

Assessing Open Data Readiness and Leveraging AI for Enhanced Sustainable Research Information Management System

AISHA ALSEDDIQUI, HODA KARTAM
Computer Department,
College of Basic Education, PAAET,
Ardiya,
KUWAIT

Abstract: - This study investigates the readiness of research institutions to implement FAIR (Findable, Accessible, Interoperable, and Reusable) and Open Data frameworks. It specifically examines five key constructs: awareness, digital literacy, technical capacity, AI readiness, and FAIR readiness, with a particular focus on the mediating role of AI readiness. Academic and research experts were sent a structured questionnaire using a quantitative, cross-sectional approach. Partial Least Squares Structural Equation Modeling (PLS-SEM) data analysis was employed to investigate direct and mediated effects among the constructs of the research. The analysis indicated that AI readiness is pivotal in improving FAIR readiness and completely mediates the connection between technological capacity and FAIR outcomes. Technical capacity greatly affects AI readiness; however, it does not immediately forecast FAIR readiness. Awareness and digital literacy showed no direct impact on FAIR preparedness, indicating the primacy of system-level integration over individual knowledge alone. The study demonstrates the importance of using AI to establish FAIR principles and promote Open Data adoption. Moreover, it provides empirical evidence highlighting the need to strategically implement AI readiness into technological infrastructures to improve data management practices. In turn, the findings allow for practical recommendations to be made that will help academic leaders and policymakers create AI and FAIR-aligned research settings in Kuwait and other similar locations.

Key-Words: - FAIR Data Readiness; Artificial Intelligence; Open Data; Research Information Systems.

Received: May 5, 2026. Revised: June 22, 2026. Accepted: July 25, 2026. Published: October 26, 2026.

1 Introduction

In an era of information and digital transformation, research increasingly relies on the smooth integration and exchange of data across disciplines and organizations. So it's not stuck in traditional silo anymore. Nonetheless, the modern world of research and digital transformation has generated complex challenges regarding data management and sharing, primarily resulting from the rapid growth of data between three different dimensions, namely velocity, volume, and variety. The shift towards seamless data integration across disciplines and institutions reflects a broader demand for high-quality research data as foundational elements not just for new knowledge generation but also for effective public policy and innovation [1]. Organizations are becoming increasingly aware that existing datasets represent valuable assets when used effectively. High-quality data are useful for replication studies, secondary analyses, and evidence-based decision-making [2]. However,

many valuable datasets remain underutilized due to challenges such as fragmented data storage, inconsistent standardization, and insufficient metadata, all of which limit their accessibility and reuse [3].

To address such challenges, a number of frameworks have been developed, such as the FAIR Data Principles (Findable, Accessible, Interoperable, Reusable), which offer structured methodologies that can be applied to render research data more usable [4]. The FAIR principles have become popular in many scientific fields (such as life sciences) and are becoming critical components of data stewardship priorities that are highlighted by many research infrastructures. In turn, this has inspired initiatives at the European level. One example of this would be the European Open Science Cloud (EOSC), which is designed to increase interoperability between standardized data repositories [5]. Further, the connection between these principles and the Open Data paradigm reveals

a common understanding that data should be not only theoretically accessible but also practically usable in order to be considered open [6].

Implementing the FAIR principles requires support at several levels, including institutional policies, appropriate technological infrastructure, and researchers with the necessary data management skills [7]. For example, in research groups, data stewards ensure that research data are managed in accordance with the FAIR principles and are well documented [8]. In addition, the further development of tools that support the FAIR principles is likely to enhance data sharing, interoperability, and reuse, thus fostering collaboration across different research fields [9]. Future developments in data management technologies and practices will not only make research data more organized, preserved, and accessible but also contribute to the effective implementation of the FAIR principles [10]. The relationship between strong institutional frameworks, technological advances, and community-driven initiatives plays a critical role in the development of environments conducive to high-quality research data thriving. Such settings can promote scientific discovery, public policy development, and innovation across the world [11]. Thus, the objective is to unlock and leverage existing resources, as well as generate more data. In turn, this means that such resources will make significant contributions to societal advancement.

2 Problem Formulation

In the modern era of information and digital transformation, research is becoming increasingly reliant on the seamless exchange of data between different disciplines and institutions and is no longer confined to traditional silos. The volume, velocity and variety of data are growing significantly, and this means that researchers and institutions have to think critically about how to manage, curate and leverage existing datasets in ways that foster innovation, scientific discovery and public policy. The volume, velocity and variety of data are growing dramatically, and researchers and institutions need to think carefully about how to manage, curate and leverage existing data sets to foster innovation, scientific discovery and public policy. High-quality research data are now critical in modern scientific publications. In fact, they are now considered critical raw materials that need to be replicated, subjected to secondary analysis, and incorporated in evidence-based decision-making. Nonetheless, significant quantities of such data are

underused. This is largely due to issues such as fragmented storage, lack of standards and poor metadata practices. To tackle these issues, international frameworks have been developed, such as the FAIR Data principles and the Open Data movement, to enhance the findability, interoperability, accessibility and reusability of research outputs [12]. Such frameworks must be consistent with the growing recognition that data need to be theoretically open and practically usable. There is thus a need for a strong relationship between institutional policy, digital infrastructure, researcher skills, and emerging technologies (e.g., artificial intelligence (AI)) as all of these work together to enable data-driven science to thrive in both developed and developing contexts.

2.1 Data-Driven Development and FAIR/Open Data Movements

There exist several global initiatives that demonstrate the rising significance of data in the realm of development since various frameworks have emerged to promote the data collection, accessibility, and utilization across multiple sectors. This phenomenon is particularly evident in developing nations. The World Bank acknowledges data as a crucial resource which plays a vital role in economic development, governance, and public service provision. Therefore, it is essential to adopt sound data practices in order to achieve such objectives [13]. According to Heeks and Renken, the concept of data justice extends beyond the availability of data to include the ethical use of data and the equitable distribution of its benefits, reflecting a critical perspective on data use in development contexts [14].

In order to ensure extensive utility of data, the FAIR (Findable, Accessible, Interoperable, and Reusable) principles have gained interest among researchers and policy makers [4]. The primary objective of these principles is to enhance machine-readability and interoperability across the globe, thus promoting a context in which data could be effectively reused in research and development endeavors. Crouch underscores that although big data provides various possibilities, strategic focus on enhancement of "little data" initiatives and citizen feedback is crucial in ensuring that data practices are locally relevant and helpful [1]. At the same time, the Open Data initiative focuses on the release of data sets for public use, promoting transparency and free data use [15]. Combination of FAIR principles and Open Data policies is essential in creating a complementary framework for contemporary research environments since both

focus on making data visible and usable [12]. Proper execution of these frameworks requires proper metadata, persistent identifier and licensing standards to ensure high quality data and promote comprehensive data reuse [16]. Studies show that data reusers value transparent reporting of the limitations of data quality [3], [17].

Moreover, as the digital landscape evolves, the necessity for innovative data management workflows becomes apparent. Yenni et al. illustrate the development of modern data workflows which automate data collection and processing, thus reducing errors and improving efficiency in data management systems [18]. By ensuring that data is up-to-date and trustworthy, such developments in data workflows promote the general goals of the FAIR and Open Data frameworks [9]. In addition to improving data accessibility, the dynamics and synergies of such frameworks enable academics and policymakers to apply data as a tool for socioeconomic growth.

Moreover, [19] explain that the ongoing improvement of data strategies highlights a need to coordinate user requirements with strong frameworks for developing data products, underscoring the significance of upholding high-quality data standards throughout the data lifecycle.

Through the realization of the data initiatives, including the FAIR principles, and the Open Data movement, the importance of forming structured framework that advocate for transparency and accessibility of data is emphasized. These initiatives are meant to change the way data is used in terms of growth impacts, particularly for developing countries.

2.2 Challenges and Opportunities in the Kuwaiti Research Ecosystem

Despite developments at the regional level, there are several challenges associated with the effective implementation of FAIR/Open Data practices in Kuwait [20], [21]. A study by Allamki [22] noted limited understanding of Open Access policies in higher education institutions, despite a favorable attitude toward them. As per the OpenDOAR statistics in 2021, only one institutional repository is available in Kuwait which highlights the early stage of development of its open science initiatives. However, global experiences like DLCM project in Switzerland and ROMOR in Palestine provide examples and guidelines for Kuwait. Both projects highlight the importance of a national approach to data management and infrastructure development in order to achieve sustainable data ecosystems [23], [24].

Therefore, the objective of the present study is to evaluate the readiness of research institutions in Kuwait regarding FAIR/Open Data practices considering five domains including: Awareness of FAIR/Open Data practices, Technical capacity, Institutional/governmental support, Digital literacy, and AI readiness. In addition, the study will explore the mediation role of AI readiness between technical capacity and FAIR/Open Data readiness.

2.3 Institutional Capacity and the Role of Policy

The readiness of institutions is also crucial to support the implementation of FAIR/Open Data standards. Some of the elements that make institutions ready for FAIR/Open Data adoption include information technology infrastructure, data storage infrastructure, data management systems, and technical personnel [7]. Institutions that have committed leadership, policy frameworks, and budget allocations for data services are more likely to show greater readiness for FAIR standards [8], [25]. Government support further strengthens these efforts [23]. For instance, some countries such as Austria have established national FAIR standards and offices [26]. In contrast, Kuwait does not have any national mandate or standard guidelines for research data sharing [15].

2.4 Digital Literacy and Researcher Readiness

In addition to structural and technical requirements, human factors also play a critical role in determining the success of data management approaches. The most critical factor here is digital literacy. Researchers need to have the skills to deal with datasets, use metadata standards, know about licenses, and engage in responsible data sharing [27]. An understanding of platforms for collaboration and repositories is also important in this case [28], since it is vitally important in interdisciplinary studies and reuse of data. Studies indicate that data literacy and FAIR principles [29] should be included in academic educational programs to bring about a cultural change in society and enhance research quality [27].

2.5 Leveraging AI to Accelerate FAIR Data Implementation

Artificial Intelligence (AI) can substantially improve research data practices. AI can contribute to the FAIRness of data by automating metadata generation, organizing unstructured data, and enabling data discovery [30]. The readiness for AI

consists of various elements, including infrastructure, skills, strategic vision, and alignment of policies. AI preparedness is one of the key elements of digital transformation in the research environment [31], [32]. AI frameworks, such as AIDRIN [33], demonstrate the required connection of technological and organizational capabilities for successful implementation of AI in research settings. Although AI readiness remains underdeveloped in Kuwait's institutional settings, its integration with FAIR/Open Data strategies represents a promising area for future advancement.

The key purpose of this research is to fill an existing research gap by providing a systematic assessment of awareness, institutional support, technical ability, digital literacy, and government policy in the research ecosystem of Kuwait. Moreover, the study examines the mediating role of AI readiness in improving FAIR/Open Data implementation and provides important insights into how to create sustainable, AI-empowered research data infrastructures.

3 Problem Solution

3.1 Research Design and Data Collection

This study used a quantitative, cross-sectional research design to evaluate the institutional readiness to adopt FAIR and Open Data practices in research environments in Kuwait. The structured questionnaire was developed based on existing theoretical frameworks and previous validated questionnaires. The questionnaire was developed to respond to five main constructs: Awareness of FAIR/Open Data (AW), e-literacy (DL), Technical Capacity (TC), AI Readiness (AR), and FAIR Readiness (FR). Each construct was measured with multiple reflective items on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree".

Data were collected from academic and research professionals through purposive sampling to ensure respondents possessed relevant experience with research data, institutional systems, and/or digital tools. Responses were screened for completeness and consistency before analysis.

3.2 Structural Model and Hypothesis Testing

The structural relationships among the constructs were analyzed using partial least squares structural equation modeling (PLS-SEM). PLS-SEM technique was used because of its efficiency in dealing with complex models and its appropriateness for prediction-oriented research

with relatively small to medium sample sizes [34]. This analytical approach is consistent with prior mediation-based PLS-SEM studies conducted in the Kuwaiti context [35], [36].

Prior to assessing the structural model, the measurement model was evaluated to ensure the reliability and validity of the constructs. Internal consistency reliability was confirmed using Cronbach's alpha and composite reliability, with acceptable values exceeding 0.70. Convergent validity was established through the Average Variance Extracted (AVE), with threshold value of 0.50. Discriminant validity was assessed using cross-loading, the Fornell-Larcker criterion, and the Heterotrait-Monotrait (HTMT) ratio. The discriminant validity results confirmed that each construct was empirically distinct from the others [37].

The structural model was then analyzed to evaluate the hypothesized relationships among constructs. To calculate path coefficients, standard errors, and significance values, a bootstrap method was employed using 5,000 subsamples. Also, the model analyzed direct and indirect relationships focusing on the importance of AI Readiness (AR) in the mediation role between Technical Capacity (TC) and FAIR Readiness (FR). Mediation was tested using the indirect effect estimation procedure through bootstrapping.

3.3 Results

The demographic profile of the study's participants (N = 296) reflects a diverse and well-distributed sample in terms of age, gender, education, research roles, academic disciplines, and experience (Table 1).

The majority of respondents were from the age group of 25-34 (52.7%), followed by 35-44 (25.3%). Thus, the sample consists primarily of early- to mid-career professionals. The gender distribution was relatively balanced, with a higher proportion of female participants (53.0%) compared to male participants (47.0%). The majority of the participants had a bachelor's degree (63.5%) while 31.8% of the participants had a master's degree and only 4.7% had a PhD degree.

Regarding professional roles, the largest proportion of participants were in administrative roles (34.1%), followed by technical staff (29.1%) and student researchers (28.4%), with academic researchers constituting 8.4% of the sample. The participants represented a wide range of disciplines, with majority of participants were from Business, Law & Education (29.7%), closely followed by Engineering, Technology & Science (29.4%),

Humanities, Arts & Social Sciences (28.0%), and Health & Life Sciences (12.8%).

Table 1. Demographic Characteristics

	Overall (N=296)
Age Group	
18-24	20 (6.8%)
25-34	156 (52.7%)
35-44	75 (25.3%)
45-54	27 (9.1%)
55-64	16 (5.4%)
65+	2 (0.7%)
Gender	
Male	139 (47.0%)
Female	157 (53.0%)
Highest Educational Qualification	
Bachelor	188 (63.5%)
Master	94 (31.8%)
Phd	14 (4.7%)
Position/Role	
Student Researcher	84 (28.4%)
Academic Researcher	25 (8.4%)
Technical Staff	86 (29.1%)
Administrative Role	101 (34.1%)
Department/Discipline	
Health & Life Sciences	38 (12.8%)
Engineering, Technology & Science	87 (29.4%)
Business, Law & Education	88 (29.7%)
Humanities, Arts & Social Sciences	83 (28.0%)
Years of Experience in Research	
0–2	99 (33.4%)
3–5	108 (36.5%)
6–10	65 (22.0%)
11+	24 (8.1%)
Institution Type	
Public	143 (48.3%)
Private	153 (51.7%)
Frequency of Working with Research Data	
Daily	102 (34.5%)
Weekly	57 (19.3%)
Occasionally	105 (35.5%)
Rarely	32 (10.8%)

Source: created by the authors

Regarding research experience, the majority of respondents reported the experience of 3-5 years (36.5%), while 33.4% of participants reported the

experience of 0–2 years, suggesting a relatively young research population. For institutional type, 48.3% of the participants were from public and 51.7% were from private sectors. Further, with regard to the frequency of working with research data, 34.5% reported daily engagement, 35.5% occasionally, 19.3% weekly, and 10.8% rarely, indicating varied levels of data handling experience across the sample participants.

The results provide descriptive statistics and reliability diagnostics for the study's core constructs: Awareness, Technical Capacity, AI Readiness, FAIR Readiness, and Digital Literacy. Item means ranged from 3.35 to 4.28, with the highest average observed in Digital Literacy (DL1), indicating participants' stronger confidence in digital tools, while lower scores in AI Readiness items (e.g., AR4 = 3.35) suggest institutional gaps in AI integration.

All item-rest correlations exceeded 0.50, indicating satisfactory item-level contributions to their respective constructs. Importantly, none of the items produced a Cronbach's alpha value—when dropped—that exceeded the overall scale reliability of $\alpha = 0.963$, demonstrating that each item contributes meaningfully to the internal consistency of the construct [38]. This further supports the robustness and reliability of the measurement model used for subsequent structural analysis.

The correlation analysis was conducted to examine the association among the study variables. The five variables included Awareness of FAIR Data Principles, Technical Capacity, AI Readiness, FAIR Data AI Readiness, and Digital Literacy (Table 2). All correlations are statistically significant at $p < 0.001$ level which shows strong associations between the variables. The correlation between the awareness of FAIR Data Principles and the Digital Literacy is positive, moderate to strong ($r = 0.689$). This suggests that higher digital literacy is associated with greater awareness. It also shows a strong correlation with AI Readiness ($r = 0.594$) and Technical Capacity ($r = 0.582$) demonstrating the association between the underlying knowledge and readiness to embrace FAIR practices and AI technologies. Technical Capacity also has a strong correlation with AI Readiness ($r = 0.648$) and Digital Literacy ($r = 0.621$). The strongest correlation was observed between AI Readiness and FAIR Data AI Readiness ($r = 0.861$), suggesting a close relationship between general AI preparedness and readiness to implement FAIR data practices. Overall, the findings indicate that higher levels of awareness, digital literacy, and technical capacity

are associated with greater AI and FAIR data readiness.

Table 2. Correlation Analysis

	AW	TC	AR	FR	DL
AW	—				
TC	0.582***	—			
AR	0.594***	0.648***	—		
FR	0.575***	0.620***	0.861***	—	
DL	0.689***	0.621***	0.569***	0.575***	—

Source: created by the authors

The structural relationships between the constructs were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. PLS-SEM was used because the objective of this study is to explain and predict FAIR Readiness and to examine the mediating role of AI Readiness. In contrast to covariance-based SEM, which primarily evaluates overall model fit, PLS-SEM emphasizes explaining variance in the dependent constructs and assessing the strength of structural relationships. This approach is therefore appropriate for analysing mediation effects and identifying key drivers of FAIR Readiness within a multi-dimensional readiness framework [34]. The analytical process in PLS-SEM consists of two main components: measurement model assessment, which evaluates the reliability and validity of the constructs, and structural model assessment, which tests the hypothesized relationships among those constructs. Figure 1 shows the basic node diagram with loading values.

Measurement model assessment was done to ensure the reliability and validity of the constructs before proceeding with structural model evaluation (Table 3, Appendix). The results demonstrated that all items had satisfactory outer loadings, exceeding the recommended threshold of 0.70, with values ranging from 0.773 to 0.919. This confirms adequate indicator reliability and supports the unidimensionality of each latent construct [37]. Furthermore, all Variance Inflation Factor (VIF) values were well below the threshold value of 5.0, indicating no issues of multicollinearity among items.

Internal consistency reliability was examined by using Cronbach's alpha and composite reliability (pa and pc), with cutoff value of 0.70. Specifically, Cronbach's alpha values ranged from 0.873 (AW) to 0.946 (FR), while composite reliability values

ranged from 0.908 (AW) to 0.959 (FR), indicating strong internal consistency among the constructs.

Convergent validity was assessed using Average Variance Extracted (AVE), where all constructs exceeded the benchmark of 0.50 [39]. The AVE values ranged from 0.663 (AW) to 0.822 (FR), suggesting that each construct explains a substantial portion of the variance in its respective indicators.

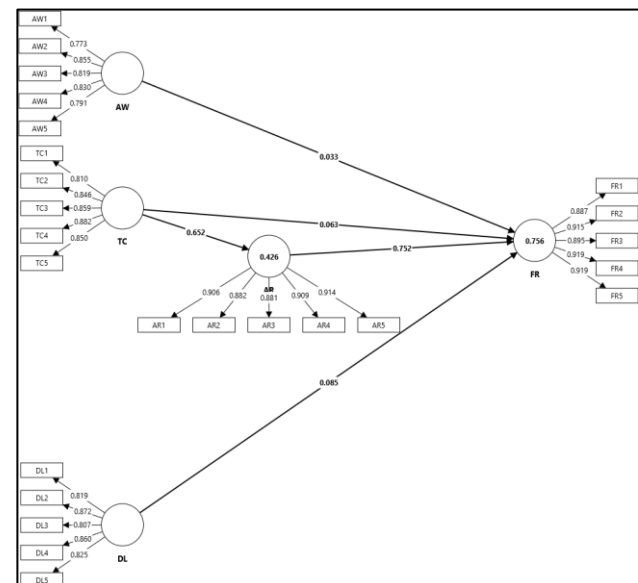


Fig. 1: Basic node diagram with loading

Source: created by the authors

Table 4 presents the cross-loadings of each item on all constructs, demonstrating that every indicator loads highest on its designated construct. This pattern supports the unidimensionality of the measurement model and confirms discriminant validity at the item-level [38]. Following the standard procedures of PLS-SEM, an item is said to have a higher loading on the associated latent construct than on any other construct, which indicates that the constructs are conceptually unique and statistically distinct within the measurement model framework.

Table 5 presents the Fornell-Larcker criterion. The diagonal values represent the square root of AVE for each construct, which is higher than the inter-construct correlations represented by off-diagonal values. The diagonal value for AR is 0.898 which is higher than its correlations with AW (0.595), DL (0.574), FR (0.862) and TC (0.652) for example. This indicates a sufficient discriminant validity, affirming that each construct captures a unique conceptual domain in the structural model [39].

Table 4. Cross Loading

	AR	AW	DL	FR	TC
AR1	0.906	0.546	0.525	0.788	0.611
AR2	0.882	0.555	0.547	0.769	0.586
AR3	0.881	0.541	0.515	0.722	0.589
AR4	0.909	0.505	0.463	0.775	0.566
AR5	0.914	0.526	0.527	0.815	0.579
AW1	0.548	0.773	0.533	0.549	0.476
AW2	0.482	0.855	0.636	0.464	0.523
AW3	0.469	0.819	0.532	0.423	0.456
AW4	0.462	0.830	0.510	0.454	0.490
AW5	0.439	0.791	0.576	0.426	0.434
DL1	0.452	0.497	0.819	0.471	0.484
DL2	0.521	0.583	0.872	0.527	0.580
DL3	0.399	0.577	0.807	0.396	0.490
DL4	0.537	0.575	0.860	0.512	0.550
DL5	0.473	0.638	0.825	0.498	0.492
FR1	0.743	0.478	0.458	0.887	0.517
FR2	0.781	0.516	0.556	0.915	0.563
FR3	0.751	0.518	0.541	0.895	0.552
FR4	0.815	0.572	0.548	0.919	0.604
FR5	0.814	0.524	0.518	0.919	0.599
TC1	0.526	0.451	0.498	0.496	0.810
TC2	0.560	0.558	0.582	0.578	0.846
TC3	0.610	0.503	0.535	0.591	0.859
TC4	0.564	0.488	0.508	0.520	0.882
TC5	0.499	0.487	0.517	0.457	0.850

Source: created by the authors

Table 5. Fornell-Larcker Criterion Results

	AR	AW	DL	FR	TC
AR	0.898				
AW	0.595	0.814			
DL	0.574	0.685	0.837		
FR	0.862	0.576	0.579	0.907	
TC	0.652	0.587	0.622	0.626	0.850

Source: created by the authors

The Heterotrait–Monotrait (HTMT) ratio of correlations is one of the most powerful methods of assessing discriminant validity in structural equation modeling (SEM) such as PLS-SEM. The HTMT values below the threshold of 0.85 (conservative) or 0.90 (liberal) are considered to be indicative of the adequate discriminant validity, [40]. The results of the HTMT analysis suggest that most of the pairs of constructs have discriminant validity with values below the recommended threshold of 0.90 (Table 6). HTMT value between AI Readiness and FAIR Readiness is above this threshold (HTMT = 0.912), which shows that there is a very strong association

between the two constructs. This result is explicitly acknowledged and suggests a close relationship between AI Readiness and FAIR Readiness. From a theoretical perspective, this association is expected, as AI Readiness represents an enabling capability, whereas FAIR Readiness reflects the institutional realization of FAIR data governance practices. Importantly, Crucially, the Average Variance Extracted (AVE) values for both AI Readiness and FAIR Readiness surpass the squared inter-construct correlation, providing further evidence for construct separation even with the high HTMT value. These results are consistent with the view that the two constructs are sequential but analytically distinct components of the readiness framework, as are the observed full mediation structure.

Table 6. HTMT Ratio Results

	AR	AW	DL	FR	TC
AR					
AW	0.651				
DL	0.622	0.776			
FR	0.912	0.625	0.624		
TC	0.704	0.656	0.689	0.672	

Source: created by the authors

Table 7 presents the direct relationships among constructs. AI Readiness (AR) significantly predicted FAIR Readiness (FR) ($\beta = 0.752$, $p < 0.001$), indicating the critical role of AI capabilities in enhancing FAIR Readiness. Further, Technical Capacity (TC) was found to be significantly predicted AI Readiness ($\beta = 0.652$, $p < 0.001$), indicating that the investments in IT infrastructure and technical resources foster AI maturity. However the effect of Awareness (AW) and Digital Literacy (DL) on FAIR Readiness was not statistically significant ($p > 0.05$), suggesting that their influence is either indirect or context specific, in line with our recent observation that soft factors impact the implementation of FAIR only when system level capabilities exist [41].

Table 8 shows the results of the mediation analysis. The indirect effect of Technical Capacity (TC) on FAIR Readiness (FR) through AI Readiness (AR) is significant ($\beta = 0.491$, $t = 10.002$, $p < 0.001$). The results confirm that AI Readiness is an important mediating variable, indicating that the positive effect of technical infrastructure on FAIR principles is not a direct effect, but rather mediated by the institution's preparedness and ability to implement AI solutions. Thus, institutions with greater technical capacity are more likely to achieve

FAIR data outcomes when they invest in AI capabilities in parallel.

Table 7. Bootstrap Results for the Inner Model Regression Paths (direct effect)

Path	Original sample (O)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Decision
AR -> FR	0.752	0.059	12.829	0.000	Supported
AW -> FR	0.033	0.043	0.759	0.448	Not Supported
DL -> FR	0.085	0.049	1.755	0.079	Not Supported
TC -> AR	0.652	0.043	15.287	0.000	Supported
TC -> FR	0.063	0.072	0.878	0.380	Not Supported

Source: created by the authors

To further quantify the strength of the mediation effect, the Variance Accounted For (VAF) was calculated as the ratio of the indirect to total effect. Technical Capacity on FAIR Readiness thru AI Readiness was $\beta = 0.491$. Direct effect was $\beta = 0.063$, total effect was $\beta = 0.554$. The resulting VAF value is 0.886, suggesting that about 88.6% of the total effect is transmitted thru AI Readiness. This supports full mediation and suggests that Technical Capacity affects FAIR Readiness mainly thru its effect on AI Readiness.

Table 8. Bootstrap Results for the Inner Model Regression Paths (Mediation Analysis)

	Original sample (O)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Decision
TC -> AR -> FR	0.491	0.049	10.002	0.000	Supported

Source: created by the authors

4 Discussion

In this research, the factors impacting FAIR and Open Data Framework implementation in Kuwaiti research institutions are empirically assessed. The findings provide important insights into the impacts that technical infrastructure, human skills,

organizational awareness, and artificial intelligence (AI) readiness have on data governance.

4.1 AI Readiness as a Strategic Enabler

Incorporating artificial intelligence (AI) into organizational frameworks is become increasingly recognized as a key component of AI readiness, which facilitates adherence to the FAIR principles of data management. Such principles include accessibility, findability, interoperability, and reusability. There is robust evidence to indicate that institutions are better able to align their data stewardship processes with these principles if they develop strong AI readiness, which ultimately improves their overall research data ecosystems. This alignment is critical as AI technologies facilitate automation, intelligent search capabilities, metadata generation, and semantic tagging, all of which play vital roles in effective data stewardship within contemporary research settings [30].

Furthermore, it was also shown that AI readiness mediates the relationship between an organization's technical capacity and its FAIR readiness. This mediation suggests that although investments in technical infrastructure are valuable, the value of such investments depends on the ability of the institution to successfully embed AI into its research management strategies. FAIR readiness is better described as a digitally-enabled process, rather than merely an outcome of technical infrastructure. In this case, AI serves as a bridging mechanism, converting raw capacity into actionable data governance frameworks, thereby improving the operational capabilities of institutions [42]. The strong dominant effect of AI Readiness on FAIR Readiness further supports its role as a central transmission mechanism rather than a competing predictor. The high explanatory power of FAIR Readiness ($R^2 = 0.756$) indicates that the successful implementation of FAIR is largely driven by an institution's ability to operationalize technical and organizational resources through AI-enabled systems. Such dominance rather than suggesting model misspecification supports the proposed full mediation structure where AI readiness acts as the primary conduit passing technical capacity to FAIR outcomes.

This bridging role becomes clearer when considering how AI-enabled functions activate the technical resources already available within an institution. AI systems support automated metadata generation, standardized classification of datasets, semantic tagging, and intelligent search capabilities—functions that directly enhance findability, accessibility, interoperability, and

reusability. In this way, AI Readiness reflects an institution's ability to operationalize its technical capacity through these intelligent functions, allowing raw infrastructure such as storage systems, repositories, and IT platforms to be utilized in ways that meet FAIR requirements.

AI Readiness and FAIR Readiness are two analytical steps in the data governance process that are closely related but are not the same thing. AI Readiness is the potential of an institution to use intelligent systems including its preparedness of infrastructure, strategic alignment, and confidence of the organization to use AI. By contrast, FAIR Readiness captures the real operational outcome of these capabilities, i.e. the extent to which data practices adhere to FAIR principles. Thus, the strong path coefficient between these constructs reflects a sequential capability-outcome relationship rather than conceptual overlap. This distinction is also evident in the full mediation effect, which suggests that technical capacity only affects FAIR Readiness after being transformed by AI-enabled processes.

The contribution of AI to improve operational efficiencies is also remarkable. Institutions that are more prepared for AI can make research workflows more efficient, reducing the usual intricacies of data landscapes. This simplifies the research processes and enables organizations to respond to the dynamic nature of data environments. AI becomes an operational enabler, rather than a mere technological asset, through enabling smart automation and promoting data-driven decision making, which profoundly transforms the way in which institutions manage and leverage their data assets for R&D purposes [43].

A comprehensive understanding of AI readiness reveals its critical position in fostering FAIR readiness and optimizing research data management. As institutions increasingly engage with sophisticated AI frameworks, their capability to integrate technology and streamline operations will likely define the future landscape of research data governance, ensuring that data practices are both innovative and aligned with the established principles of effective data management [44].

4.2 Technical Capacity as a Foundational Driver

Technical skills are also key to an institution's readiness to adopt artificial intelligence (AI) solutions. Institutions that have strong digital infrastructure [45] – such as reliable data storage, large data repositories and advanced IT systems – are much better positioned to incorporate AI

technologies. This is in line with findings from other related studies, which show that digital infrastructure provides the foundation for innovation and facilitation of systemic transformation [46]. For example, organizations with high levels of IT resources (e.g., experienced IT workers and relevant technologies) are more capable to leverage AI effectively [31]. In parallel with the need for AI readiness, Newby et al. underscore the importance of sufficient infrastructure, with sufficient IT resources needed to support technology adoption [47].

However, while a strong technical capacity is necessary, it is not sufficient for readiness for effective AI integration. In fact, recent studies have shown that advanced infrastructure does not necessarily lead to data practices that reflect the FAIR (Findable, Accessible, Interoperable and Reusable) principles, and that an extra level of strategic alignment and intelligent application of technology is needed [48]. For example, Jöhnk et al. found that the complexities related to AI adoption emphasize the need of tailored strategies that are not just about infrastructural readiness [31]. This emphasizes the need for organizations to have the infrastructure as well as the strategic mindset and understanding of AI applications to implement effective solutions.

Moreover, previous studies highlight the importance of human factors such as training and confidence in the use of AI technologies, thereby connecting the concept of technical capacity with human capital development [49], [50]. The link between an organisation's technical infrastructure and human capacity suggests that both are needed to optimise AI readiness. Karaca et al. [51] embrace this argument by stating the need for training programmes that teach future professionals the skills to interact successfully with AI systems. So this shows a direct relationship between the educational programs and the level of AI readiness in the medicine domain [52].

To summarize, although effective technical skills are required to adopt AI technologies, strategic alignment and educational initiatives are also critical in improving infrastructure and human readiness to use such technologies. It is essential to understand this relationship between technology and human factors in order to establish an environment that facilitates the successful incorporation of AI across various sectors.

4.3 Limited Direct Impact of Awareness and Digital Literacy

No significant, direct impacts on awareness of FAIR/Open Data and digital literacy were found to exert any significant, direct impacts on FAIR readiness, despite expectations to the contrary. This may be a result of the contextual realities present in Kuwait's research ecosystem, in which institutional structures and national mandates for Open Data are still in their infancy. Moreover, awareness and literacy may serve as critical preconditions, but their influence is weak in the absence of relevant organizational frameworks and implementation pathways. Similar findings have been revealed for other developing and transitional systems, in which individual readiness has failed to result in institutional transformation when structural support has not been established [14].

These results show that capacity building efforts are still important but need to be complemented by institutional policies, automated systems, and coordinated strategies to reach FAIR maturity. Awareness and skills alone will not guarantee system-level behavioural or procedural change.

The nonsignificant direct effects of Awareness and Digital Literacy do not confirm that these factors are unimportant. Rather, it suggests that awareness and digital skills serve as foundational enablers that support system-level capabilities, such as technical infrastructure and AI readiness, rather than being direct determinants of FAIR readiness. This indicates that individual knowledge may not be enough to implement FAIR-compliant practices without institutional and technological support. The present results underscore the importance of Awareness and Digital Literacy, but **alternative** model specifications could explore whether their effects are conditional rather than direct, for example through non-linear relationships, threshold effects or subgroup differences. The present study prioritizes a parsimonious explanation of the core readiness mechanism, leaving these analytical extensions for future investigation.

5 Conclusion

In this research, a timely and evidence-based evaluation of institutional readiness for FAIR and Open Data adoption in Kuwait has been conducted. This assessment has included organizational, technical, and technological components. This study incorporates a robust PLS-SEM framework, which presents AI readiness as a mediator between technical skills and FAIR outcomes. In turn, this

demonstrates that the presence of infrastructure alone is not sufficient and a strategic capability to leverage AI is also required.

Importantly, The policy discourse stresses the importance of awareness and digital proficiency. Neither of these two factors, however, was found to have a significant direct impact on FAIR readiness in this study. Individual competencies are necessary but not sufficient for enacting real change. Institutional transformation requires the development of coherent mechanisms, iude clear governance frameworks, enabling organizational structures and integrated technological systems. The results suggest that system-level interventions are important for translating data management principles into sustainable research practices. So that's why it's important to create interventions that integrate AI functionality into data management workflows. This research thus provides actionable insights for Kuwait and other emerging research ecosystems. AI should thus be considered a strategic infrastructure tool for research data governance, and not merely considered a technological asset. It is recommended that institutions prioritize investments in AI frameworks, training, and digital workflows to effectively operationalize FAIR principles.

This study proposes a new framework for implementing FAIR readiness in the digital era, focusing specifically on the symbiotic relationship between infrastructure, intelligence, and institutional will. To advance open science and research innovations in Kuwait and other similar contexts, it is critical to strengthen this triad.

5.1 Future Research Directions

Future research should consider exploring the relationship between the organizational culture, leadership and change management and adoption of FAIR principles. In addition, comparative studies among GCC countries would be important to emphasize local patterns and harmonize support policies. Meanwhile, longitudinal studies can be used to monitor and track institutional progress in terms of FAIR compliance over time. In future, studies with larger samples could also be beneficial in evaluating the measurement invariance of AI Readiness in different public and private institutions. To achieve this, multi-group or MICOM processes should be considered. Additionally, future studies should consider alternative model specifications, such as higher-order or second-order factor structures. Nonetheless, it is important to remember that the present study employs a sequential mediation framework to preserve the conceptual differences between AI

Readiness as an enabling capability and FAIR Readiness as an actual governance outcome. Post-hoc power analyses and larger samples could be included in future studies to further confirm the strength of the non-significant direct effects identified for Awareness and Digital Literacy.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

References:

- [1] Crouch, L. (2015). A relevant data revolution for development. RTI Press. <https://doi.org/10.3768/rtipress.2015.pb.0007.1506>.
- [2] Hilbert, M. (2015). Big data for development: A review of promises and challenges. *Development Policy Review*, 34(1), 135-174. <https://doi.org/10.1111/dpr.12142>.
- [3] Yoon, A. (2016). Data reusers' trust development. *Journal of the Association for Information Science and Technology*, 68(4), 946-956. <https://doi.org/10.1002/asi.23730>.
- [4] Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., ... & Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data*, 3, 160018. <https://doi.org/10.1038/sdata.2016.18>.
- [5] Jacobsen, A., Azevedo, R., Juty, N., Batista, D., Coles, S., Cornet, R., ... & Schultes, E. (2020). FAIR principles: Interpretations and implementation considerations. *Data Intelligence*, 2(1-2), 10-29. https://doi.org/10.1162/dint_r_00024.
- [6] Faniel, I., Kriesberg, A., & Yakel, E. (2015). Social scientists' satisfaction with data reuse. *Journal of the Association for Information Science and Technology*, 67(6), 1404-1416. <https://doi.org/10.1002/asi.23480>.
- [7] Cox, A. M., Kennan, M. A., Lyon, L., Pinfield, S., & Sbaffi, L. (2019). Maturing research data services and the transformation of academic libraries. *Journal of Documentation*, 75(6), 1432-1462. <https://doi.org/10.1108/JD-12-2018-0211>.
- [8] Koers, H., Bangert, D., Hermans, E., van Horik, R., de Jong, M., & Mokrane, M. (2020). Recommendations for services in a FAIR data ecosystem. *Patterns*, 1(5), 100058. <https://doi.org/10.1016/j.patter.2020.100058>.
- [9] Goble, C., Cohen-Boulakia, S., Soiland-Reyes, S., Garijo, D., Gil, Y., Crusoe, M., ... & Schober, D. (2020). FAIR computational workflows. *Data Intelligence*, 2(1-2), 108-121. https://doi.org/10.1162/dint_a_00033.
- [10] Hidalgo, A., Goodall, J., Anyika, C., Matthews, B., & Catlow, C. (2022). Designing a data infrastructure for catalysis science aligned to FAIR data principles. *Catalysis Communications*, 162, 106384. <https://doi.org/10.1016/j.catcom.2021.106384>.
- [11] Ivanova, I., Brown, N., Fraser, R., Tengku, N., & Rubinov, E. (2019). FAIR and standard access to spatial data as the means for achieving sustainable development goals. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-4/W20, 33-39. <https://doi.org/10.5194/isprs-archives-xlii-4-w20-33-2019>.
- [12] Boeckhout, M., Zielhuis, G., & Bredenoord, A. (2018). The FAIR guiding principles for data stewardship: Fair enough? *European Journal of Human Genetics*, 26(7), 931-936. <https://doi.org/10.1038/s41431-018-0160-0>.
- [13] World Bank. (2021). *World Development Report 2021: Data for Better Lives*. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-1600-0>.
- [14] Heeks, R., & Renken, J. (2016). Data justice for development. *Information Development*, 34(1), 90-102. <https://doi.org/10.1177/0266666916678282>.
- [15] AlGhurair, S., AlMatori, K., AlHassawi, M., & AlSubaie, R. (2017). Open Government Data in the State of Kuwait. 26th Meeting of the INTOSAI Working Group on IT Audit, Korea.
- [16] Jones, S., & Grootveld, M. (2017). How FAIR are your data? Zenodo. <https://doi.org/10.5281/zenodo.1065991>.
- [17] Khaleghian, H., & Shan, Y. (2023). Developing a data quality evaluation framework for sewer inspection data. *Water*, 15(11), 2043. <https://doi.org/10.3390/w15112043>.
- [18] Yenni, G. M., Christensen, E. M., Bledsoe, E. K., Supp, S. R., Diaz, R. M., White, E. P., &

- Ernest, S. K. M. (2019). Developing a modern data workflow for regularly updated data. *PLoS Biology*, 17(1), e3000125. <https://doi.org/10.1371/journal.pbio.3000125>.
- [19] Liu, Z., & Yao, T. (2024). Strategizing earth science data development. *Scientific Data*, 11(1). <https://doi.org/10.1038/s41597-024-03531-6>.
- [20] Alrabea, K. J., Alsaffar, M., Alsafran, M. A., Alsaber, A., Almutairi, S., Al-Saeed, F., & Alkandari, A. M. (2024). Artificial intelligence and cybersecurity within a social media context: Implications and insights for Kuwait. *Journal of Science and Technology Policy Management*. <https://doi.org/10.1108/JSTPM-12-2023-0224>.
- [21] AlHussainan, O. N., AlFayyadh, M. A., Al-Sabe, A., & Alkandari, A. M. (2022). The factors of e-government service quality in Kuwait during the Coronavirus Disease 2019 pandemic. *International Journal of Electronic Government Research*, 18(1), 1-19. <https://doi.org/10.4018/IJEGR.313176>.
- [22] Allamki, Z. (2013). The readiness of open access policy implementation: A case study within a Kuwaiti higher education institute (Doctoral dissertation). University of Salford.
- [23] Burgi, P.-Y., Blumer, E., & Makhoulf-Shabou, B. (2017). Research data management in Switzerland: National efforts to guarantee the sustainability of research outputs. *IFLA Journal*, 43(1), 5-21. <https://doi.org/10.1177/0340035216678238>.
- [24] Awadallah, R., Alagha, I., & Miksa, T. (2019). Setting up open access repositories: Challenges and lessons from Palestine. *OSF*. <https://doi.org/10.17605/OSF.IO/XP93J>.
- [25] AlReshaid, F., Park, K. M., Vogel, B., Graca, A., & Ikwuegbu, O. (2025). Collaborative leadership dynamics: Joint evolution of chair and CEO roles. *Journal of Strategy and Management*, 18(4), 793-820.
- [26] Bardel, F., & Hasani-Mavriqi, I. (2023). FAIR Data Austria: Capacity building for research data infrastructure. *Data Intelligence*, 5(2), 167-182.
- [27] Koltay, T. (2017). Data literacy for researchers: Expanding competencies. *Journal of Librarianship and Information Science*, 49(1), 3-14.
- [28] Carlson, J. (2010). The Data Curation Profiles Toolkit: User guide. Purdue University Libraries. <https://doi.org/10.5703/1288284314996>.
- [29] Gonzalez Soltero, R., Pino Garcia, D., Bellido, A., et al. (2024). FAIR data management: A framework for fostering data literacy in biomedical sciences education. *BMC Medical Research Methodology*, 24, 284. <https://doi.org/10.1186/s12874-024-02404-1>.
- [30] Hecker, D., Voss, A., & Wrobel, S. (2022). Data ecosystems: A new dimension of value creation using AI and machine learning. In *Designing Data Spaces* (pp. 211-224). Springer. https://doi.org/10.1007/978-3-030-93975-5_13.
- [31] Johnk, J., Weissert, M., & Wyrski, K. (2020). Ready or not, AI comes - An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), 5-20. <https://doi.org/10.1007/s12599-020-00676-7>.
- [32] Clark, T., Caufield, H., Parker, J. A., Al Manir, S., Amorim, E., Eddy, J., ... & Munoz-Torres, M. C. (2024). AI-readiness for biomedical data: Bridge2AI recommendations. *bioRxiv*. <https://doi.org/10.1101/2024.10.23.619844>.
- [33] Hiniduma, K., Byna, S., Bez, J. L., & Madduri, R. (2024). AI Data Readiness Inspector (AIDRIN) for quantitative assessment of data readiness for AI. In *Proceedings of the 36th International Conference on Scientific and Statistical Database Management (SSDBM '24)*. ACM. <https://doi.org/10.1145/3676288.3676296>.
- [34] Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107-123.
- [35] Al-Shamali, S., Al-Shamali, A., AlSaber, A., Haffar, M., Alkandari, A. M., Alkashti, F., & Aljuwaisri, A. (2025). Understanding mobile payment platform adoption: The mediating role of perceived security and trust in the Kuwaiti market. *International Journal of Customer Relationship Marketing and Management*, 16(1), 1-24.
- [36] Alsabab, M., Alsaber, A., AlReshaid, F., Moharrak, M., Boresli, N., & Al-Kandari, A. (2025). Exploring the convergence of technology acceptance and financial literacy: A study on sustainable credit card use in an emerging economy. *International Review of Management and Marketing*, 15(4), 45-57.
- [37] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to

- report the results of PLS-SEM. *European Business Review*, 31(1), 2-24.
- [38] Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.
- [39] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- [40] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115-135.
- [41] Alkandari, F., Alsaber, A., Al-Kandari, A., Alboloushi, B., & AlMutairi, S. (2024). Enhancing the effectiveness of digital transformation on teaching in higher education in Kuwait. *Frontiers in Education*, 9, 1417062. <https://doi.org/10.3389/feduc.2024.1417062>.
- [42] Jankovic, S., & Curovic, D. (2023). Strategic integration of artificial intelligence for sustainable businesses: Implications for data management and human user engagement in the digital era. *Sustainability*, 15(21), 15208. <https://doi.org/10.3390/su152115208>.
- [43] Roundy, P. (2022). Artificial intelligence and entrepreneurial ecosystems: Understanding the implications of algorithmic decision-making for startup communities. *Journal of Ethics in Entrepreneurship and Technology*, 2(1), 23-38. <https://doi.org/10.1108/jeet-07-2022-0011>.
- [44] Visconti, R. (2024). Collaborative natural and artificial intelligence: A multilayer network interpretation. Preprints. <https://doi.org/10.20944/preprints202407.0777.v1>.
- [45] Alainati, S., Alsaber, A., Alkandari, A., AlReshaid, F., & Alaslawi, H. (2025). Employee performance in the digital era: The interplay of digital competencies, agility, and creativity. *International Journal of Operations and Quantitative Management*, 31(2), 354-375.
- [46] Al-Okaily, M., Al-Quran, L., Jassem, S., & AlReshaid, F. (2025). FinTech innovation in the digitalization era: A bibliometric literature review. *Global Knowledge, Memory and Communication*.
- [47] Newby, M., Nguyen, T., & Waring, T. (2014). Understanding customer relationship management technology adoption in small and medium-sized enterprises. *Journal of Enterprise Information Management*, 27(5), 541-560. <https://doi.org/10.1108/jeim-11-2012-0078>.
- [48] Holub, P., Kohlmayer, F., Prasser, F., Mayrhofer, M., Schlunder, I., Martin, G., ... & Litton, J. (2018). Enhancing reuse of data and biological material in medical research: From FAIR to FAIR-Health. *Biopreservation and Biobanking*, 16(2), 97-105. <https://doi.org/10.1089/bio.2017.0110>.
- [49] Luckin, R., Cukurova, M., Kent, C., & du Boulay, B. (2022). Empowering educators to be AI-ready. *Computers and Education: Artificial Intelligence*, 3, 100076. <https://doi.org/10.1016/j.caeai.2022.100076>.
- [50] Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of Business Research*, 131, 485-494. <https://doi.org/10.1016/j.jbusres.2020.08.018>.
- [51] Karaca, O., Caliskan, S., & Demir, K. (2021). Medical artificial intelligence readiness scale for medical students (MAIRS-MS): Development, validity and reliability study. *BMC Medical Education*, 21(1), 112. <https://doi.org/10.1186/s12909-021-02546-6>.
- [52] Jones, O., Matin, R., Schaar, M., Bhayankaram, K., Ranmuthu, C., Islam, M., ... & Walter, F. (2022). Artificial intelligence and machine learning algorithms for early detection of skin cancer in community and primary care settings: A systematic review. *The Lancet Digital Health*, 4(6), e466-e476. [https://doi.org/10.1016/s2589-7500\(22\)00023-1](https://doi.org/10.1016/s2589-7500(22)00023-1).

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)

This article is published under the terms of the Creative Commons Attribution License 4.0

https://creativecommons.org/licenses/by/4.0/deed.en_US

APPENDIX

Table 3. Outer model summary table for PLS-SEM

Construct	Item	Loading	VIF	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AR	AR1	0.906	3.632	0.940	0.941	0.954	0.807
	AR2	0.882	2.975				
	AR3	0.881	3.025				
	AR4	0.909	3.865				
	AR5	0.914	4.057				
AW	AW1	0.773	1.674	0.873	0.877	0.908	0.663
	AW2	0.855	2.385				
	AW3	0.819	2.306				
	AW4	0.830	2.156				
	AW5	0.791	1.996				
DL	DL1	0.819	2.156	0.893	0.898	0.921	0.700
	DL2	0.872	2.670				
	DL3	0.807	2.150				
	DL4	0.860	2.443				
	DL5	0.825	2.062				
FR	FR1	0.887	3.211	0.946	0.947	0.959	0.822
	FR2	0.915	3.990				
	FR3	0.895	3.399				
	FR4	0.919	4.196				
	FR5	0.919	4.197				
TC	TC1	0.810	2.005	0.904	0.907	0.928	0.722
	TC2	0.846	2.293				
	TC3	0.859	2.443				
	TC4	0.882	3.063				
	TC5	0.850	2.657				

Source: created by the authors