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Leveraging AI-Driven Digital Apps to Enhance Patient Compliance: An AI Technology Innovation in Health Care

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ABSTRACT

The astonishingly low adherence levels to medication for chronic conditions: in the opinion of a systematic review published in Annals of Internal Medicine, 20-30% of all prescriptions were not taken as directed. Such non-adherence to prescribed drugs leads to deaths annually, as well as visits to the emergency departments and hospitalizations, and further strains the finances of healthcare systems. Human engagement to enhance adherence has been proven to be relatively costly and therefore out of reach to many. To reduce these compliance challenges, various organizations are looking for new ways that employ artificial intelligence technologies to assist patients' adherence by employing chatbots, wristband sensors, and digital applications. The paper develops an interest in the analysis of the usage of digital applications in relation to patients' compliance. The study sampled multiple research constructs, such as empathetic responses and relational behaviors, communication skills, health coaching, therapeutic interventions, assessing the quality of healthcare, provision of health information, and giving health advice. Responses from patients pertaining to these research constructs were collected to evaluate the effectiveness of digital applications. The study investigates the extent of digital applications in prompting patients about their medication schedules, and the delivery of dosing recommendations and alerts personalized for the patient and longitudinal tracking of the patient's progress, concluding that advances in artificial intelligence technologies improve the care of patients.

Keywords: Artificial Intelligence, Technology Innovation, Digital Apps, Health Care, Patients' compliance

INTRODUCTION

There is no agreement on what AI really is. Generally, it means a computer that can imitate human thinking, like reasoning, finding meaning, learning from experience, and achieving goals without being specifically told what to do. Generally, there are three types of AI Systems designed to mimic human thinking and behavior are known as "strong AI." Those that can achieve results similar to humans but use different approaches are called "weak AI." There are also "in-between" systems that are influenced or inspired by human reasoning.

Most of the important work in the industry is going in that area today (Hammond, 2015).Artificial Intelligence encompasses the utilization of computerized systems (hardware or software) to emulate intelligent behavior with minimum human involvement, which in the medical field can be categorized into two branches: virtual (i.e., informatics and deep learning) and physical (i.e., robotic-assisted systems) (Hamet & Tremblay2017).

AI has various potential applications in healthcare, such as facilitating early detection, diagnosis, management, and treatment of medical conditions; enhancing patient engagement and medication adherence; assisting the elderly; promoting health; providing counseling; streamlining administrative tasks; and supporting education and training for healthcare professionals (Benjamens et al.,2020; Davenport & Kalakota,2019, A review of AI-based health coaching systems for patients with non-communicable diseases identified seven potential roles: developing adherence, informing, motivating, reminding, preventing, building a care network, and entertaining. This paper examines the application of AI in assessing and enhancing medication adherence among patients with non-communicable diseases (NCDs)(TahriSqalli& Al-Thani, 2020).

Most internet users would be open to employing health chatbots, yet skepticism about this technology is likely to reduce interaction.

To obtain the highest uptake and utilization, intervention designers concentrating on AI-led health chatbots must apply user-centered and theory-based techniques that address patients' issues while maximizing user experience. When building and measuring the success of health chatbots, it is important to include patients' views, motivation, and skills (Nadarzynski et al.,2019). AI technologies are expected to significantly improve healthcare by enhancing prognosis, diagnostics, and care planning. As a result, numerous companies and governments are investing in developing AI-driven clinical tools. Patients are the primary beneficiaries, and their perceptions may influence their adoption. However, certain issues and hazards must be addressed before standard clinical practice(Esmaeilzadeh,2020).

The Fox Rothschild LLP publication is also an example of how AI transforms the healthcare sector, mainly in the compliance of patient care. The paper briefly covers how AI will be applied in diagnostics, treatment, and administrative processes with respect to data protection and regulatory compliance (Kagan,2024).

A strong argument for or against investing in a health care AI solution hinges on the potential positive economic impact. Particularly pertinent to the healthcare provider, insurer, pharmaceutical, and medical technology industries. There have been several assessments of the societal and patient benefits and overall economic impact of digital health solutions in the literature, but the particular economic impact of artificial intelligence in healthcare has received only infrequent attention (Wolff et al., 2020).

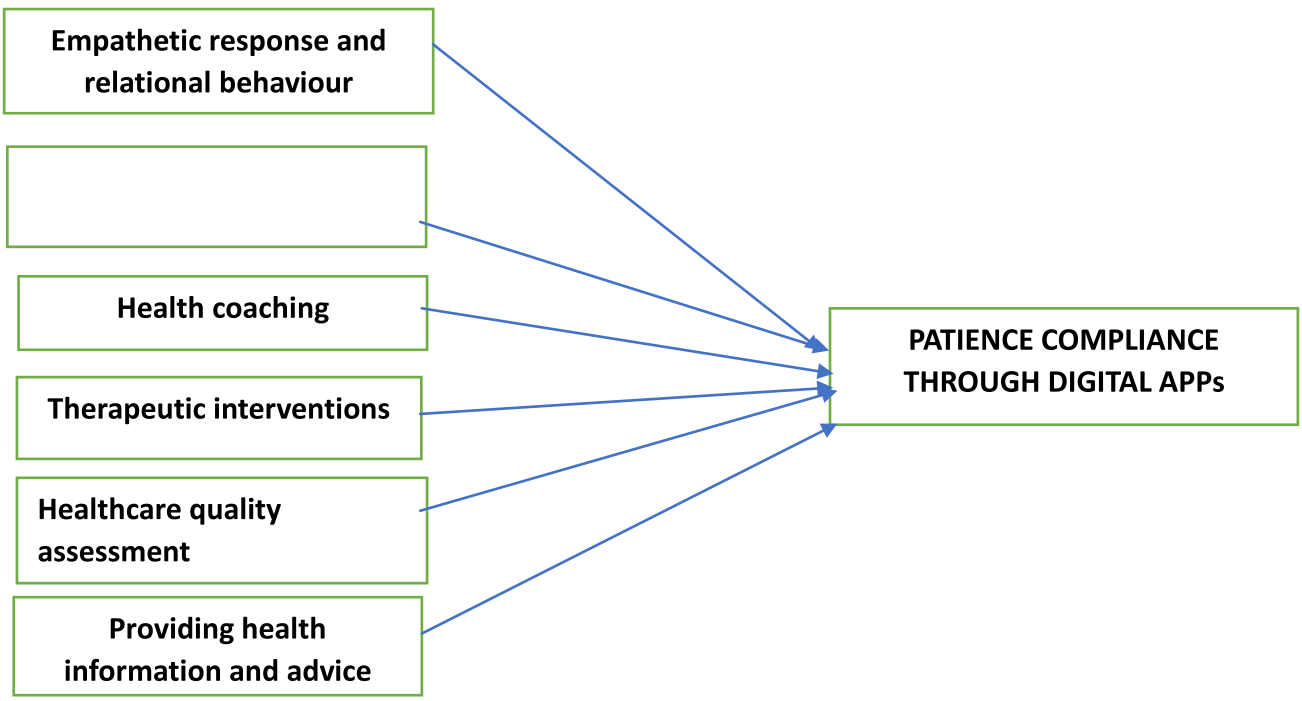
Objectives of the Study

- To analyze the role of **e**mpathetic responses and relational behavior through digital apps on patient compliance
- To examine the effective communication through Digital apps on patient's compliance.
- To evaluate the impact of digital health coaching and Patient's compliance.
- To assess the significance of therapeutic intervention delivered digitally in improving patient's compliance
- The objective is to assess the impact of healthcare quality assurance on the continued utilization of digital health applications for patient adherence.
- The study aims to examine the impact of delivering precise health information and advice on compliance rates via digital applications.

Hypothesis of the Study

H1: Empathetic responses and relational behaviour through digital apps have positive relation with /significantly improve patient compliance
H2: Effective communication through Digital apps has a positive relationship with patient compliance.
H3: Digital health coaching has a positive relationship with Patients compliance.
H4: Digital app-delivered therapy treatments have a positive relation with patients' adherence to treatment plans.
H5: Patient adherence rates are directly impacted by the quality assurance of digital healthcare applications.
H6: Patient compliance is substantially increased by the provision of precise health information and advice through digital applications.

Conceptual Framework



DATA ANALYSIS & INTERPRETATION

Cronbach Alpha

Table -1: Reliability Analysis of Variables

Reliability Statistics	
Cronbach's Alpha	N of Items
.937	28

Cronbach's Alpha is a statistical measure meant to give an estimate of the internal consistency of a psychometric test or survey hence determining its reliability. A Cronbach's Alpha value of 0.937 for that specific test or survey in question proves to be an extremely strong measure of internal consistency.

A high value reflects a high level of reliability of the measurement of the items, which are questions or indicators, in the survey or test. Thus, the observation is that the items are probably measuring the same conceptual or construct. The Cronbach's Alpha falls between 0 and 1 with higher values indicating greater dependability. The general trend is that any value higher than 0.7 is acceptable, above 0.8 is pretty good, and above 0.9 is excellent.

Confirmatory Factor Analysis

Table -2: Fit Indices Confirmatory Factor Analysis

Fit Indices	Recommended	Observed
CMIN	Greater than 5 Terrible, Greater than 3 Acceptable, Greater than 1 Excellent	**2.085**
CFI	Less than0.90 Terrible, Less than 0.95 Acceptable, Greater than 0.95 Excellent	**0.988**
TLI	Greater than 0.9	**0.932**
PNFI	Greater than 0.5	**0.654**
RMSEA	Greater than 0.08 Terrible, Greater than 0.06 Acceptable, Greater than 0.05 Excellent	0.06

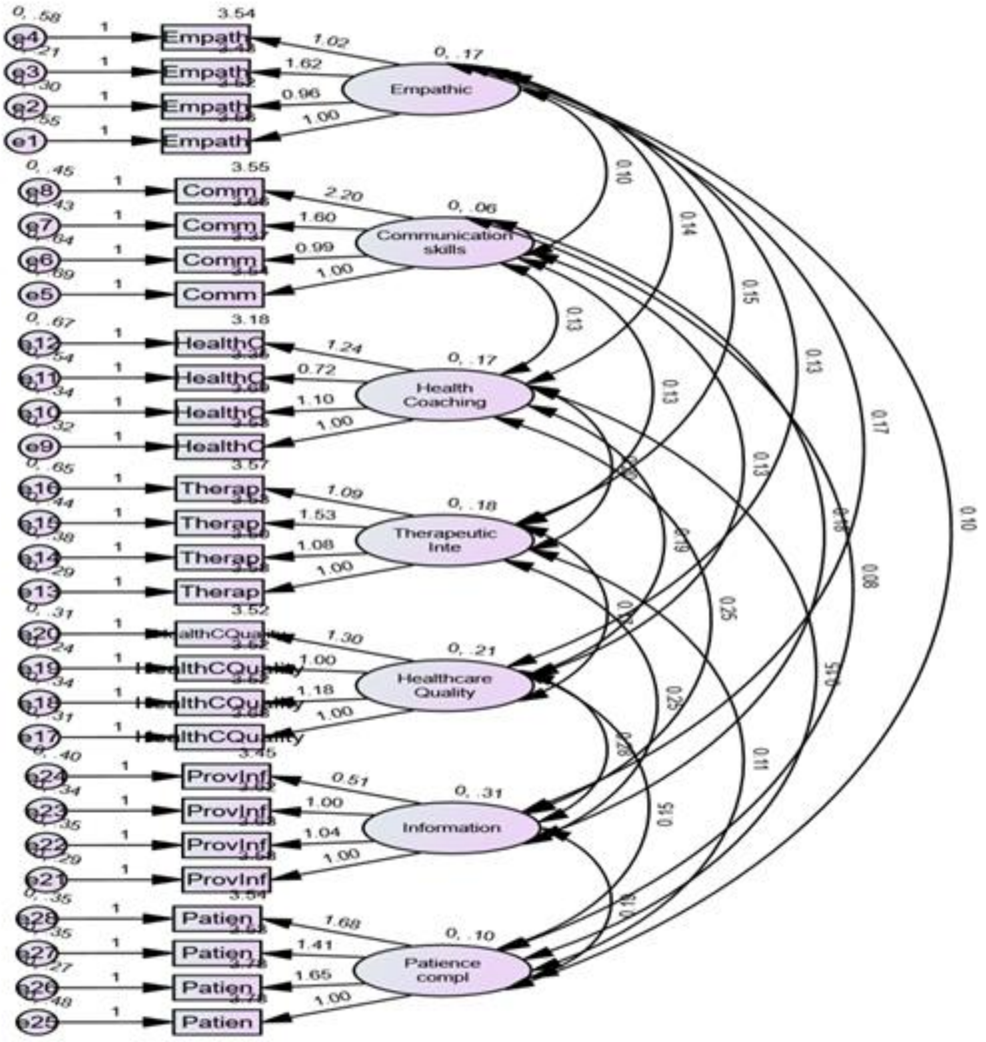
Chi-Square/df: A measured value of 2.085 indicates that the fit level for this model is acceptable. As the value lies within the accepted limits, the model is properly specified, and a lower value usually implies better fit.

A **Comparative Fit Index** shows that the model has a good fit to the data. This is indicated by the great observed value of 0.988. Values greater than 0.95 indicate a strong relationship between the actual and predicted data.

The value of **Tucker-Lewis Index** comes to be 0.932, which exceeds the limit of 0.9. This suggests that the model is a good fit for the data.

PNFI (Parsimonious Normed Fit Index): The model gets a good score of 0.654, meaning that the model is somewhat parsimonious but effective in describing the data's variance and covariances.

RMSEA (Root Mean Square Error of Approximation): The model exhibits an appropriate fit against the population covariance matrix by displaying an observed value of 0.06, falling within the acceptable range. Even though a lower RMSEA value would mean a better fit, for most research purposes, this is a good enough level.



DISCUSSIONS

Findings of this sort provide empirical support to the idea that the model rather accurately represents the dataset and serves as a basis for valid research. Future studies may consider opportunities for improving the model-such as re-specification of specific pathways or addition of new data points-to attain levels of CMIN and RMSEA approaching the threshold of acceptability. According to fit indices, this model has sufficient robustness to underpin both theoretical and practical implementations within the domain, with reliable interpretations and informed decision-making.

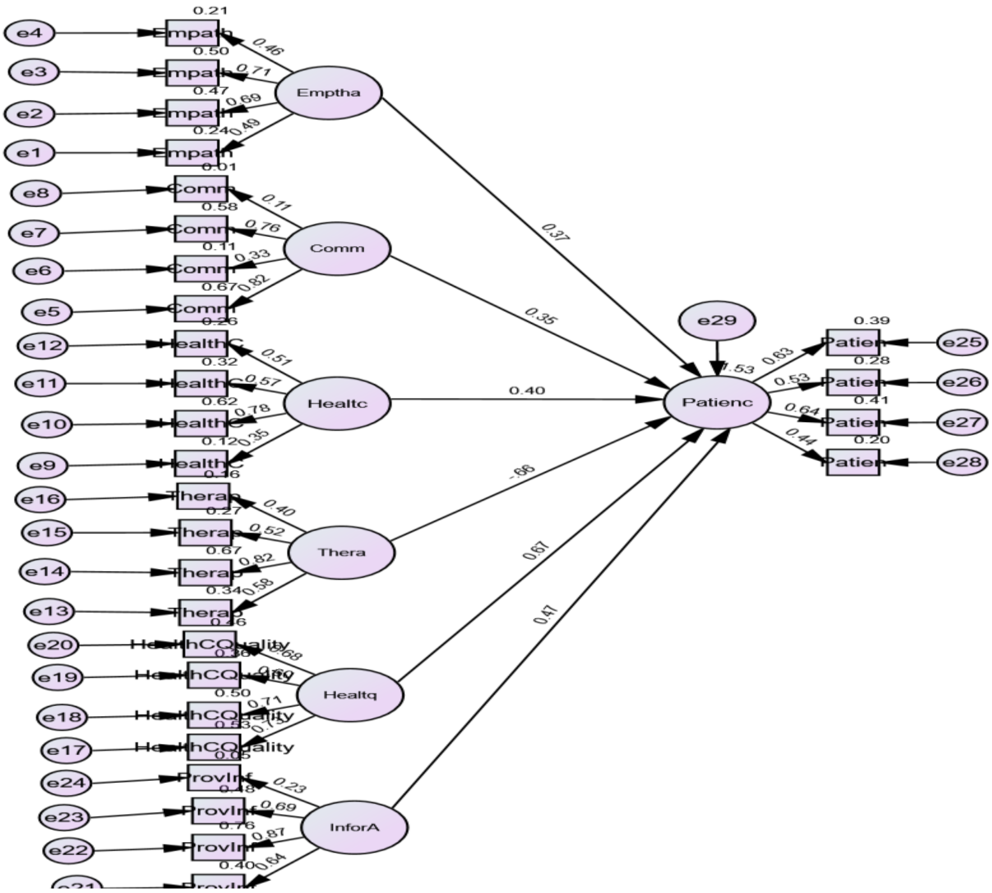
Structure Equation Model

Table -2: Fit Indices Structure Equation Model

Fit Indices	Recommended	Observed
CMIN	Greater than 5 Terrible, Greater than 3 Acceptable, Greater than 1 Excellent	**2.578**
CFI	Less than0.90 Terrible, Less than 0.95 Acceptable, Greater than 0.95 Excellent	**.985**
TLI	Greater than 0.9	**.953**
PNFI	Greater than 0.5	**.540**
RMSEA	Greater than 0.08 Terrible, Greater than 0.06 Acceptable, Greater than 0.05 Excellent	**0.064**

The CMIN statistic, with an observed value of 2.578, means that the model falls within acceptable bounds. This further suggests, despite some differences between the data and the model, such differences fall within a reasonable span and, therefore, indicate the model has been well described.The comparison fit index is 0.985 excellent-this means that the model and data are very well aligned.

The value here indicates that the proposed model is really very close to the data captured.The Tucker-Lewis Index (TLI) yields the observed value of 0.953, which is beyond the threshold value of 0.9; therefore, the model fairly well describes the data set.The Parsimonious Normed Fit Index (PNFI) is observed to be at 0.540, an acceptable value. This would mean that the model is quite parsimonious and fit the variance and covariance adequately in the data.The RMSEA yields an observed value of 0.064, which is within acceptable limits. This means that the model fits the population covariance matrix satisfactorily. Meaning its complexity is justified by its goodness of fit.



DISCUSSION

Overall fit of the proposed model is robust as supported by analysis of fit indices. Comparative and incremental fit indices, namely, CFI and TLI are particularly strong. They fall in the excellent range. The model has a very good prediction accuracy combined with proper adjustment for the model's complexity. This makes the model to be very compatible with the data. Despite their sufficiency, the values of CMIN and RMSEA suggest there is room for enhancement. Apparently, some inadmissible discrepancies within the model exist as indicated by the CMIN value, whereas the RMSEA at the upper threshold of what is acceptable still indicates the presence of misspecifications in the model or the need for more data to reduce errors in estimation.It is critical to, therefore, focus on improving aspects where the fit is barely adequate, even though the model does perfectly well across the indexes that propose a strong theoretical fit. Upcoming steps to improve the precision of the model and further diminish the RMSEA may involve reviewing the framework of the model, additional in the inclusion of variables, or increasing the sample size. Such steps would enhance the applicability of the model in practical applications and strengthen its reliability in its use in deriving credible conclusions.

Hypothesis Testing

Hypothesis	P-Value	Result
H1: Empathetic response & relational behavior and Patience compliance through Digital Apps	0.00	Significant
H2: Communication skills and Patience compliance through Digital Apps	0,00	Significant
H3: Health coaching and Patience compliance through Digital Apps	0.00	Significant
H4: Therapeutic interventions and Patience compliance through Digital Apps	0.00	Significant
H5: Healthcare quality assessmentand Patience compliance through Digital Apps	0.00	Significant
H6: Providing health information and advice and Patience compliance through Digital Apps	0.00	Significant

INTERPRETATION

For all hypotheses, the existence of a statistically significant correlation between every variable and patient adherence facilitated by digital applications was found based on a P-value of 0.00. Under this level of significance, the effects noticed are most likely not the result of mere chance.

Empathetic response & relational behavior (H1): The notable P-value indicates that the augmentation of empathetic responses and relational behaviors facilitated by digital applications markedly enhances patient compliance. This underscores the critical role of emotional and relational dimensions in patient interactions conducted through digital mediums.

Communication skills (H2): Effective communication is essential for adherent patient behavior, making this theory important. Based on this, it is expected that healthcare providers utilizing digital applications aimed to enhance communication would have patients comply with the treatment protocols based on increased compliance.

Health coaching (H3): Digital health coaching initiatives demonstrate effectiveness in promoting patient adherence, as indicated by the significant correlation identified between patient compliance and health coaching. This suggests that customized coaching could play a crucial role within digital health programs.

Therapeutic interventions (H4): The statistically significant findings of this hypothesis offer additional support for the proposition that therapy administered through digital applications enhances patients' compliance with treatment regimens. This underscores the validity of integrating digital therapeutic resources into patient care.

Healthcare quality assessment (H5): A close relationship exists between the evaluation of healthcare quality and patient adherence, meaning that digital applications are most likely to greatly improve patient adherence through an evaluation and fine-tuning of healthcare quality. Thus, this further emphasizes having high-quality digital health solutions.

Providing health information and advice (H6): Indeed, health information and advice digital applications are good compliance patients, as shown by the P-value: this hypothesis was significant. And all the more reason patients should have ready access to trustworthy records when they need them.

DISCUSSION

The results of this study reveal that empathic communication, effective health coaching, therapeutic approaches, quality assessment, and health-related information indeed enhance the compliance of patients. Moreover, the findings of this research emphasize the possibility of new digital applications with improved healthcare through higher patient adherence in following the treatment protocols.Since the findings were remarkable for all the hypotheses, healthcare practitioners and developers of applications should think about including these features into their offerings in digital health. Digital health applications have enormous potential to drive positive implications in patient adherence and resultant health outcomes through enhanced communication, relational dynamics, and provision of comprehensive health information.

CONCLUSION

Advancements in healthcare about improvement compliance on patients through digital applications and artificial intelligence technologies mark the advancement of healthcare. These technologies offer either personalized or timely access to health management resources that promote patient involvement and compliance with treatment plans provided. Digital health applications generate copious amounts of health-related information for enhanced diagnosis and tailored intervention.

Artificial intelligence further enhances these features by analyzing data offering predictive insights and personalized health suggestions. Wearable technologies, and especially remote monitoring systems can enable constant health monitoring, timely provision of medical intervention, and support ongoing patients. Privacy and security have become paramount; hence, there is a need to ensure protection measures of patient data and confidence building.

Digital exclusion needs to be addressed so that access to these innovative drugs does not become biased, especially against disadvantaged groups. Ethical considerations, such as bias in the AI algorithms, are also managed to ensure fair and effective healthcare delivery. In general, digital applications and AI technologies have the potential to significantly improve patient adherence and health outcomes, depending on the proper resolution of concerns related to privacy, security, and equity.

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