The Implementation of AI-Enabled Medical Support Systems: A Systematic Review and Meta-Analysis Based on the Universal Theory of Acceptance and Use of Technology

Anne-Kathrin Kleine

University of Munich

[Anne-kathrin.kleine@psy.lmu.de](mailto:Anne-kathrin.kleine@psy.lmu.de)

Keywords: UTAUT; clinical decision support systems; meta-analysis

# Abstract

## Research goals and why the work was worth doing

Artificial intelligence (AI) enabled clinical decision support systems (CDSS) may help clinicians diagnose diseases and forecast disease courses, select appropriate treatment regimens, and predict treatment outcomes (e.g., Davenport & Kalakota, 2019). The use of AI tools has become widespread in some healthcare areas. For example, radiologists use AI recommendations to detect cancerous lumps (van Leeuwen et al., 2021). At the same time, healthcare practitioners often do not adopt available tools (e.g., Sendak et al., 2020). The reasons for the individual non-adoption of available tools range from a general reluctance to base decisions on algorithms and data privacy concerns to the belief that these tools do not offer any benefits for their care (e.g., Shaw et al., 2019).

Based on the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003; Venkatesh et al., 2016), the current meta-analysis examines the predictors and boundary conditions of the intention to use AI-enabled CDSS. Over the past years, the UTAUT has been applied extensively to study the acceptance and intention to use AI-enabled tools in healthcare (e.g., Fan et al., 2020; Tamori et al., 2022). Despite the accumulation of research in this domain, we still lack a comprehensive overview and empirical integration of research findings on the antecedents of the intention to use AI-enabled CDSS among clinicians. The generated insight may ease the adoption of AI-enabled CDSS, thus enhancing efficiency and effectiveness in healthcare (Shaw et al., 2019).

## Theoretical background

The UTAUT provides a theoretical framework that explains the relationship between technology, environment, and user characteristics with the behavioral intention to use a specific technology. It includes four main predictors: a) performance expectancy (does the tool enhance their performance?), b) effort expectancy (are they able to use the tool?), c) social influence (do others believe that the tool should be used?), and d) facilitating conditions (does the existing infrastructure support the use of the tool?). We additionally include variables as predictors that are not part of the original model but that have been used extensively in UTAUT-based research in the healthcare domain (e.g., trust and perceived knowledge; Arfi et al., 2021; Gado et al. 2022). Finally, we conduct sub-group and moderation analyses that account for specific contextual (e.g., organization type, healthcare area) and individual (e.g., age, gender) boundary conditions of the relationship between UTAUT predictors and the intention to use AI-enabled CDSS.

## Design and methodology

We follow the PRISMA guidelines for systematic reviews and meta-analyses (Page et al., 2021). First, we search electronic databases (e.g., Web of Science, PsycInfo, and ProQuest) using the keywords “medicine”, “utaut”, and related terms. Second, we conduct forward searches in Google Scholar of studies citing Venkatesh et al. (2003). Third, we search abstracts of relevant conference proceedings. We exclude articles if they are not published in English, focus on tools that do not fall within the definition of AI-enabled CDSS, do not measure the intention to use or the actual use of AI-enable CDSS, or do not include predictor variables included in the UTAUT research model. We meta-analytically assess the bivariate relationship between UTAUT predictors and outcomes. In addition, we conduct moderation analyses to evaluate the influencing effect of contextual (e.g., clinical context, healthcare domain) and individual (e.g., age, location) variables.

## Expected results

We expect the results to be available by mid-December 2022.

## Limitations

Other theories, such as the framework of Nonadoption, Abandonment, and Challenges to the Scale-Up, Spread, and Sustainability (NASSS) of health and care technologies (Greenhalgh et al., 2017) may be helpful in understanding influencing factors embedded in the broader political, regulatory, and sociocultural system (Shaw et al., 2019). In addition, we expect most of the studies included in the meta-analysis to use self-report measurements, possibly increasing the risk of common method bias (Podsakoff et al., 2003).

## Conclusions

By applying the UTAUT to the context of AI-enabled CDSS and considering individual and contextual boundary conditions, we counter some of the criticism regarding the overly simplistic approach of UTAUT research (Shachak et al., 2019). A meta-analytic approach allows us to rigorously examine the value of applying the UTAUT to the context of AI-enabled CDSS and suggesting empirically-based modifications and extensions to the existing framework. The insight may be used in educational programs that aim at easing the adoption of AI tools, thus potentially increasing the effectiveness and efficiency of modern healthcare.

## Relevance to the congress theme

The motto of the congress, “The future is now,” also applies to work in the healthcare sector. The current meta-analysis contributes to acquiring urgently needed competencies regarding the adoption of AI-enabled CDSS among healthcare practitioners.

# References

Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, *167*, 120688. <https://doi.org/10.1016/j.techfore.2021.120688>

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98. <https://doi.org/10.7861/futurehosp.6-2-94>

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2020). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). *Annals of Operations Research*, *294*(1), 567–592. <https://doi.org/10.1007/s10479-018-2818-y>

Gado, S., Kempen, R., Lingelbach, K., & Bipp, T. (2022). Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence? *Psychology Learning & Teaching*, *21*(1), 37–56. <https://doi.org/10.1177/14757257211037149>

Greenhalgh, T., Wherton, J., Papoutsi, C., Lynch, J., Hughes, G., A’Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond Adoption: A New Framework for Theorizing and Evaluating Nonadoption, Abandonment, and Challenges to the Scale-Up, Spread, and Sustainability of Health and Care Technologies. *Journal of Medical Internet Research*, *19*(11), e8775. <https://doi.org/10.2196/jmir.8775>

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, n71. <https://doi.org/10.1136/bmj.n71>

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*, 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>

Sendak, M. P., D’Arcy, J., Kashyap, S., Gao, M., Nichols, M., Corey, K., Ratliff, W., & Balu, S. (2020). A Path for Translation of Machine Learning Products into Healthcare Delivery. *EMJ Innovations*. <https://doi.org/10.33590/emjinnov/19-00172>

Shachak, A., Kuziemsky, C., & Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. *Journal of Biomedical Informatics*, *100*, 103315. <https://doi.org/10.1016/j.jbi.2019.103315>

Shaw, J., Rudzicz, F., Jamieson, T., & Goldfarb, A. (2019). Artificial Intelligence and the Implementation Challenge. *Journal of Medical Internet Research*, *21*(7), e13659. <https://doi.org/10.2196/13659>

Tamori, H., Yamashina, H., Mukai, M., Morii, Y., Suzuki, T., & Ogasawara, K. (2022). Acceptance of the Use of Artificial Intelligence in Medicine Among Japan’s Doctors and the Public: A Questionnaire Survey. *JMIR Human Factors*, *9*(1), e24680. <https://doi.org/10.2196/24680>

van Leeuwen, K. G., Schalekamp, S., Rutten, M. J. C. M., van Ginneken, B., & de Rooij, M. (2021). Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. *European Radiology*, *31*(6), 3797–3804. <https://doi.org/10.1007/s00330-021-07892-z>

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. <https://doi.org/10.2307/30036540>

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). *Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead* ({{SSRN Scholarly Paper}} No. 2800121).