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Integrating AI Tools across the Psycho-Oncology Continuum: From Biomarker Detection to Patient Rehabilitation

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ABSTRACT: The concept of psycho-oncology revolves around addressing the emotional, social, and psychological challenges faced by individuals with cancer. Artificial intelligence (AI) can be integrated within this field since it offers distress screening, enhanced medicinal decision-making, and digitally based rehabilitation systems. The purpose of this study is to explore the prospective role of AI within the psycho-oncology continuum through the Partial Least Squares Structural Equation Modelling (PLS-SEM) method. The analysis is based on 100 responses that were measured using 15 Likert-scale indicators and organized into three reflective constructs labelled R1, R2, and R3. According to the model's measurements, the internal consistency of the model was in order, with a Cronbach's alpha of 0.881, 0.914, and 0,884 for R1, R2, and R3 respectively. In a similar vein, the values of composite reliability ranged from 0.900 to 0.929, while the average variance extracted (AVE) had its range of values from 0.678 to 0.744. Additionally, the HTMT values of 0.620, 0.371, and 0.543 supported discriminant validity. The positive paths between R1 and R2 (β = 0.575) and R1 and R3 (β = 0.348) were observed within the structural model. R1 exemplified 33.1% of the variance in R2 and 12.1% of the variance in R3. Thus, the findings collected through the PLS-SEM process offer preliminary evidence that the integration of AI is associated with improved patient and clinician outcomes in the context of psycho-oncology. However, the model didn't cover all aspects such as accounting for the influence of socioeconomic factors, comparing the proposed system with text-only AI, or assessing system readiness independently of patient autonomy. Therefore, although a relationship can be established between the use of AI and the enhancement of psycho-oncological healthcare systems, further research with comprehensive data and detailed models is required to create casual relationships through comparative effectiveness.

1. INTRODUCTION

Cancer, in its essence, is a transformative phenomenon that has generated complex challenges within the realm of modern medicine, thereby mandating a comprehensive care approach that amalgamates the use of biological pathology in tandem with the often-overlooked psychological interventions (Biemar & Foti, 2013). Although the last century has seen a phase of proliferating medical breakthroughs in oncological science and molecular immunology, the persisting rate of 10 million annual deaths as reported by the WHO in 2020 determines the disease as a critical global health threat that warrants further research to enable augmented clinical outcomes through the 21st century (Piña-Sánchez et al., 2021). In fact, approximately four in ten or around 37% of all new cancer cases can be preventable. From the causes displayed in Figure 1, tobacco remains the largest preventable risk factor, followed by cancer-causing infections, alcohol use, excess body weight, air pollution, and UV radiation (World Health Organization: WHO, 2026). Thus, in today's climate where cancer causes one of every six deaths globally, there is sustained effort in the development of psycho-oncology to effectively treat cancer, an approach that lies amidst the more systematic treatments that range from complex surgeries to stem cell therapy (Kaur et al., 2023).

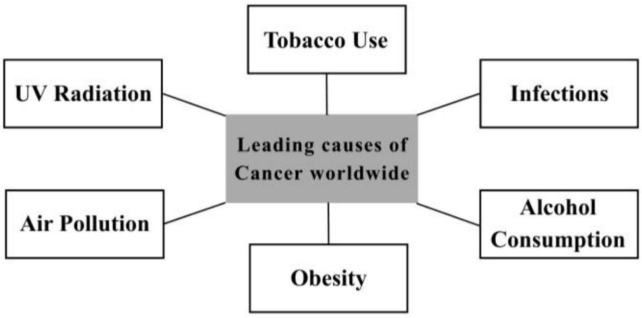

Figure 1: Leading causes of cancer worldwide

At its core, psycho-oncology is a multidisciplinary field that attempts to tackle cancer, even in its fatal stages, through a nuanced focus on social, psychological, and behavioural factors that may be consequential to the effectiveness of treatment. Initially, psychotherapeutic measures were centric only to distress screening, a limiting factor that has been enhanced over the past decade, with a renewed emphasis on caregiver support, along with a focus on psychotherapeutic and palliative care, thereby driving more enhanced patient-centered outcomes (Teo et al., 2019). Statistically, many of the average annual deaths occur in the later stages of disease and while an individual's oncological experience may depend upon varied traits and demographics, a universal reality includes the significant and often debilitating psychological burden of symptoms. Through that lens, clinical evidence reveals the dominance of depression as a symptom that is highly correlated with abysmal health outcomes. Being proven as the most frequent and widespread symptom that influences increased mortality rates and an accelerated progression of disease, addressing factors like depression is crucial to enhance patient care throughout the oncology continuum (Barrera & Spiegel, 2014). To enable improved clinical prognosis, meta-analytic evidence propounds the employment of psychosocial interventions, a suggestion that is supported by the results of a bladder cancer study that uncovered how 77.5% of patients suffered from depression-centric symptoms while 69.3% were victims of anxiety (Anghel et al., 2025). Despite statistically significant data proving that cancer patients face intensive depression and anxiety, though, prevalence of psychological treatments remains low. In fact, psychological treatment uptake in routine care was studied, where only 9% of cancer patients were exposed to psychotherapeutic care in the first 3 months, with the highest exposure rate being 19% at 9 months (Nunes-Zlotkowski et al., 2025).

In this context of an emphasis on the advancement of psychotherapeutic interventions, the integration of artificial intelligence offers an avenue that promises scalable and personalized psychological support through the stages of oncology, beginning from biomarker detection and sustaining beyond rehabilitation as well. Artificial intelligence, inclusive of computer vision and machine learning, produce algorithms and analysis that show not only biomedical improvements but also substantial progress in psycho-oncological care - a phenomenon that uniquely bridges the gap between the direct physical illness of patients and their indirect emotional well-being (Upadhyay et al., 2025). Undoubtedly, a psychiatric nursing lens has proven invaluable in the implementation and success of multidisciplinary care practices. However, the inclusion of AI tools and models as depicted in Figure 2 enable frameworks that guarantee accelerated psychosocial support at earlier stages than expected, thereby potentially reducing the frequency of cancer cases. Apart from enabling more efficient analysis of clinical data, AI processes move beyond the conventional reliance on patient self-reporting, rather creating more data-driven yet personally nuanced strategies that individually resonate with the future needs of patients (Masood, 2026).

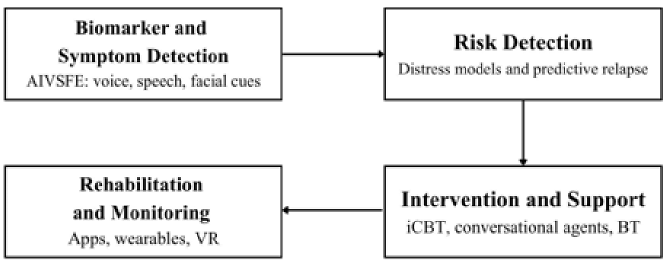

Figure 2: AI Tools Across the Psycho-Oncology Continuum

Admittedly, while AI has historically been prioritized primarily for biomedical data inspection, the asymmetry created by its lack of optimization in the psycho-oncology continuum can be alleviated through the AI-based implementation of the trimodal approach, which has a specialized focus on language, facial expressions, and speech (Urrutia et al., 2026). While there is an increase in the optimization of mobile applications and other digital health solutions, current and future developments are anchored to the integration of AI and VR, both of which supplement personalized therapeutic strategies (Lin et al., 2026). The use of interventions constituting AI-enhanced expressive writing and clinician-guided digital support is on the rise too, but there's an emphasised advocacy for more hybrid psychological models that amalgamate AI's scalability with grounded human empathy (Yang et al., 2026). Additionally, there remains an undeniable necessity to bridge the gap between proliferating technological advancement and the upcoming approach for holistic patient treatment, a phenomenon that can be worked upon through the convergence of AI. Over the years, there have been many publications revolving around AI and oncology, but very few account for the prospective optimization of AI when addressing the true stakeholders - our clinicians and patients themselves (Pandav et al., 2025).

Furthermore, while there lies the argument that AI may not be considered authentically empathetic, the focus today has transformed to investigating how generative AI can metamorphose care systems in a primarily digital future, thereby enabling a synergy between humans and machines in upcoming healthcare frameworks. In coherence with the adaptation to more holistic treatment systems in the field of oncology, this paper focuses on empirically developing an integrated AI framework that can potentially be applicable within the psycho-oncology continuum, thus bridging the gap created by the lack of psychological attention during clinical practice in oncology. Consequently, the fundamental purpose of this study is to create a policy framework that outlines the design of a multimodal AI clinician adoption and distress-screening model. Through this, the key objective is to overcome the limited, text-centric, and largely Western-concentrated evidence base from prior studies while simultaneously accounting for challenges ranging from intervention and outcome mapping gaps to ethical and implementational barriers of eHealth workflows. Ultimately, the paramount aim of this study is to create a prospective framework for a validated, cross-specialty tool that integrates the upcoming concept of artificial intelligence within practices constituting psychological, oncological, neurological, and general medicinal ones.

The remainder of this paper is organized as follows. Section 2 details a thorough literature review that examines existing AI applications, while Section 3 presents the research question and the study's hypotheses, both of which are backed by identified improvement scope. Section 4, moreover, outlines the research methodology by employing the Partial Least Squares Structural Equation Modelling (PLS-SEM) to investigate associations between AI-enabled constructs and psycho-oncological outcomes. Section 5 presents the results, followed by a discussion that situates the findings within a broader framework, while ultimately, Section 6 concludes the paper through a synthesis of key contributions, acknowledged limitations, and proposed future implementations.

2. LITERATURE REVIEW

Thoroughly understanding and acknowledging the impact of AI within the healthcare ecosystem, as shown below in Figure 3, is crucial to uncover the prospective scope of AI in context to the psycho-oncology continuum.

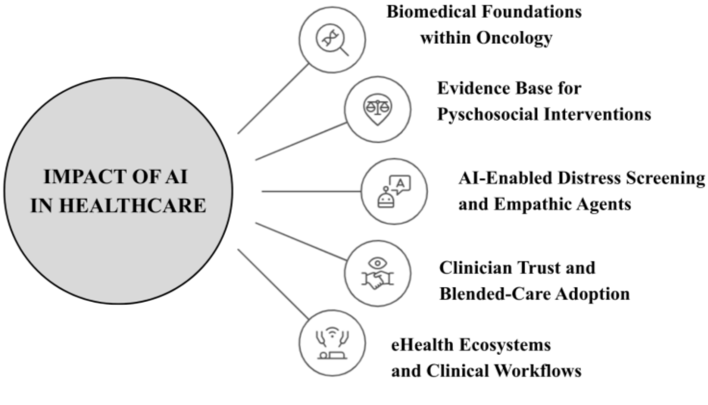

Figure 3: The Multifaceted Impact of AI in Healthcare

2.1 Biomedical Foundations: Why Precision Oncology Needs a Psychosocial Layer

Recently, there have been burgeoning advances in cancer genomics, epigenomics, metastatic-cascade research, and tumor biology. However, this exploration has had the tendency of overlooking patients' personomics, a term described by Roy Ziegelstein in 2015 as the social, cultural, psychological, and behavioural factors that influence a patient's level of engagement and adherence to the treatment and rehabilitation through the oncological journey. In fact, despite the imperative nature of maximizing engagement for long-term, chronic conditions like cancer, the average nonadherence to treatment lies at approximately 43%. Likewise, the importance of patient-centered care is underscored through a meta-analytical study that defines the risk of nonadherence as 1.53 times higher when there's a family conflict as compared to when there isn't (Krause et al., 2025). Thus, it is necessary to employ a holistic approach adapted to patients' individual experiences, as accomplished by the IOM, which classifies the phenomenon of care into eight dimensions: beginning with 1) respect for patients and ending with 8) access to care (Adi-Wauran et al., 2025). The value of such a framework is strongly supported by the idea that research integrating oncology and mental health constitutes only 0.26% of all oncology publications and 0.51% of all mental health publications in the last 10 years - a statistic that effectively pronounces upon the importance and validity of a personalized patient care system which considers personomic factors (McFarland et al., 2014).

2.2 Evidence Base for Psychological and Psychotherapeutic Interventions

With psychiatric disorders being a widespread phenomenon associated with increased rates of morbidity and mortality, psychotherapeutic interventions are becoming vital. Additionally, the identified co-occurrence between psychiatric problems and serious medical disorders further emphasizes upon the requirement for psychosocial care (Cook et al., 2017). Although there are multiple psychotherapy-based perspectives and models, empirical development is stalled by the lack of "component analyses" through a strong conceptual framework to enable an efficient display and execution of all research and findings. This must be then improved by focusing on cost-effective and large-scale public health treatment strategies, which can be enhanced through the deep research of e-mental health tools, Internet-based treatments or AI interventions, for example (Emmelkamp et al., 2013).There is compelling evidence in support of meaning-centered therapy through improved communication skills between patient and healthcare professionals, which is indicated to ameliorate treatment adherence and overall quality of life (Teo et al., 2019). Moreover, in order to address the increased rate of cancer worldwide and the characteristic reports of demoralisation, depression, and trauma, empirically evidenced psychosocial interventions such as CBT, narrative mindfulness, support-expressive therapy, or counseling is essential. This necessity is only amplified by research that reveals how at least 30-35% of cancer patients suffer from psychiatric disorders, without accounting for those with more mild mental health symptoms or those who remain undiagnosed (Caruso & Breitbart, 2020). While the interdisciplinary field of psycho-oncology is relatively new, it aims to employ personalized care to tackle the gaps created by only clinically focused precision medicine. In this path, AI offers transformative potential, as depicted in the chronologically oriented diagram in Figure 4, through virtual assistants, chatbots, machine learning systems, and conversational agents, all of which can be adapted to replicate human-like interactions and to aid healthcare systems as a whole (Kadam et al., 2025).

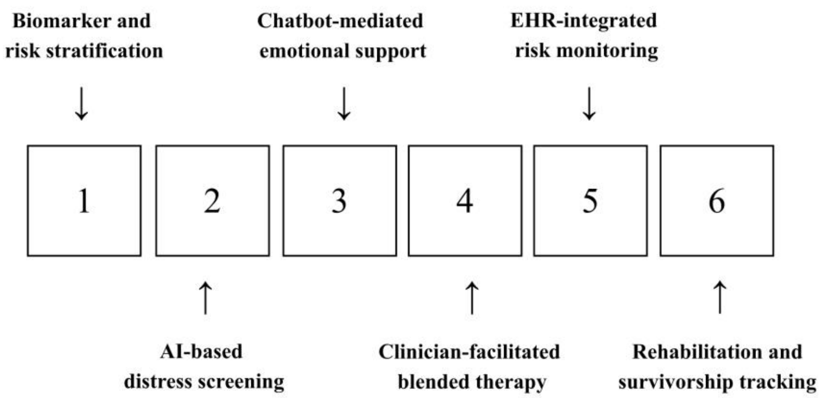

Figure 4: The Use of AI Within the Psycho-oncology Continuum

Additionally, by using an ideal combination of clinicians, ethicists, and developers to create human-like yet data-driven AI solutions, there lies potential to remedy previous oncological treatment systems, all of which overlooked a variety of crucial factors that contribute to defining an individual's experiences and responses. For instance, sex and gender, despite being sociodemographic factors with perceptible influence on susceptibility to cancer, response to tumors, or survival after treatment, are all underutilized in clinical research and biomedical oncological processes. In this context, refined AI models could optimize sex- and gender-specific data to curate reliable patient stratification, facilitate predictive diagnostic and prognostic modeling, create targeted treatment plans, or even formulate customized therapy opportunities (Karnwal et al., 2026).

2.3 AI-Enabled Distress Screening and Empathic Conversational Agents

Furthermore, with the revolutionary inclusion of artificial intelligence in psycho-oncology, there is immense value in optimizing empathic AI. Specifically, this refers to the integration of emotional intelligence within the biological and clinical approach to oncological care. While empathic AI does promise advances in psychosocial care through the consideration of personomics, its implementation must be backed by appropriate ethical measures for comfort, safety, and privacy (White et al., 2026). Another transformative factor in psycho-oncology, though, includes the use of generative AI, which offers unprecedented AI-automated technologies ranging from emotional distress screening and hybrid human-AI care models to chatbot interventions and interactive digital tools for coping (Bires et al., 2025). In addition to that, machine learning and algorithmic optimization allows for real-time data analysis, which could enable reduced clinician workload and proactive, timely interventions within healthcare frameworks. However, as Figure 5 displays through a representation of the necessary measures that must be taken with the use of AI, despite its potential in aiding psycho-oncological processes, it is undeniably imperative that the significance of authentic human conversation itself isn't entirely discounted (Kim et al., 2025).

Figure 5: Ways to Ensure Optimal Use of AI in Psycho-Oncology

2.4 Clinician Trust, Blended-Care Adoption, and Systemic Barriers

Through an overarching lens, it is integral to address the significant psychosocial gaps barriers within the continuum of psycho-oncology - a phenomenon that can be gradually overcome through the systemic incorporation of artificial intelligence and digital tools. However, despite the pervasiveness of psychiatric disorders through an individual's cancer journey, the uptake of psychological treatment systems remains disturbingly low (Nunes-Zlotkowski et al., 2025). Research indicates, though, that iCBT (internet-delivered cognitive behavioural therapy) and BT (blended therapy) offer significant psychosocial support. Even so, while iCBT undoubtedly offers cost-effective solutions, it's believed to have relatively less patient uptake, largely because most patients are reported to prefer face-to-face treatment. An alternative to this is offered by the inclusion of BT, which adroitly amalgamates online-based patient therapy with live psychologist sessions, thereby eliminating the gap of patient isolation and low engagement levels while simultaneously propelling trust and adherence with treatment procedures (Davies et al., 2020). Another working application is wearable devices that consistently monitor recovery after cancer surgery. Being used primarily by older patients, this device proved effective in terms of smartphone integration and compatibility, along with which it served as an ideal mechanism for those living alone. Moreover, almost all patients using the technology reflected high trust within it, thereby indicating the potential of an approach combining human support, blended care, and potentially AI application as well (Duin et al., 2026). The concept of a blended model is further amplified by the ideation of a framework on the intersection of palliative care and survivorship. With potential of improving quality of life and enhancing care and treatment systems, a holistic approach comprising palliative care can prove essential in offering individuals purpose, dignity, and continuous support (Al-Khaifi et al., 2026).

2.5 eHealth Ecosystems and AI-Integrated Workflows

Ultimately, the advancements in the rising field of psycho-oncology can be best proliferated through innovations within the sectors of digital health and generative AI, both of which have the prospective ability to be adapted within mobile applications, LLMs (large language models), and even virtual reality to enhance emotional health and wellbeing across the psycho-oncology continuum. By integrating artificial intelligence to automate regular tasks and curate individual medical data documents, along with optimizing its use in care personalization, AI-based tools and technology can better improve the oncological process while also alleviating the burdensome role of family members or caregivers (Barrett & Uhey, 2026). Additionally, apart from the emphasis on the power of complex AI-based algorithms and machine learning strategies, meta-analytical research heavily points to a "Triadic Relational Model" framework, which outlines a holistic and well-rounded analysis of the effects of psychosocial technology on patients, providers, and caregivers too, thereby working towards improving healthcare processes and eventual outcomes (Saikia & Borthakur, 2025). Ultimately, a blended-care model could also be worked upon. This could be done through HITL (Human-in-the-Loop) systems, which offer human presence and professional clinician oversight within AI-based application frameworks, while the framework itself simultaneously informs patients of prospective risks (Mathes et al., 2026). Similarly, the IoMT or "Internet of Medical Things" is a system of amalgamated and interconnected medical tools and devices that work together to enable more proactive, personalized, and patient-centered care. However, the reality of barriers in terms of data privacy, faulty technology, or overall usability continue to remain and must be tackled for all prospective and upcoming AI-based tools in the context of enhancing the psycho-oncology continuum (Thaker et al., 2025).

- RQ1: How far does adding facial-expression and vocal-tone data, beyond voice and speech-semantic input, give multimodal AI distress screening an observable advantage over text-only tools currently used in psycho-oncology, in terms of diagnostic accuracy and generalizability?
- RQ2: Among the various clinician- and system-level factors, which ones carry the most weight in shaping trust and adoption of AI-integrated psycho-oncology care across different specialties?
- RQ3: When AI-enabled and eHealth tools are integrated within clinical workflows, to what extent is patient emotional wellbeing and to equity of access across different socioeconomic backgrounds accounted for?
- H1: Diagnostic accuracy and generalizability across populations will be significantly higher for multimodal AI distress-screening systems than for unimodal, text-only alternatives.
- H2: Clinician trust in AI-integrated psycho-oncology care will depend significantly on the readiness, development, and eventual advancement of systems, along with the extent of the preservation of patient autonomy, which stands independent of the singular force of intervention outcomes.
- H3: Patient emotional wellbeing will improve with the integration of AI distress screening into clinical workflows, but this improvement will be notably curtailed among blue-collar and low-income patients.

3. RESEARCH METHODOLOGY

Although cancer is a primarily biological disease, operative cancer care demands addressing psychological burdens like treatment-related depression and uncertainty, which underscores the significance of routine distress screening. This is further emphasized by Indian oncology research, which indicated considerable patient distress levels and low reference to psycho-oncological services, all of which were amplified by limited time availability, generic screening tools, and language barriers due to cultural diversity (Normen et al., 2021). In such instances, AI-based tools offer potential to address these challenges by rapidly processing vocal patterns and facial expressions to enable effective emotional assessment within cancer patients (Urrutia et al., 2026). In summation, this study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to investigate how AI can be integrated across the psycho-oncology continuum through hybridized and personalized support to create a blended care model that balances efficiency with responsibility (Bires et al., 2025). The PLS-SEM process was selected since it uses multiple indicators to measure latent constructs and then decode the relationship between these constructs, thereby validating predictive latent-variable models and enhancing the quality of psychosocial support (Henseler et al., 2014).

3.1 Research Design

The survey design used was quantitative and cross-sectional, while the empirical model was assessed using PLS-SEM in SmartPLS. This allowed an effective examination of the relationship between the chosen latent constructs, which created an exploratory and simultaneously prediction-oriented framework. The analysis consists of 100 respondent records on 15 observable indicators, all of which were measured using a 5-point Likert scale. In the SmartPLS output, the indicators were arranged within three reflective constructs labelled R1, R2, and R3. The results document, however, doesn't provide adequate demographic information to assert specific clinical expertise, socioeconomic status, or other required characteristics. Accordingly, such factors are not claimed here.

3.2 Measurement Model

The given measurement model was evaluated using Cronbach's alpha, outer loadings, composite reliability, HTMT, AVE, the Fornell-Larcker criterion, and cross loadings. For reflective outer loadings and internal-consistency measures, any values above 0.70 are treated as evidence for acceptable reliability, while AVE values above 0.50 were used to support convergent validity. In addition, HTMT was a discriminant-validity condition.

3.3 Structural Model

The structural model, as shown in Figure 6, was created and assessed using path coefficients, R-squared values, and f-squared effect sizes. The consequently supplied output constitutes two structural paths: R1 → R2 and R1 → R3. Having no separate path from R2 → R3, it doesn't report a socioeconomic moderator, and similarly, it doesn't even display separate paths from system readiness and autonomy preservation to clinician paths (Henseler et al., 2014).

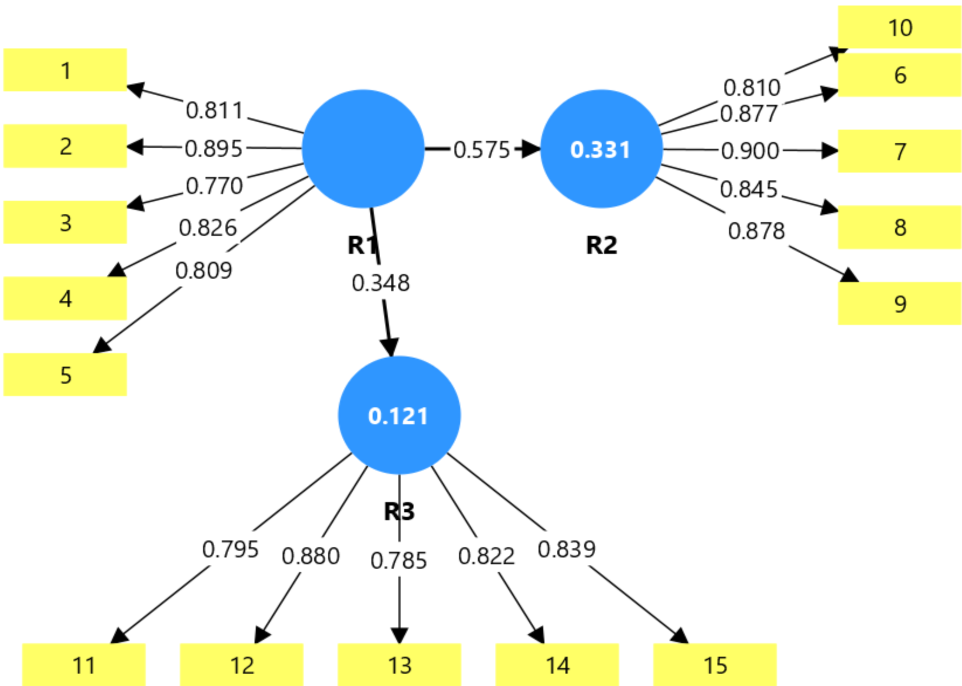

Figure 6: PLS-SEM Framework for the Psycho-Oncology Continuum

The data-based model set out by Figure 6 displays multifaceted symbols, beginning with the blue circles that indicate the latent constructs (R1, R2, and R3) that can't be directly measured and are therefore measured through the yellow boxes, which represent the observed indicators or items (questionnaire statements) that were used to understand the significance of each construct. Additionally, the arrows pointing towards the yellow boxes reflect how each latent construct is connected to a survey item, while the arrows between the blue boxes themselves represent the hypothesized structural relationships. For instance, in the given model, the values R1 → R2 (β = 0.575) and R1 → R3 (β = 0.348) demonstrate how the constructs are statistically related.

4. RESULTS

4.1 Measurement Model Results

As depicted below, Table 1 reports construct reliability and validity from the SmartPLS output. In that context, Cronbach's alpha reached 0.881 for R1, 0.914 for R2, and 0.884 for R3, with composite reliability at 0.900, 0.929, and 0.903 respectively, and the alternate composite reliability figures at 0.913, 0.936, and 0.914. Furthermore, AVE stood at 0.678 for R1, 0.744 for R2, and 0.681 for R3. In summation, all the collected values were above the 0.50 threshold, which supports convergent validity for the three constructs.

Table 1: Results of the Measurement Model

Construct	Cronbach α	Composite Reliability	AVE
R1	0.881	0.900	0.678
R2	0.914	0.929	0.744
R3	0.884	0.903	0.681

Moreover, outer loadings ranged from 0.770 to 0.900. R1 loadings were 0.811, 0.895, 0.770, 0.826, and 0.809; R2 loadings were 0.810, 0.877, 0.900, 0.845 and 0.878; and R3 loadings were 0.795, 0.880, 0.785, 0.822 and 0.839. For these figures, every reported indicator exceeded the minimum value of 0.70, as required.

4.2 Discriminant Validity

The HTMT matrix reports 0.620 for R1-R2, 0.371 for R1-R3 and 0.543 for R2-R3, all of which are well below the 0.85 threshold. The Fornell-Larcker is similar: the square roots of AVE (0.823 for R1, 0.863 for R2, 0.825 for R3) lie above the corresponding inter-construct correlations in each case. The cross-loadings reinforce this further, with every indicator loading most strongly on its own assigned construct rather than on any other. Thus, taken together, all these three measurement methods confirm discriminant validity across the model.

Table 2: Values for Discriminant Validity

Construct Pair	HTMT	Assessment
R1–R2	0.620	Supported
R1–R3	0.371	Supported
R2–R3	0.543	Supported

4.3 Structural Model Results

The structural model produced two positive path coefficients: R1 → R2 ($\beta = 0.575$) and R1 → R3 ($\beta = 0.348$). The supplied results document, though, doesn't display bootstrap t-statistics, p-values, or even confidence intervals. Therefore, although the direction and magnitude of the paths can be reported as done in Table 3, statistical significance cannot be claimed from the supplied output alone.

Table 3: Results of the Structural Model

Path	β	R^2	f^2
R1 → R2	0.575	0.331	0.494
R1 → R3	0.348	0.121	0.138

For R2, R^2 is 0.331 and the adjusted R^2 is 0.324, depicting that R1 accounts for roughly 33.1% of the variance in R2. R3, however, showed a weaker fit, with R^2 at 0.121 and adjusted R^2 at 0.112, so R1 explains only about 12.1% of the variance here. The f-square values support this pattern, pointing to a stronger effect of R1 on R2 than on R3.

5. DISCUSSION

This study underscores three primary constructs: AI-enabled multimodal psycho-oncology integration (R1), clinician and system-level AI adoption and trust (R2), and patient-centered outcomes (R3). Within the framework, R1, which is the primary starting construct that then extends to the constructs of R2 and R3, captures the perceived practicality of multimodal distress screening, voice and speech analysis, or other applied AI technologies. The five indicators linked to R1 range from 0.770 to 0.895, delineating that the indicators effectively measure the constructs. Moreover, although R2 identifies the overall confidence and readiness to incorporate AI within psycho-oncology, its five indicators display particularly strong loadings (0.810 to 0.900 only), with R2 having the highest reliability (Cronbach's $\alpha = 0.914$). The path between R1 and R2 being 0.575 implies a relatively strong positive relationship that empirically supports RQ2 by revealing how trust for AI use in psycho-oncology increases as clinician adoption and perceived AI capability increases. Subsequently, R3 - with indicators' load between 0.785 and 0.880 and a Cronbach's α of 0.884 - expresses strong internal consistency with the relationship between AI or eHealth integration and patient wellbeing across varied access-related outcomes. In addition, the path from R1 to R3 is 0.348, thereby highlighting a positive association between the integration of AI and the patient-structured construct, while consequently providing support for the portrayed relationship in RQ3.

The results provide encouraging exploratory evidence for a relationship between AI integration and clinician- and patient-oriented outcomes. The strongest structural relationship is R1→R2 ($\beta=0.575$), with $f^2=0.494$ and $R^2=0.331$. This indicates that the R1 construct has substantial predictive relevance for R2 within the tested model. The R1→R3 relationship is smaller but positive ($\beta = 0.348$; $f^2 = 0.138$; $R^2 = 0.121$), indicating that AI-related integration may also be relevant to patient-oriented outcomes, although most of the variance in R3 remains unexplained. The findings are consistent with emerging psychosocial-oncology literature. Recent evidence indicates that AI-enabled distress assessment using speech semantics and facial-expression approaches may be acceptable to cancer patients, although the evidence base remains small and heterogeneous. Research in Indian oncology, as mentioned previously, has also shown that distress screening does not automatically result in psycho-oncology referral, demonstrating the importance of workflow integration and implementation factors. In addition, the measurement model is a strength. In that context, all outer loadings exceed 0.70, Cronbach's alpha values exceed 0.80, composite reliability values exceed 0.90, AVE exceeds 0.67 for all constructs, and HTMT values remain well below conservative thresholds. This indicates reliable and distinguishable operationalized constructs. The structural findings should not, however, be interpreted as evidence that AI has clinically improved diagnostic accuracy or patient wellbeing in a causal manner. The study is cross-sectional and the supplied output does not contain bootstrapped significance results. Furthermore, the exact predictors and moderator specified in H1-H3 are absent from the current structural model that is depicted. Therefore, the appropriate interpretation is exploratory rather than causal.

6. FUTURE SCOPE & LIMITATIONS

Future research should draw on a broader, multi-specialty sample spanning more oncologists, psycho-oncologists, nurses, psychologists and allied healthcare professionals, thereby moving beyond a narrow respondent base. Further, testing H2 will require splitting the current composite into separate constructs, namely system readiness, clinician trust, autonomy preservation, intention adoption, workflow integration, and evidence strength. H1 calls for actual diagnostic-performance data, benchmarking multimodal AI against text-only screening on AUC, sensitivity, specificity, precision, recall and F1-score, since perception-based measures alone cannot confirm accuracy gains. In addition, integrating socioeconomic status as a moderator, examined through interaction analysis or PLS-MGA, would test the attenuation effect proposed under H3. A longitudinal design tracking distress, quality of life, treatment engagement, and rehabilitation outcomes over time would address the limits of the present cross-sectional data. It is also primordial that fairness audits across socioeconomic groups, gender, age, language and geographic setting should precede any clinical rollout. Moreover, deployment itself should retain clinician oversight, informed consent, privacy protection, and explainability as fixed design requirements, not simply optional additions. Combining speech, facial-expression, and semantic signals with validated psycho-oncology instruments would therefore round out the multimodal framework beyond what any single data stream permits.

The study, although nuanced with a variety of respondents ranging from psychiatrists and neurologists to general medicinal practitioners and psycho-oncologists, constitutes a sample of only 100 respondents, which limits generalizability. Causality, moreover, cannot be established by the given cross-sectional design. Even the significance of the pathways between constructs remains to be independently confirmed since the bootstrapped t-values, p-values, and confidence intervals are not expressed within the supplied results. The current model, with the three consolidated constructs, doesn't directly represent every variable in the original research questions and hypotheses. For instance, the singular influence of perception-based PLS-SEM cannot enable the explicit diagnostic and performance comparison that is necessitated. Similarly, the supplied model lacks the multi-group analysis and socioeconomic regulation required by H3. Overall, the results don't provide sufficient demographic information to assert individual representation, thereby determining that the findings shouldn't be classified as conclusive clinical evidence and should instead be considered as preliminary and investigative.

7. CONCLUSION

This analysis illustrates what PLS-SEM can offer when applied to AI integration across the psycho-oncology continuum. Reliability and validity indicators were consistently strong across the measurement model: Cronbach's alpha fell between 0.881 and 0.914, composite reliability between 0.900 and 0.929, and AVE between 0.678 and 0.744, while both HTMT and Fornell-Larcker criteria confirmed discriminant validity between constructs. At the structural level, R2 and R3 both showed positive associations with R1, at $\beta = 0.575$ and $\beta = 0.348$ respectively, with corresponding R^2 values of 33.1% and 12.1%. Taken together, these results lend support to the general claim that perceived AI integration relates to both clinician-level and patient-level outcomes within this model. That said, the current output stops short of confirming H1, H2 and H3 in their full form. Diagnostic-performance comparisons were not conducted, clinician and system-level predictors were not separated into distinct constructs, and socioeconomic moderation was not tested. What this study offers, then, is an exploratory basis rather than confirmatory evidence, one that a larger and clinically validated study on psycho-oncology AI could build on.

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