technology characteristic (TECH), and Initial trust (IT). The study also identifies statistically significant differences in AI usage based on gender variable, with females demonstrating a higher level of AI usage in comparison to males. Furthermore, the study highlights diverse applications of AI in the field of mental health, including AI-assisted assessments (AAA), chatbots for psychotherapy support (CPS), and data analytics for personalized treatment recommendations (DAPTR). By incorporating mental healthcare professionals' (MHPs) perspectives, this research significantly contributes to a comprehensive understanding of the acceptance and utilization of AI technology in psychotherapy. The findings offer valuable insights into MHPs' perceptions, concerns, and perceived advantages associated with integrating AI technology within clinical settings in the field of mental health.

Keywords: mental health; artificial intelligence; mental health professionals; quality of technology; artificial intelligence operations

1. Introduction

There is a substantial global gap between the need for mental healthcare (MHC) and the availability of such service. Despite mental health disorders are prevalent worldwide, affecting one in 10 people globally, only 1% of the healthcare workforce provides mental health services worldwide[1–3]. Moreover, the expense of mental health services is high, making it challenging for financially burdened individuals to access them as they are deemed a luxury expense[4]. Besides structural barriers, the negative stereotypes and discrimination associated with mental illness create a significant obstacle that hinders people from seeking help for their

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mental health issues[5]. The rise of artificial intelligence (AI) technology in MHC has been driven by the need to expand access to MHC and counteract the stigma associated with mental health conditions[6–13]. The utilization of AI technology in MHC is increasingly seen as a potential primary solution to address various challenges in the field, Examples of these challenges include restricted availability of treatments, the exorbitant cost of MHC services, as well as delays, inaccuracies, and inefficiencies in delivering care[14–16]. The reason for this is that AI Technology has the ability to deconstruct the intricate biopsychosocial aspects of mental health conditions and enhance the nosology of prognostic, treatment, and preventative paradigms[17–25].

AI technology applications involve the delivery of MHC services through digital technology and online platforms. According to Paganini et al.[26], the most commonly used therapeutic approaches, such as cognitive behavioral therapy CBT, psychodynamic therapy PDT, psychoanalytic therapy PAT, and Systematic and Integrative methods, can be adapted for digital delivery. Furthermore, acceptance and commitment therapy (ACT), mindfulness-based therapy (MFT), and interpersonal therapy (IPT) have been adapted into self-help interventions, which can be administered online with or without guidance[26]. Research findings from a meta-analysis of 92 studies indicate that these interventions are equally effective in supporting clients, comparable to traditional face-to-face psychotherapy[27–29].

AI is related to the efficacy of internet-based psychotherapy interventions in a number of ways. Artificial intelligence (AI) can be used to expand the population to whom mental health services are available through internet-based psychotherapeutic interventions. People who might not have access to traditional therapy because of financial, geographical, or other limitations can receive instant support from AI-driven chat-bots or virtual therapists. AI is capable of analyzing enormous volumes of data to customize psychotherapy treatments. AI systems are able to customize interventions to meet the needs of each individual user by learning about their preferences, actions, and reactions. By addressing particular issues and taking into account the user's individual characteristics, this personalization increases the therapy's effectiveness[15,16,22,30]. AI technology has evolved over the years to include different levels of human guidance through various digital channels. It offers several advantages over traditional face-to-face therapy, such as remote communication, greater flexibility in accessing mental health services, and increased privacy. Various meta-analyses have consistently indicated that computer-aided cognitive behavioral therapy (CCBT), delivered through desktop or mobile applications, is comparable to or more effective than traditional cognitive behavioral therapy (CBT). In 2006, the National Institute for Health and Clinical Excellence in England endorsed the use of computerized CBT packages for the treatment of depression, panic disorders, and phobias, recognizing their clinical effectiveness and cost efficiency[31–35]. Additionally, research indicates that individuals facing mental health challenges have reported highly positive experiences with AI chatbots[36–37]. The perception of anonymity associated with AI technology in MHC can also mitigate the fear of judgment and stigmatization, making clients more willing to engage in therapy and discuss sensitive issues[37]. Additionally, greater levels of self-disclosure during AI interventions have been linked to improved therapy outcomes and emotional and psychological benefits[36,38].

Despite existing research on the knowledge and perspectives of MHPs towards the intersection of AI technology MHC, there is limited research in this area specific to the Arab country context. This article has two primary research goals. The first goal is to investigate how Mental Health Professionals (MHPs) perceive and interact with AI applications in MHC settings. It's important to take into account factors that could compromise the validity, generalizability, and reliability of the results when talking about a study's limitations. A small sample size could make it more difficult to extrapolate results to a larger population. The study's conclusions might not apply to other contexts, populations, or settings. Results might not apply to other socioeconomic or cultural groups[36,38,39].

To improve the findings' generalizability, future studies could examine the subject with a bigger and more varied sample and look into how demographic factors affect the effects that are seen analyzing the research topic's cross-cultural aspects to see if the findings hold true in various cultural contexts. Furthermore, this presents an opportunity to explore the potential influence of cultural factors on the patterns or relationships that have been observed.

2. Background

We find ourselves at a crucial juncture within the fourth phase of industrial development, often referred to as the "digital revolution". This era builds upon previous stages such as the mechanical, electrical, and internet ages, and is marked by a convergence of various technologies[40–42]. Artificial Intelligence technology, commonly abbreviated as AI technology, was originally coined by the father of Artificial Intelligence John McCarthy, who defined it as "the science and engineering of making intelligent machines, especially intelligent computer programs"[43,44]. Recent studies demonstrated AI as a computer-based program that can learn autonomously from data to perform tasks commonly associated with Human cognitive abilities, such as visual perception (VP), problem-solving (PS), speech recognition (SR), language translation (LT), and decision-making (DM), have been explored extensively[45,46].

In psychotherapy, artificial intelligence (AI) refers to the application of computer technologies and algorithms to enhance or facilitate various parts of the therapeutic process. Enhancing mental health outcomes is the ultimate aim of AI in psychotherapy, while it can take many different shapes and serve a variety of purposes. Artificial intelligence (AI) can evaluate large patient data sets, including behavioral patterns, language usage, and other relevant information, to assist in the diagnosis and assessment of mental health conditions. Machine learning algorithms may be able to identify patterns that human physicians would overlook. Artificial intelligence (AI) can evaluate large patient data sets, including behavioral patterns, language usage, and other relevant information, to assist in the diagnosis and assessment of mental health conditions. Machine learning-based algorithms could be able to identify tendencies that medical professionals would miss. Artificial Intelligence has the ability to analyze patient data and tailor treatment plans to each patient's needs and preferences. AI can help create more tailored and effective treatment plans by considering the unique characteristics, experiences, and responses to interventions of each individual[47,48].

3. AI in MHC

AI technology has been applied across a wide range of healthcare settings, providing a high-performance and accurate system work with efficiency[49–51]. Despite significant advancements in applying AI technology to physical health, the utilization of AI technology in the realms of MHC and neurobiological research has remained relatively limited, despite the pressing need to identify and treat mental disorders[52–54]. Presently, AI technologies are increasingly seen as a potential solution to address various challenges in MHC, including limited treatment accessibility, high costs, and inefficiencies in care delivery[55–57]. Through the use of advanced algorithms, machine learning techniques (ML), and big data analysis, AI applications have the potential to provide MHPs with valuable insights, personalized interventions, and improved decision-making support[21]. AI can enhance prognosis by analyzing individual characteristics, treatment histories, and response data, assisting in tailoring treatment plans to meet specific patient needs[58]. By personalizing interventions, AI can improve treatment outcomes, patient engagement, and resource allocation in mental health care settings[59]. AI also shows promise in mental health diagnosis, as algorithms can analyze complex datasets encompassing brain imaging, genetic information, and clinical assessments to identify patterns and biomarkers of mental health disorders, enabling accurate and timely interventions[60–62]. Furthermore, AI enables the prediction of treatment response, relapse risk, and disease progression by analyzing longitudinal data from wearables, digital health records, and patient-reported outcomes[63]. This proactive approach can prevent relapse or worsening of symptoms. However, the adoption of AI technology in clinical settings is impeded by MHPs' overall perceptions and beliefs about AI, leading to a gap between the development of AI technology and its practical implementation. AI applications in MHC. The field of MHC has a long history of AI applications, dating back to the 1960s with the development of ELIZA, a computer program that simulated a psychotherapist through conversation. Since then, AI technology in mental health care has evolved significantly. Some of the most influential breakthroughs in this field include the use of natural language processing NLP, data analytics (DA), and machine learning ML[17,64,65].

Additionally, advancements in cognitive computing technology (CCT) and facial recognition software (FR) facilitate the identification of a patient's mental health status by tracking body language and facial expressions[66]. AI technology has shown its effectiveness in the field of MHC through diverse applications, covering a broad spectrum of disorders and distresses. NLP techniques enable the analysis of text data, allowing for the detection of depression through sentiment analysis of social media posts[64,67]. Digital clinical notes (DCN) can also be analyzed using NLP algorithms to assess the risk of suicide by offering valuable insights for clinicians and contributing to suicide prevention efforts[68–71]. AI-powered chatbots have increasingly become prevalent as interactive tools that offer emotional support and guided self-help techniques to individuals who are facing episodes of anxiety or distress[72,73]. Moreover, these AI-powered chatbots act as easily accessible resources for individuals seeking assistance in dealing with symptoms of depression, offering necessary coping strategies and interventions[74,75]. The integration of Virtual Reality Exposure Therapy (VRET) with AI algorithms has facilitated immersive and interactive therapeutic experiences, particularly in the application of exposure therapy (ET) as a treatment modality for anxiety disorders including post-traumatic stress disorder (PTSD) and various types of phobias. AI algorithms adapt virtual environments and scenarios based on individual responses, facilitating personalized interventions and controlled triggers exposure[76,77].

Furthermore, AI has the ability to analyze speech patterns (SP) which contributes to early detection and risk assessment (RA). Early indicators of Alzheimer's disease (AD) can be identified through AI algorithms, facilitating early intervention[60,78,79]. Furthermore, AI can monitor social media data to assess suicide risk, allowing for timely interventions and prevention efforts[80,81]. AI-powered mental health apps and wearable devices provide valuable self-management and monitoring tools[82,83]. Mood-tracking features in apps assist individuals with bipolar disorder in monitoring their moods and identifying patterns[84–86]. Moreover, mental health apps offering stress level monitoring and relaxation techniques benefit individuals seeking overall mental well-being[87,88]. Lastly, personalized digital therapeutics driven by AI analyze user input, behavior, and preferences to tailor interventions such as internet cognitive- behavioral therapy (iCBT), mindfulness exercises, and relaxation techniques[89–91]. These interventions are customized to meet individual needs, enhancing treatment outcomes.

4. Conceptual framework

The study of user behavior in the field of Information Systems (IS) research has a strong focus on understanding how individuals adopt and utilize IS. Over the years, various models have been introduced to elucidate the intentions and behavior of individuals in relation to their usage of IS. The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are commonly employed theories in this domain. These theories are widely utilized to understand user behavior (UB) and their intentions in utilizing technology[92,93]. The core ideas in these theories revolve around the concepts of perceived usefulness (PU) and perceived ease of use (PEOU), which refer to how users perceive the performance and effort required to use the technology. These theories emphasize the importance of users' perceptions (UP) in shaping the acceptance of using technology. TAM and UTAUT incorporate the socio-psychological theories of Planned Behavior (TPB) and Reasoned Action (TRA)[94]. These theories introduce social and cognitive concepts as additional factors that influence users' behavior within the models[94,95]. After a critical review of these theories, the integration of eight influential theoretical models, namely TRA, MM, TAM, TPB, MPCU, IDT, and SCT, the UTAUT model is widely regarded as a highly comprehensive theory and becomes a broad, robust, and powerful framework that is well-suited for examining the utilization of technological innovations[96,97]. **Figure 1** demonstrates the model, proposed by Venkatesh[93] in 2003, which illustrates the UTAUT dimensions of performance expectancy, effort expectancy, social influence, and facilitating conditions, and their impact on behavioral intention and use behavior. There are two main research goals for this article. The initial objective is to look into how AI applications are viewed and used by Mental Health Professionals (MHPs) in MHC settings. The second objective is to learn more about the factors that influence MHPs' acceptance and use of AI interventions for psychotherapy.

1) What are the primary determinants that impact mental health professionals' adoption and utilization of AI technology in MHC settings?
2) Does the level of AI usage exhibit statistically significant variations with respect to variables such as gender, profession, age, and experience?

Understanding MHPs' perceptions, interactions, acceptance, and use of AI applications, as well as investigating the variables influencing their adoption choices, are the main goals of these research questions.

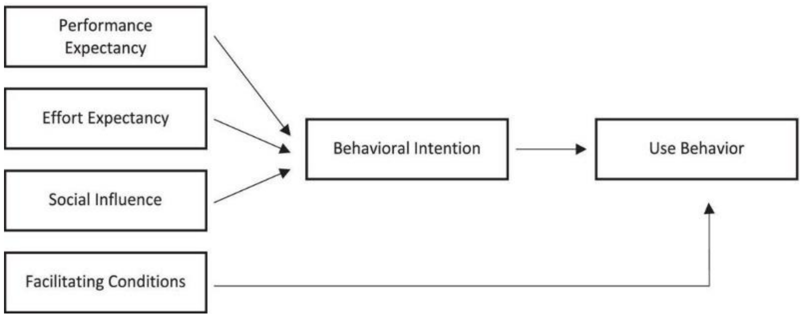

Figure 1. The unified theory of acceptance and use of technology[93].

The UTAUT model is employed to explain user intentions and subsequent usage behavior in relation to adopting information systems. The model incorporates four essential constructs that impact user behavior regarding technology usage. These constructs, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), were identified by Venkatesh[93] as influential factors in understanding technology acceptance and adoption. Generally, the first three factors directly impact attitude or intention to use, while the fourth factor has a direct or indirect influence on user behaviors. In addition, factors such as gender, age, experience, and voluntariness of use has been suggested to mediate the relationship between the four constructs mentioned above and their influence on technology utilization[93,98–100]. Moreover, Waehama et al.[101]. have commended the UTAUT model for its ability to account for at least 70% of technology acceptance behavior, surpassing other models that can only explain up to 40%. The UTAUT model is also recognized for its effectiveness in assessing the acceptance of new and emerging technologies. Tran et al.[102] decided to enhance the model by incorporating five additional factors: task complexity (TC), personal innovation in IT (PI), technology characteristics (TECH), initial trust (IT), and perceived substitution crisis (PSC). TC refers to the level of difficulty in assigned tasks and influences the acceptance of AI support by MHPs to enhance their performance. PI reflects an individual's inclination to adopt IT innovations, TC encompass the features of the system that enable users to accomplish tasks[102]. SC identified as a possible obstacle for MHPs when considering the integration of technology into their future medical practice[103]. According to Mcknight et al.[104], initial trust in the context of technology refers to the belief in the capabilities of technology rather than its intentions or motives[104]. The conceptual framework employed in the study is depicted in **Figure 2** (Tran et al.[102]).

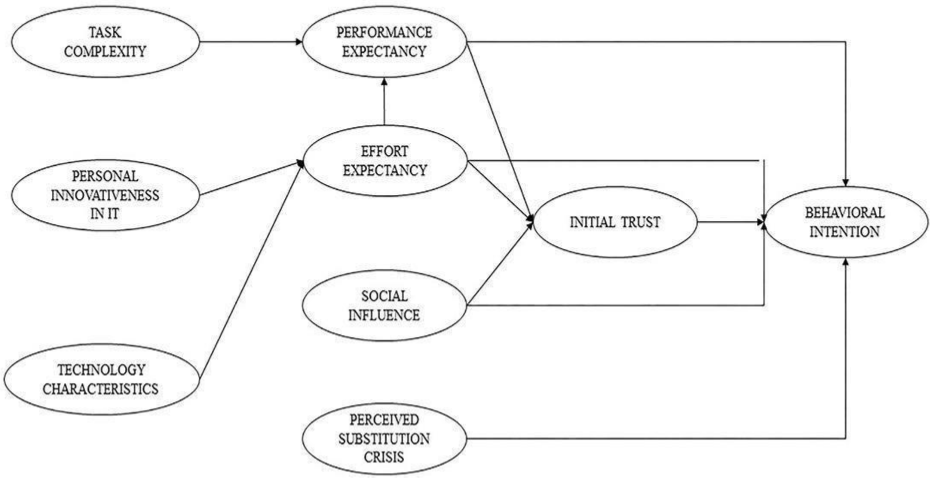

Figure 2. Theoretical Model.

The extensive body of research conducted using this model attests to its effectiveness in analyzing adoption patterns in various technological domains, encompassing innovative approaches and diverse cultural and social contexts[63,105–107]. By employing UTAUT, we can gain insights into the various factors that influence MHPs' perceptions towards implementing AI technology in MHC, leading to a better understanding of the acceptance and successful integration of AI technologies in mental healthcare settings. In this study, we propose utilizing the UTAUT model as a conceptual framework to explore MHPs' perceptions of implementing AI technology in Therapeutic practices. While the TAM focuses on individual-level factors, UTAUT provides a more comprehensive framework by incorporating additional factors such as social influence SI, facilitating conditions FC, and user characteristics UC. UTAUT's comprehensive outlook is especially pertinent for comprehending the intricate dynamics associated with the acceptance and implementation of AI in psychotherapy.

5. Method

A cross-sectional study was conducted with a descriptive-analytical approach to examine MHP's attitude towards AI-PT. Aljasmi et al.[108] suggest that utilizing this method facilitates the acquisition of information regarding pertinent variables in a structured and precise manner. The purpose of employing this approach is to offer a detailed and accurate depiction of the phenomenon being studied. MHPs were recruited through various channels, including professional e-mail lists, social media platforms, and personal networks across UAE. The sample population for the study was selected using convenience sampling. Prior to the survey, informed consent was obtained from each participant, and anonymity was ensured to maintain confidentiality. The participants were duly informed about the anonymity of their responses to protect their privacy. According to the information stated in some research statistics, an initial sample size of 30 participants was selected for pre-testing the online survey to assess its usability and technical performance. Following their consent, Participants were instructed to complete a set of anonymous online questionnaires on Google form. A questionnaire was utilized in a specific sequence, which typically required around 15 minutes to finish.

6. Participants

The study consisted of 349 certified MHPs in UAE (292 females, 57 males).

Table 1 presents the characteristics of the study sample in relation to the variables.

Table 1. Number and Percentage of the Participants.

Factors	Frequency	Percentage %
Gender		
Male	57	16.3
Female	292	83.7
Total	349	100%
Profession		
Psychologist	92	26.4
Counselor	106	30.4
Psychiatrist	38	10.9
Others	113	32.4
Total	349	100%
Age		
22–35 years	198	56.7
36–45 years	91	26.1
More than 45years	60	17.2
Total	349	100%
Experience		
0– 4years	42	12.0
5–10 years	158	45.3
More than10years	149	42.7
Total	349	100%

7. Measures

The researchers utilized the Unified Theory of Acceptance and Use of Technology (UTAUT) to evaluate attitudes toward AI technology. The demographic survey included questions covering basic sociodemographic variables (gender, age, experience, and profession). To measure MHPs' attitudes toward the adoption of AI technology, we utilized a questionnaire developed by Tran et al., 2021 to measure participants' attitudes toward AI technology usage. The questionnaire demonstrated good reliability and validity measures. The construct of initial trust had the lowest average score of 03.00 (*SD* = 00.90), while the highest mean score of 03.80 (*SD* = 00.90) was observed for the *TC* construct. The Cronbach's alpha coefficients, ranging from 00.738 to 00.909, indicated strong internal consistency among the constructs. The convergent validity of the constructs was supported, as all item loadings exceeded 00.70, and the average variance extracted (AVE) values for each construct surpassed 0.5. This indicates that the measurement items reliably capture the underlying constructs. Furthermore, discriminant validity was established, as the square root of AVE for each construct was greater than its correlation coefficient with other constructs. These findings provide evidence for the distinctiveness of the measurement constructs and their ability to measure separate concepts. The structural model analysis revealed that social influence significantly influenced behavioral intentions ($\beta = 0.527$, $p < 0.05$), while other constructs did not show associations. The overall model explained 47.6% (R^2 = 0.476) of the variance in behavioral intentions. Effort expectancy (β = 0.201, $p < 0.05$) and social influence (β = 0.574, $p < 0.05$) had positive effects on initial trust, indicating that individuals who perceived the task to be less effortful and were influenced by others had higher levels of initial trust. However, no significant association was observed between performance expectancy and initial trust. The results revealed that the model accounted for 47.9% of the variation in initial trust (R^2 = 0.479). These findings offer valuable insights into the interrelationships among constructs and enhance our understanding of the factors that influence the adoption of technology within the specific study population. To align with the study's specific focus on AI technology MHC, the phrasing of the 18 items in the UTAUT was modified to reflect MHC specifically, rather than AI technology in general as in the original UTAUT version. In the field of information systems and technology acceptance, one popular model is the Unified Theory of Acceptance and Use of Technology (UTAUT). It indicates a customization of the UTAUT model for a particular context if you have changed the wording of the 18 items in the UTAUT to explicitly reflect Mental Health Care (MHC) rather than general AI technology. It would be beneficial if you could share the updated items or particulars about how each item was changed to reflect MHC in order to give more precise assistance. In this manner, depending on the adjustments you've made, I can provide more focused insights or feedback. Participants rated the items on a Likert scale ranging from strongly disagree to strongly agree.

8. Results

Question 1: What are the primary determinants that impact mental health professionals' adoption and utilization of AI-based psychotherapeutic techniques (AI-PT)? To address the primary inquiry of the study, we performed calculations of the arithmetic mean and standard deviation for each of the nine domains encompassed by the UTAUT model. Subsequently, the domains were arranged in descending order based on their respective arithmetic means, as illustrated in **Table 2**.

Table 2. The arithmetic means and standard deviation of the UTAUT model domains and their ranking in descending order.

Domain no.	Domain	Mean	Std. Deviation	Order
6	TC: Task characteristic	3.78	0.67	1
1	PE: Performance expectancy	3.71	0.43	2
9	BI: Behavioral Intentions	3.45	0.88	3
4	PT: Personal innovativeness in IT	3.43	0.45	4
3	SI: Social influence	3.39	0.40	5
2	EE: Effort expectancy	3.36	0.62	6
8	PSC: Perceived substitution crisis	3.09	0.49	7
7	TECH: Technology characteristic	3.06	0.73	8
5	IT: Initial trust	2.98	0.64	9

The ranking of the domains within the UTAUT model, based on the results presented in **Table 2**, reveals that the top-ranked domain is *TC* (Average: 3.781, Standard Deviation: 0.675), followed closely by *PE* (Average: 3.717, Standard Deviation: 0.430). In the third position is *BI* (Average: 3.450, Standard Deviation: 0.881), while *PI* (Average: 3.438, Standard Deviation: 0.455) takes the fourth spot. *SI* (Average: 3.396, Standard Deviation: 0.407) ranks fifth, and *EE* (Average: 3.365, Standard Deviation: 0.620) comes in sixth. *PSC* (Average: 3.090, Standard Deviation: 0.499) secures the seventh position, while *TC* (Average: 3.068, Standard Deviation: 0.735) is second to last. Finally, *IT* (Average: 2.987, Standard Deviation: 0.647) occupies the last place in the ranking. Question 2: Do AI-based technology usage levels vary depending on gender, age profession, and experience?

Table 3 presents the outcomes indicating significant variations in the arithmetic mean of AI usage levels based on gender. To determine the statistical significance of these differences, an independent samples t-test was performed, comparing the relevant groups.

Table 3. The arithmetic means and standard deviations of the level of AI usage according to gender.

Gender	*F*	Mean	Std. Deviation
Male	57	3.30	0.15
Female	292	3.37	0.20

Table 3 presents the outcomes indicating significant variations in the arithmetic mean of AI usage levels based on gender. To determine the statistical significance of these differences, an independent samples t-test was performed, comparing the relevant groups. The results are presented in **Table 4**, providing valuable insights into the significance and implications of this variation.

Table 4. Independent Sample T-test to identify the level of AI usage according to gender.

Gender (Effect Size)	*F*	Mean	*T*	Df	Sig
Male (57)	0.158	3.30	−2.860	98.490	0.005*
Female 209 (292)	0.208	3.37	-		

*Statistically significant at level (0.05).

The results presented in **Table 4**, strongly indicate statistically significant differences ($p \leq 0.05$) in the arithmetic means of AI-based technology usage levels between genders. Male participants had an arithmetic mean of 3.307, whereas females had an arithmetic mean of 3.376. The calculated statistical value (t) of 0.005 provides robust support for the presence of a statistically significant disparity. These findings suggest that females exhibit a higher level of AI-based technology usage compared to males. In order to assess how the adoption of AI-based technology varies across different professional categories, we calculated the average values and standard deviations of AI adoption.

Table 5 demonstrates significant differences in the arithmetic mean of AI-based technology usage levels based on different professions. The arithmetic mean for Psychiatrists was (3.437), Counselors was (3.386), Psychologist was (3.337), and 3.343 for the (other group). To determine the statistical significance of these differences, a One-way ANOVA test was performed. The results of this analysis are presented in **Table 6**.

Table 5. The arithmetic means and standard deviations of the level of AI usage according to profession.

Profession	*F*	Mean	Std. Deviation
Psychiatrist	38	3.43	0.14
Counselor	106	3.38	0.21
Psychologist	92	3.33	0.16
Others	113	3.34	0.23

Table 6. One-way ANOVA test results for the level of AI usage according to profession.

Source	Sum of squares	Df	Mean square	*F*	Sig.
Between Groups	0.370	3	0.12	3.063	0.028*
Within Groups Professional	13.883	345	0.04	-	-
Total	14.253	348	-	-	-

*Statistically significant at level (0.05).

Table 6 indicates statistically significant differences ($p \leq 0.05$) among the levels of AI usage across different professional categories (Psychiatrist, Counselor, Psychologist, and others in the psychological field).

The calculated statistical value (F) was 3.063, which is below the significance level of $p \leq 0.05$, indicating the presence of statistically significant differences. To determine the specific category, the Tukey HSD test was employed. The results are displayed in **Table 7**.

Table 7. Results of the Tukey HSD test for post-comparisons for the level of AI usage according to profession.

(I) Profession	(J) Profession	Mean Difference (I-J)	Sig.
Psychiatrist	Counselor	0.05	0.532
	Psychologist	0.09*	0.050
	Other	0.09	0.061
Counselor	Psychiatrist	−0.05	0.532
	Psychologist	0.04	0.323
	Other	0.04	0.389
Psychologist	Psychiatrist	−0.09*	0.050
	Counselor	−0.04	0.323
	Other	−0.01	0.997
Other	Psychiatrist	−0.09	0.061
	Counselor	−0.04	0.389
	Psychologist	0.01	0.997

*Statistically significant at level (0.05).

The findings presented in **Table 7** demonstrate that there are statistically significant differences between Psychiatrists and Psychologists regarding the level of AI usage, favoring Psychiatrists. However, no statistically significant differences were observed among the other professional groups such as (Counselor and Psychologist). This indicates that in terms of AI usage, Psychiatrists exhibit a distinct advantage compared to Psychologists, while the remaining professional categories do not exhibit significant differences. To address the question pertaining to the influence of age on the level of AI usage, we calculated the arithmetic means and standard deviations for AI usage based on different age groups. The results of these calculations are presented in **Table 8**, providing insights into the variations in AI usage across different age categories.

Table 8. The arithmetic means and standard deviations of the level of AI usage according to age.

Age	*F*	Mean	Std. Deviation
22–35 years	198	3.35	0.20
36–45 years	91	3.38	0.19
more than 45 years	60	3.35	0.21

From **Table 8**, it is evident that there are variations in the arithmetic mean of the level of AI-based technology adoption based on different professions. Psychiatrists had an arithmetic mean of 3.437, Counselors had an arithmetic mean of 3.386, Psychologists had an arithmetic mean of 3.337, and the other group had an arithmetic mean of 3.343. A One-way ANOVA test was conducted. The findings are summarized in **Table 9**.

Table 9. One-way ANOVA test results for the level of AI usage according to profession.

Source	Sum of squares	Df	Mean square	*F*	Sig.
Between groups	0.074	2	0.03	0.901	0.407
Age within groups	14.179	346	0.04	-	-
Total	14.253	348	-	-	-

*Statistically significant at level (0.05).

The results presented in **Table 9** reveal that there are no statistically significant differences ($p \leq 0.05$) in the extent of AI adoption across the age groups. The calculated statistical value (F) of 0.901 is lower than the significance level ($p \leq 0.05$), indicating that age does not exert a significant influence on AI usage levels. Therefore, it can be concluded that age does not have an impact on the utilization of AI technology adoption. To examine the impact of experience on the extent of AI technology utilization, calculations of the mean and standard deviation we conducted for various experience categories. The results are shown in **Table 10**.

Table 10. The arithmetic means and standard deviations of the level of AI usage according to experience.

Experience	***F***	**Mean**	**Std. Deviation**
0–4 years	42	3.31	0.22
5–10 years	158	3.35	0.22
more than 10 years	149	3.38	0.17

Based on the data presented in **Table 5**, it is evident that there are variations in the average AI technology usage levels across different experience categories. Specifically, the "0–4 years" group had an average AI usage of 3.319, the "5–10 years" group had an average AI usage of 3.356, and the "more than 10 years" group had an average AI usage of 3.388. To assess the statistical significance of these differences, A one-way ANOVA test was conducted. The results of this test are summarized in **Table 11**.

Table 11. One-way ANOVA test results for the level of AI usage according to experience.

Source	**Sum of squares**	**Df**	**Mean square**	***F***	**Sig.**
Between Groups	0.178	2	0.08	2.192	0.113
Experience Within Groups	14.075	346	0.04	-	-
Total	14.253	348	-	-	-

*Statistically significant at level (0.05).

The results displayed in **Table 6** suggest that there are no statistically significant differences ($p \leq 0.05$) in the extent of AI usage among experience groups (0–4 years, 5–10 years, and more than 10 years). The computed statistical value (F) of 2.192 is lower than the significance level ($p \leq 0.05$), indicating that experience does not exert a significant influence on AI usage levels. Therefore, it can be concluded that the utilization of AI remains unaffected by experience.

9. Conclusion

The findings indicate that MHPs' adoption of AI-based psychotherapeutic techniques is influenced by various factors. Task characteristics TC and performance expectancy EE emerged as the primary determinants, highlighting the importance of understanding the specific and expected outcomes of AI psychotherapeutic techniques. Gender differences were observed, with females demonstrating higher levels of AI technology usage compared to males. Among different professional categories, psychiatrists exhibited the highest adoption, while age and experience did not significantly impact AI utilization. These insights provide valuable guidance such as incorporation of algorithms and computational technologies to improve or facilitate different aspects of the therapeutic process for the development and implementation of effective and implementable AI systems in mental health settings, emphasizing the need to consider contextual factors and individual expectations to promote successful adoption and utilization.

10. Discussion

There are two main research goals for this article. The initial objective is to look into how AI applications are viewed and used by Mental Health Professionals (MHPs) in MHC settings. The second objective is to learn more about the factors that influence MHPs' acceptance and use of AI interventions for psychotherapy.

1) What are the primary determinants that impact mental health professionals' adoption and utilization of AI technology in MHC settings? 2) Does the level of AI usage exhibit statistically significant variations with respect to variables such as gender, profession, age, and experience? Understanding MHPs' perceptions, interactions, acceptance, and use of AI applications, as well as investigating the variables influencing their adoption choices, are the main goals of these research questions. The results show that a number of factors affect MHPs' adoption of AI-based psychotherapy techniques. The main determinants were found to be task characteristics (TC) and performance expectancy (EE), emphasizing the significance of comprehending the attributes and anticipated results of AI psychotherapy approaches. There were gender disparities noted, with females using AI technology at higher rates than males. Psychiatrists were the most adoptive of all professional categories; age and experience had no discernible effect on AI usage. These insights highlight the necessity of taking individual expectations and contextual factors into account to promote successful adoption and utilization, which offers helpful guidance for the development and implementation of practical and effective AI systems in mental health settings[1,13,28].

Based on the results obtained from the study, it can be concluded that the primary determinants impacting mental health professionals' adoption and utilization of AI-based psychotherapeutic techniques are task characteristics and performance expectancy, as they were ranked the highest among the nine domains of the UTAUT model. Indeed, the findings imply a link between task characteristics and performance expectations, as well as the aim of mental health providers to adopt AI-enabled technologies. Prospective and present mental health practitioners, on the other hand, may be skeptical of using AI technology for various objectives in their (future) practice. When given with AI-generated input regarding diagnostic or treatment decisions, for example, they may be hesitant to accept AI-based suggestions due to the far-reaching ramifications of incorrect predictions or because they feel undermined in their role as therapists. Simultaneously, they may be willing to incorporate AI-generated feedback on their interviewing skills. Although research into practitioners' acceptance of AI-enabled technologies in mental health care has begun, there is a lack of specificity in determining usage intention, limiting the findings. According to the task-technology fit theory (TTF) model, TTF is significantly affected by technology characteristics and task characteristics, which ultimately predict its usefulness. Khadragy et al.[71] posited that the acceptance of technology depends on how the new technology fits with the requirements of the task, and enterprise content management (ECM) recognized its efforts as to how it enhances the continued intentions of users. In this view, Almarzouqi et al.[42] postulated that poor technology characteristics decrease the user's intentions to continue using technology and vice versa. Previous studies have studied the relationship between task characteristics and technology characteristics in TTF. Salloum et al.[23] posited that task characteristics and technology characteristics are essential predictors of the user's perceived TTF in the chatbot system. On the other hand, previous research has found a strong relationship between performance expectancy and the use of technology, and extending this to AI-enabled products would be natural. Several studies have found a link between AI and enhanced performance, which can be interpreted as an association with performance expectancy. Recent research has revealed a direct link between AI use and performance and effort expectations. The existing research supports the strong claim that AI aversion drives AI adoption. Furthermore, significant variations were observed in the level of AI usage based on gender and profession. Females exhibited a higher level of AI usage compared to males, and among different professions, Psychiatrists demonstrated a distinct advantage in AI usage over Psychologists. However, no significant differences were found in the level of AI usage based on age and experience. Therefore, age and experience do not seem to have a significant influence on the adoption and utilization of AI psychotherapeutic techniques. It's important to consider factors that could compromise the validity, generalizability, and reliability of the results when talking about a study's limitations. A small sample size could make it more difficult to extrapolate results to a larger population. The study's conclusions might not apply to other contexts, populations, or settings. Results might not apply to other socioeconomic or cultural groups. Of course! One of the most crucial parts of academic writing is making recommendations for future research topics. This helps to steer the line of further investigation. To improve the findings' generalizability, future studies could examine the subject with a bigger and more varied sample and investigate how demographic factors affect the effects that are seen. analyzing the research topic's cross-cultural aspects to see if the findings hold true in various cultural contexts. Furthermore, this presents an opportunity to explore the potential influence of cultural factors on the patterns or relationships that have been observed.

Author contributions

Conceptualization, SAA and MMA; methodology, AA; software, FS; validation, EA, SA and HEF; formal analysis, AAA; investigation, SAA, MMA and FS; resources, AA and SA; data curation, EA and SA; writing—original draft preparation, SAA, EA, SA, HEF and AAA; writing—review and editing, AA; visualization, FS; supervision, SAA; project administration, EA and SA; funding acquisition, HEF and MMA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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