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Research paper

A Study on Acceptance of the Digital Transformation of the Radiology Diagnosis Process Using AI-Enriched Tools: Scientific, Marketing and Management Implications

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ABSTRACT

As it happens in every major technological breakthrough, acceptance is an issue. Especially when this new technology causes transformation of existing business process, to which all stakeholders have to adapt. This is particularly the case with AI-enriched radiology tools that have started finding their way into the medical practice of several parts of the world. This mixed, qualitative and quantitative, study shows that TAM2 is still relevant to be used a driver of such studies for newer digital technologies and also that it has the power to produce meaning and actionable results. Moreover, this results can be perfectly exploitable from a marketing management perspective, since they provide the basis for a behavioural segmentation of the respondents along the well-known innovation adoption curve, enabling significant positioning and product launching decisions.

1. Introduction

Artificial Intelligence (AI), the main driver of the fourth industrial revolution (Erik R, 2017), is slowly but steadily taking part into the digital solutions that transform business processes, including the medical sector. Big data utilization in the healthcare has opened new grounds in shifting clinical practice from episodic analysis of disparate datasets, to algorithms relying on consistently updated datasets (Obermeyer and Emanuel, 2016). Machine learning algorithms have already been employed for several purposes, from risk prediction of cardiac arrest in infants, to cancer detection in radiology and health indicators of mental fatigue (Yamada and Kobayashi, 2018).

Our study focuses on radiology, because it has greatly benefitted from processing capabilities in sensing, image processing, etc. Diagnostic imaging revolutionized modern clinical practice and research, but such rapid growth also introduced challenges such as low-value utilization, higher-cost imaging services, and high volumes of images. Relying on images for better diagnoses, an increasing burden is placed on radiologists to read images quickly and accurately. To alleviate this situations, AI has been called upon, to assist the medical personnel. AI was initially applied in radiology to detect microcalcifications in mammography in 1992; ever since, radiology seems ready to grow together with AI (Driver, 2019).

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The millions of radiology reports and billions of images now archived in digital form represent the concept of "big data" and constitute the required substrate for AI research (Thrall JH, 2018). The chest X-ray is the most common imaging examination in the world, with 2 billion performed per year (Topol 2019).

The popularity of chest radiography is explained by its widespread availability worldwide and its utility in various diagnoses. Interestingly, the availability of labeled images which comprises the currency of AI research, is greatest with chest radiographs. For these reasons, chest radiography has garnered the greatest interest amongst AI researchers and continues to be an active research area (Kulkarni 2020).

Among the most popular medical AI datasets to date is known as ChestX-ray14. It is available to use for free, and is still amongst the largest publicly available datasets globally (Wang X, 2017, Kulkarni S, 2020). However, ChestX-ray14 has its weaknesses. For instance, diagnostic uncertainty permeates the dataset, and hence practicing radiologists are able to recognize that there is a level of uncertainty with many radiological diagnoses, and this is evident from the ChestX-ray14 dataset. Furthermore, many of the labels overlap with each other radiologically; for instance, pneumonia can have a similar appearance to atelectasis, resulting in difficulties in discrimination between the two conditions. Additionally, there is no definitive evidence affirming whether the radiological diagnosis was correct (Kulkarni S, 2020).

The applications of AI in radiology go quite far beyond the intuitive use for automating image interpretation, with functions in image acquisition, management and population screening that will probably be more abundant in the coming years due to the value that would be provided in optimizing daily practice workflows (Lakhani P, 2017, Vyborny C.J, 1997). The disruptive power of AI has started transforming the radiology diagnosis business process. Recognizing that the basic steps of this business process comprise of planning (tools set-up), radiology scanning, image production, prioritization, image assessment, diagnosis, delivery of results to the patient, second level analysis. It is of critical importance that AI augments and enriches the prioritization, image assessment, diagnosis tasks of the business process in order to improve the quality of service to the patients and enable radiologists cope with the constantly increasing volume of required results.

The integration of artificial intelligence (AI) into medical diagnostics has sparked intense debate among healthcare professionals, particularly concerning its acceptance by physicians. On one hand, AI holds the promise of revolutionizing medical practice by improving diagnostic accuracy, reducing the time required to evaluate patients, and providing quick access to a vast database of medical knowledge. On the other hand, this technology raises legitimate concerns, not only about its reliability but also about its potential impact on the medical profession.

The primary obstacle to AI acceptance by physicians lies in the perception of a threat to their expertise and autonomy. According to a study by Reddy et al. (2019), a significant portion of physicians expresses reservations about the possibility of AI eventually replacing them, fueling a general mistrust in these technologies. This fear is exacerbated by the complexity and opacity of AI algorithms, often perceived as "black boxes" whose decisions are not always understandable to end users (Tonekaboni et al., 2019). Moreover, the potential for diagnostic errors, though rare, is sufficient to raise doubts about the reliability of AI, especially when decisions carry critical consequences for patients (Topol, 2019).

However, a closer analysis reveals a paradox to this initial resistance. While some physicians fear that AI might replace their expertise, they gradually realize that this technology can actually become a valuable ally in their daily practice. For instance, AI excels at processing and analyzing large amounts of data, a task that can quickly exhaust a human being. Studies by Parikh et al. (2019) show that AI can read and interpret thousands of medical images or test results in record time, allowing physicians to focus their attention on more complex and nuanced aspects of diagnosis. Furthermore, AI offers a solution to the information overload faced by physicians, particularly with the growing volume of scientific literature published each year. It has become practically impossible for a clinician to stay up-to-date with all the advancements in their field, but AI can bridge this gap by synthesizing the latest research and integrating it into its recommendations.

It is also crucial to emphasize that, despite AI's advancements, medical diagnosis remains a deeply human process. AI can propose diagnoses and recommendations based on available data, but the final decision rests with the physician. This interaction between AI and the clinician is essential because it combines the computational power of AI with the clinical judgment, experience, and contextual understanding that only a physician can offer (Jiang et al., 2017). Thus, rather than replacing doctors, AI positions itself as a complementary tool, designed to enhance the efficiency and accuracy of care while leaving the final decision to the human professional.

Our study attempts to analyze factors that influence the acceptance of the use of AI in radiology, which digital transforms the business processes of healthcare services provision in the radiology profession.

2. Literature review

The Technology Acceptance Model (TAM), proposed by Davis and Bagozzi in 1989, remains a crucial theoretical framework for understanding the adoption of new technologies, including artificial intelligence (AI) in medicine, and particularly in radiology. This model identifies two key variables—perceived usefulness (PU) and perceived ease of use (PEOU)—as the primary determinants of technology acceptance and effective use. These concepts are particularly relevant when analyzing the integration of AI into radiology, a field where the complexity of tasks and the significance of clinical decisions make technological adoption both critical and delicate.

Perceived usefulness (PU) is defined as the degree to which a person believes that using a specific technology will enhance their job performance. In the context of AI in radiology, this variable is of paramount importance, as radiologists are increasingly confronted with growing volumes of medical imaging data to process, which intensifies the pressure on their time and cognitive resources. According to a study by Meyer et al. (2018), radiologists who perceive AI as a speed and accuracy tool, are more likely to adopt it. AI is perceived as enhancing diagnostic efficiency by not only reducing the time required to analyze images, but also by offering levels of precision that sometimes surpass those achieved through traditional methods. Another study by Recht and Bryan (2017) emphasizes that the perceived usefulness of AI in radiology is closely linked to its ability to reduce diagnostic errors, a crucial factor in a field where accuracy is vital for patient care.

In parallel, Perceived Ease Of Use (PEOU) refers to the extent to which a person believes that using a technology will be free of effort. This variable is also essential for the adoption of AI in radiology, as radiologists, although experts in their field, are not necessarily trained to such technologies. A complex or difficult-to-master interface could deter healthcare professionals from adopting them. Research conducted by Gong et al. (2019) indicates that the acceptance of AI by radiologists is heavily influenced by how easily they can interact with the software and how well it integrates into their existing workflow. The easier AI is perceived to use, the more likely radiologists are to adopt it.

It is also worth noting that PU and PEOU are often interconnected. For instance, a technology perceived as useful, but difficult to use, may face adoption barriers, as potential users might doubt their ability to fully leverage it. This is particularly relevant in radiology, where radiologists must not only perceive AI as an enhancement to their practice but also believe they can easily integrate this technology into their work environment without disrupting their daily routines. A study by Langlotz et al. (2019) demonstrated that the successful integration of AI in radiology depends not only on its ability to improve clinical outcomes (PU) but also on its compatibility with existing information systems and its accessible learning curve (PEOU).

Furthermore, the relationship between PU, PEOU, and the adoption of AI in radiology is mediated by other contextual factors, such as ongoing training, organizational support, and social norms within the medical community. For example, Shen et al. (2021) highlight that adequate training of radiologists in the use of AI can significantly improve PEOU by reducing initial resistance due to unfamiliarity with the technology. Additionally, organizational support, in the form of resources and time allocated for learning new technologies, can also positively influence PEOU and, by extension, PU.

Finally, it is crucial to emphasize that while TAM is a powerful model for understanding AI adoption in radiology, it does not fully capture the complexity of acceptance dynamics in this field. For instance, a study by Pakdemirli (2020) suggests that factors such as trust in AI algorithms and ethical concerns related to clinical decision-making autonomy also play a decisive role. These dimensions add additional layers to the interpretation of PU and PEOU, indicating that AI adoption in radiology is influenced not only by performance and ease-of-use considerations but also by broader perceptions regarding safety and medical responsibility.

In conclusion, the concepts of perceived usefulness and perceived ease of use from the TAM are fundamental to understanding the adoption of AI in radiology. These variables directly influence radiologists' willingness to integrate AI into their practice by shaping their perception of the added value and ease of use of these technologies. Recent studies demonstrate that to maximize AI acceptance, it is crucial to enhance the perception of its clinical utility and reduce barriers to its use through intuitive interfaces and adequate training. However, other contextual and psychosocial factors must also be considered for a comprehensive understanding of AI acceptance in medicine.

3. Methodology

We use a mixed quanti/quali method as proposed by Creswell & Clark (2017), Venkatesh et. al. (2013) to measure technology acceptance. An exploratory qualitative study was carried out with three specialists, followed by a confirmatory quantitative survey with a sample of experienced practitioners.

Firstly, a qualitative study was carried out with three experts: a university radiology professor, a radiology department head in a private hospital and a radiologist in a diagnostic center, whose profiles are described in the following table:

Profiles of interviewed experts for the qualitative survey:	Experience (in years)	Number of cases treated per year	Hopital size (No. of students or patients per year)
Professor of radiology at university	25	1.400 yearly screening cases overall. 130 cases treated with AI assisted tools	3.000-5.000 patients per year
Head of radiology department in a private hospital	30	7.000 yearly screening cases overall. 2.500 cases treated with AI assisted tools	4.000-5.000 patients per year
Radiologist in a diagnostic centre	35	10.000 yearly screening cases overall. 6.000 cases treated with AI assisted tools	6.000-7.000 patients per year

The interview guide was based on previous surveys conducted by the European School of Radiology (ESR 2018, 2022). The draft Questionnaire was validated with the help of a Field Expert in Medical Physics, in order to ensure the relevancy of all questions as well as the inclusion of all aspects that the use of an AI tool in HealthCare might involve. Initially, a pre-read material was created to introduce the interviewees to the topic and then the interviews run.

The aim of the interviews was to explore their interviewees' understanding of the AI technology introduced into their work setting, including their perceptions of the associated risks and benefits for patients, and the likely challenges posed for its adoption. The interview questions were organized in five groups in an attempt to cover all the aspects of the AI technology risks and benefits in Healthcare and more specifically in Radiology:

(1) Perception of AI applications impact on Radiology/ Medical Imaging Operations
(2) Quality of medical services provided by implementing AI
(3) AI-specific knowledge
(4) Open and proactive attitude
(5) Legal implications of AI systems

The preliminary results acquired were proved to be helpful in terms of understanding the overall attitude towards the emerging AI technology by Radiologists in Greece.

In a second phase, the results of these interviews were used as a basis for drawing up a questionnaire for professionals. Out of 130 questionnaires distributed to experimented professionals, 89 were returned. Answers to the questions in the Lickert scale (mostly disagree, disagree, neutral opinion, agree, and mostly agree) was conveniently given by the respondents, whose demographic data are shown in Appendix 1.

Regarding the quantitative part of the study, statistical analysis of the data collected by the questionnaires, quantitative variables were expressed as mean (Standard Deviation) or as median (interquantile range). Qualitative variables were expressed as absolute and relative frequencies. Qualitative variables were expressed as absolute and relative frequencies. Mann-Whitney test was used for the comparison of continuous variables between two groups and Kruskall-Wallis test among more than two groups. Wilcoxon test was used for the comparisons between the scores. Bonferroni correction was used in case of multiple testing in order to control for type I error. Spearman correlation coefficients (rho) were used to explore the association of two continuous variables. Linear regression analysis in a stepwise method (p for entry 0.05, p for removal 0.10) was used in order to find independent factors associated with participants' Behavioral Intention to Use (BIU) score. Adjusted regression coefficients (β) with standard errors (SE) were computed from the results of the linear regression analyses. Log transformations were made for the linear regression model. Internal consistency of the questionnaire was evaluated via Cronbach's alpha. Scales with reliabilities equal to or greater than 0.70 were considered acceptable. All reported p values are two-tailed. Statistical significance was set at $p<0.05$ and analyses were conducted using SPSS statistical software (version 26.0).

The questionnaire was structured according to the adapted TAM2 model (Venkatesh & Davis, 2000) shown below*:

* Source of picture: realkm.com/2016/08/24/extended-technology-acceptance-model-tam2-personality-tkms-series/

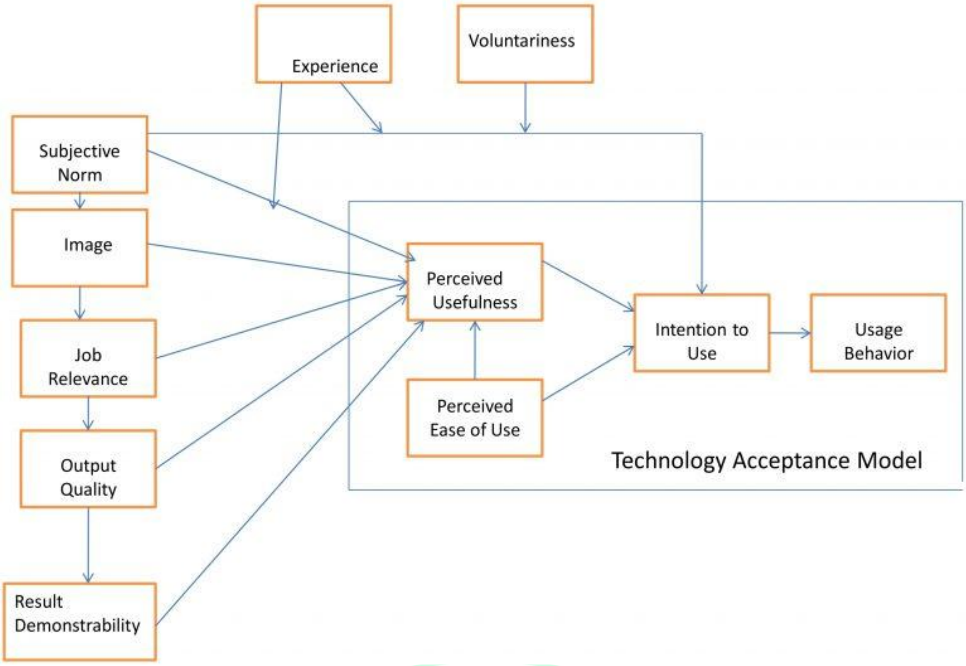

Fig. 1 TAM2 model as used in practice

Job relevance and output quality have not been taken into account in our research as determinants of perceived usefulness because they are both positive by default and are not expected to play any role in differentiating the results. This is because the former, job relevance, has been ensured since the study focuses on radiologists and their medical practice, while the latter, output quality, is the aim of any technological tool used by medical doctors. Moreover, the qualitative analysis performed by the three interviews prior to the questionnaires guided us to focus on Behavioral Intention to Use, Usefulness, Voluntariness, Ease of Use and Social influences.

Table 1 Participants' attitudes on AI applications

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Agree/ Strongly agree (%)	Mean (SD)
	N (%)	N (%)	N (%)	N (%)	N (%)		
Behavioral Intention to Use							
Given the opportunity. I would like to use AI applications.	0 (0)	3 (3.4)	7 (7.9)	44 (49.4)	35 (39.3)	88.8	1.25 (0.74)
AI applications are compatible with my work.	1 (1.1)	2 (2.2)	13 (14.6)	42 (47.2)	31 (34.8)	82.0	1.12 (0.82)
Usefulness							
Using AI applications could save me time.	0 (0)	3 (3.4)	8 (9)	47 (52.8)	31 (34.8)	87.6	1.19 (0.74)
Using AI applications would help me make diagnosis faster.	0 (0)	2 (2.2)	12 (13.5)	53 (59.6)	22 (24.7)	84.3	1.07 (0.69)
Using AI applications would help me make more accurate diagnosis.	0 (0)	4 (4.5)	16 (18)	54 (60.7)	15 (16.9)	77.5	0.9 (0.72)
Using AI applcations enhances my effectiveness at my job.	0 (0)	3 (3.4)	18 (20.2)	45 (50.6)	23 (25.8)	76.4	0.99 (0.78)
Using AI Applications in my job increases my productivity.	0 (0)	3 (3.4)	22 (24.7)	41 (46.1)	23 (25.8)	71.9	0.94 (0.8)
Using AI applications in my job could reduce my daily workload.	0 (0)	15 (16.9)	22 (24.7)	38 (42.7)	14 (15.7)	58.4	0.57 (0.95)
The use of AI applications could help me take better care of patients.	1 (1.1)	5 (5.6)	20 (22.5)	50 (56.2)	13 (14.6)	70.8	0.78 (0.81)

Voluntariness							
Although it may be useful. the use of AI applications will certainly not be mandatory in my work.	3 (3.4)	20 (22.5)	25 (28.1)	35 (39.3)	6 (6.7)	46.1	0.24 (0.99)
My use of AI applications will be voluntary.	1 (1.1)	7 (7.9)	23 (25.8)	47 (52.8)	11 (12.4)	65.2	0.67 (0.84)
Ease of Use							
AI applications are not too complicated to use.	1 (1.1)	6 (6.7)	33 (37.1)	42 (47.2)	7 (7.9)	55.1	0.54 (0.78)
Getting the information I want from AI applications is easy.	1 (1.1)	6 (6.7)	33 (37.1)	45 (50.6)	4 (4.5)	55.1	0.51 (0.74)
Learning to use an AI application is easy.	0 (0)	8 (9)	42 (47.2)	35 (39.3)	4 (4.5)	43.8	0.39 (0.72)
Becoming an expert in using AI applications is easy.	2 (2.2)	15 (16.9)	49 (55.1)	21 (23.6)	2 (2.2)	25.8	0.07 (0.77)
AI applications makes it easy to recognize key information.	0 (0)	4 (4.5)	27 (30.3)	55 (61.8)	3 (3.4)	65.2	0.64 (0.63)
AI applications use understandable graphics & terminology.	0 (0)	9 (10.1)	33 (37.1)	44 (49.4)	3 (3.4)	52.8	0.46 (0.72)
Social influences							
Using AI applications improves my job performance.	0 (0)	2 (2.2)	18 (20.2)	55 (61.8)	14 (15.7)	77.5	0.91 (0.67)
Using AI applications improves my prestige at the workplace.	0 (0)	7 (7.9)	20 (22.5)	48 (53.9)	14 (15.7)	69.7	0.78 (0.81)
The use of AI applications can improve the prestige of the Institution I work for.	0 (0)	5 (5.6)	11 (12.4)	46 (51.7)	27 (30.3)	82.0	1.07 (0.81)

A schematic that can visualize the results of the above survey to demonstrate the antecedents for Intention to Use looks like Figure 2.

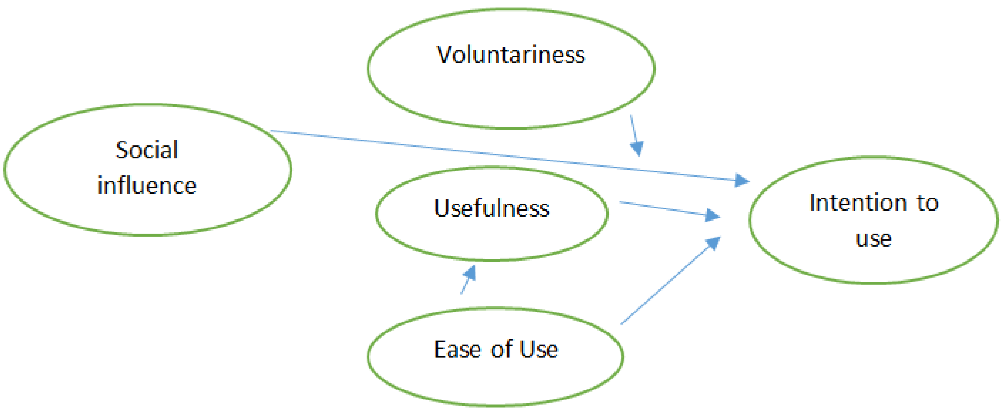

Fig. 2 Antecedents of Intention to Use as produced by the quantitative rsearch

Regarding Behavioral Intention to Use, the percentages of agreement were 82% for the statement "*AI applications are compatible with my work*" and 88.8% for the statement "*Given the opportunity, I would like to use AI applications*".

Regarding Usefulness, the percentages of agreement ranged from 58.4% to 87.6%. More specifically, 58.4% of the participants agreed/ strongly agreed with the statement "*Using AI applications in my job could reduce my daily workload*" and 87.6% with the statement "*Using AI applications could save me time*". Moreover, 84.3% of the sample agreed/ strongly agreed with the statement "*Using AI applications would help me make diagnosis faster*".

Regarding Voluntariness, the percentages of agreement were 46.1% for the statement "*Although it may be useful, the use of AI applications will certainly not be mandatory in my work*" and 65.2% for the statement "*My use of AI applications will be voluntary*".

Regarding Ease of Use, the percentages of agreement ranged from 25.8% to 65.2%. More specifically, 25.8% of the participants agreed/ strongly agreed with the statement "*Becoming an expert in using AI applications is easy*" and 65.2% with the statement "*AI applications makes it easy to recognize key information*". Moreover, 55.1% of the sample agreed/ strongly agreed with the statements "*AI applications are not too complicated to use" and "Getting the information I want from AI applications is easy*".

Regarding Social influences, the percentages of agreement were 69.7% for the statement "*Using AI applications improves my prestige at the workplace*", 77.5% for the statement "*Using AI applications improves my job performance*" and 82% for the statement "*The use of AI applications can improve the prestige of the Institution I work for*".

Within each sector, items were averaged and their scores were computed. Thus, in each sector, the score could range from -2 to 2, with higher values indicating more positive attitudes. Participants' scores are presented Table 2.

Table 2 Participants' scores in each sector

	Min	Max	Mean (SD)	Median (IQR)	Cronbach's
Behavioral Intention to Use	-1.00	2.00	1.19 (0.72)	1 (1 – 2)	0.83
Usefulness	-0.86	2.00	0.92 (0.61)	1 (0.57 – 1.14)	0.89
Voluntariness	-1.00	2.00	0.46 (0.75)	0.5 (0 – 1)	0.72
Ease of Use	-1.00	1.50	0.43 (0.51)	0.5 (0 – 0.83)	0.79
Social influences	-1.00	2.00	0.92 (0.63)	1 (0.67 – 1.33)	0.76

Although AI is being recently introduced in the field of radiology, our study found that almost half of the participants had a good basic understanding of this technology. Notably, 20% of participants were feeling unfamiliar with AI. The level of experience in AI, was also evenly divided among the subgroups of participants, with only 28.3% having experience in AI, while 42.7% had either some if any at all. In our study 48.3% of the respondent were comfortable with what AI means, although only 6.7% were very satisfied and were working with AI in their current practice. Our results, are comparable with other similar survey studies (Abuzaid, 2022, Qurashi, 2021). In one study (Abuzaid, 2022), almost 40% (n = 61) of the participants were not familiar with AI, while 30.1% (n = 46) were familiar with the basics of AI, and only 14.4% were very satisfied and were working with AI in their current practice.

Despite the lack of experience, the majority of our respondents feel either confident (49.4%), or very confident (15.7%) towards AI in Radiology. Interestingly, 88.8% of the participants responded that given the opportunity, they would like to use AI applications. This finding attests to the role of personal innovativeness in IT, which has been recognized as an antecedent to the extended TAM2 model introduced by Van Raaij and Schepers (2008). Therefore, overall sentiments regarding career prospects in radiology were generally optimistic and in concordance with some other studies. In the study of Waymel (2019) respondents had the feeling of receiving insufficient previous information on AI, although they are willing to improve their knowledge and technical skills on this field. On the contrary, in the survey of the European Society of Radiology, only 13.3% of the total 690 respondents indicated that they had intentions to acquire AI tools (European Society of Radiology, 2022).

Regarding the usefulness of AI in Radiology, 58.4% of the participants agreed that it could reduce the daily workload, and 87.6% appreciated it could save time or it would help to make diagnosis faster. On the contrary in another study, only 22.7% experienced a significant reduction of their workload, whereas the majority (69.8%) found that there was no such effect (Waymel, 2019). In our study, saving time and faster diagnosis were the most desirable parameters of usefulness, while accurate diagnosis and less daily workload, were of significantly less concern. The usefulness of AI applications, differed significantly according to years of experience. More specifically, participants with less than 20 years of experience in radiology had significantly greater usefulness score compared to participants with 20-30 years of experience, thus, greater age was associated with lower Usefulness score and hence less intention to use.

Most participants considered that AI applications will either be easy or not too complicated to use, however there is low interest among Radiologists in becoming experts in this field. In our study, age was not significantly associated with Ease of Use. On the contrary, greater confidence, familiarity and experience on AI applications were the factors that were significantly associated with greater Ease of Use score. In a similar study from Singapure (Ooi SKG, 2021), the majority of the respondents considered AI in radiology more exciting (76.0%), and would still choose to specialize in radiology if given a choice (80.0%). Most of the respondents considered that AI applications may improve the prestige of the institution, rather than their job performance or their personal professional prestige. In our study, a greater Ease of Use score was significantly associated with greater Social influences score. Interestingly, females had significantly greater Behavioral Intention to use AI applications compared to males. A similar conclusion was not recorded in other studies.

4. Discussion

Given the above results, scientific as well as managerial implications can be extracted. First of all, our approach based on the TAM2 method gave comparable results with similar survey studies that used other approaches, as far as intention to use is concerned, especially in not familiar to AI cohorts.

In terms of the positive attitude shown in the results, despite the lack of experience, is congruent with another study where respondents of insufficient previous information on AI, they are willing to improve their knowledge and technical skills on this field. However, there is significant disparity the European Society of Radiology's results, showing only 13.3% having an intention to acquire AI tools. This can be affected by several factors having to do with the explorative nature of respondents, both as personalities and as related to their origins, degree of understanding of digital technologies, kind of exposure that AI-enriched tools outside their medical practice etc.

Regarding the usefulness of AI in Radiology, our approach gave very similar results to previous ones. Therefore, TAM2 can arguably be considered as appropriate in applying it to new digital technologies adoption, such as AI in radiology, since the results don't variate significantly to those of other similar ones.

From a managerial perspective, our results fit well to classic Rogers (1983) curve of innovation adoption, since AI is clearly transforming innovatively the entire radiology's business process. This is of particular importance to marketing people, because they would like to know behaviours of main profiles, when launching such new digitally augmented products. To this end, our research results are interpreted into three profiles along the Rogers' Innovation Adoption Curve.

Profile A: Innovators

Characteristics of this profile consist of employment of a few years of field expertise in University Research & Development programs for AI. Specifically, one of our Interviewees, who has an Innovator profile (first Radiologist in Europe who implemented AI technology in his Diagnostic Center specialized in Breast screening), stated that he was a Research team member for AI in Medical imaging in the past. Under this aspect, experts who have come in close contact with AI during their early years and elaborated research are considered to have a deep knowledge of the benefits and the limitations of the tool, they understand its value proposition and are willing to use it long before it becomes a status quo.

Profile B: Early Adopters & Early Majority

Two profiles are extremely close to each other, so much that there could be no easy distinction, thus we will explore the characteristics as one profile only, with the following characteristics: Radiologists in Greece of all subspecialties with less than 20 years of field experience are more willing to use AI applications during their daily practice. The majority of them work for the private sector (private hospitals or diagnostic centers) and most of them are females. They have a good level of IT skills and they state that they have great confidence, familiarity and experience on AI applications. They understand the benefits and the usefulness of the tool (PU) that is considered to have a high degree of reliability. Radiologists of this profile are convinced that AI could improve their efficiency both in accuracy of results and in time as it could save them time and help make diagnosis faster. The Social Influence factor is also taken into consideration by this profile as these Radiologists strongly agree that AI can improve the prestige of the institution they work for.

For this profile, the Ease of Use of the AI tool (PEOU) is not an important adoption factor. Additionally, practically they don't consider that AI will reduce their daily workload.

Profile C: Late Majority & Laggards

This profile is related to Radiologists with more than 20 years of field experience, no matter the subspecialty. The survey analysis showed that greater age was associated with lower Usefulness score. These Radiologists do not have a high level of IT skills and they think that becoming an expert in using AI applications is not easy. The majority of this profile works for the Public Sector in Greece. Nevertheless, Radiologists of this profile believe in the Ease of Use (PEU) of the AI applications and they strongly agree that AI makes it easy to recognize key information.

5. Conclusions

"AI-powered medical imaging systems can produce scans that help radiologists identify patterns – and help them treat patients with emergent or serious conditions more quickly. The goal: more accurate, quality care." (ESR, 2018) This statement explains eloquently our position that that use of AI-enriched tools digitally transforms the radiology diagnosis process and, even more, business processes, which are out of scope of this study.

From the scientific point of view, TAM2 is attested to be relevant as a technology acceptance model for newer digital technologies, such as AI.

From the managerial, and especially marketing management perspective, useful and actionable implications have been identified. The results indicate that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), Subjective Norm/ Image and Voluntariness, associated with years of Experience and IT skills confidence significantly affect Greek Radiologists' behavioral intention to use AI. Specifically, age was significantly and negatively associated with Usefulness. Thus, greater age was associated with lower Usefulness score. On the contrary, greater confidence, familiarity and experience on AI applications were significantly associated with greater Behavioral Intention to Use. Females had significantly greater Behavioral Intention to Use score compared to males.

Overall, this study shows that the attitude of Radiologists in Greece is rather positive towards the adoption of AI based tools in Medical Imaging but still with a sceptical stance. We have been able to describe Radiologist profiles related to the Innovation Adoption Curve approach, meaning that the Acceptance of AI Applications in Greece is scaled and varies according to defined adoption criteria. These marketing implications can be useful when positioning and launching such new products in the local market and, similarly, to other European markets.

Declarations

All authors declare that they have no conflicts of interest.

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APPENDIX 1

		N	%
Gender	Male	30	33.7
	Female	59	66.3
Age, mean (SD) 51.1 (8.9)			
Educational Level	MD	100	100
	MSc	14	15.7
	Phd	34	38.2
Workplace	Private Sector	49	55.1
	Public Sector	40	44.9
Field of Expertise	Abdominal	11	12.4
	Breast	4	4.5
	Neuro	6	6.7
	Cardiac	8	9.0
	Musculoskeletal	5	5.6
	Thoracic	2	2.2
	More than one	53	59.6
Years of Experience in Radiology	0-5	8	9.0
	5-10	4	4.5
	10-20	31	34.8
	20-30	28	31.5
	30+	18	20.2