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Evenly Is Even Better? Digital Competitiveness and the Quality of Medical Research

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Abstract: The combination of rapid advances in digital technology and the COVID-19 pandemic has increased the importance of knowledge sharing and balanced advances in medical research. This study explored how digital competitiveness influences the diverse quality of medical research in vital areas. Based on our synthesized framework of research quality, we found that digital competitiveness benefits medical research broadly but not evenly. While digital competitiveness was positively associated with impactful research across all four fields in vital areas, the relationship between digital competitiveness and science-based and explorative research varied depending on the field. By focusing on the quality of medical research rather than a specific medical service, our study offers meaningful implications for knowledge sharing and collaborative research, which are key conditions for the sustainable development of medicine.

Keywords: digital technology; quality of medical research; COVID-19

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1. Introduction

Digital technologies have significantly accelerated advancements in medical research. Particularly, the COVID-19 pandemic has accelerated the progress of both the development and utilization aspects of digital technology in medical research [1,2]. Digital technologies have also revolutionized the way we cope with the pandemic [3]. This is because digital technologies have increased the speed with which we can manage and utilize large volumes of medical data. In this context, digital technologies have been actively utilized to solve major clinical issues and fight diseases, and their use in the medical field is expected to grow steadily in the future.

Employing digital technologies in medicine requires integrated systems that incorporate knowledge across multiple fields, including medicine, technologies, and institutional systems [1,4–6]. Complex challenges, such as pandemics, make it especially critical to share and integrate expert knowledge to benefit patients [7]. For instance, COVID-19 has increased the need for customized treatments and multidisciplinary teams (MDTs) to support physicians in optimizing cancer care [8,9].

The use of digital technology in medical research has great potential. Appropriate use of digital technology can significantly improve efficiency and efficacy in clinical trials, which is essential for high-quality medical research [10–13]. However, incautious adoption of unproven technologies can cause unintended or unexpected side effects. Although it is clear that the adoption of digital technologies can facilitate the development of medical research, the benefits may not be evenly distributed across diverse fields. Thus, digital technology might benefit medical research broadly but not necessarily.

This study explores how digital competitiveness impacts the quality of medical research. Using country-level data on digital competitiveness and medical research quality in vital areas (e.g., surgery, internal medicine, pediatrics, perinatology and child health, obstetrics and gynecology, and internal medicine), we conducted an empirical analysis considering three types of medical research quality to address three questions: (1) "Does digital competitiveness lead to more science-based research?"; (2) "Does digital competitiveness lead to more impactful research?"; (3) and "Does digital competitiveness lead to more explorative research?". We then examined the cross-field variances in the vital areas.

We found that, while digital competitiveness was positively associated with impactful research across fields in vital areas, the relationship between digital competitiveness and the other two types of research quality varied by field. For example, digital competitiveness benefitted all three types of research quality in surgery but only one type in obstetrics and gynecology.

We found that digital competitiveness is related to higher impactful research in all four fields: surgery, pediatrics, perinatology and child health, obstetrics and gynecology, and internal medicine. Certainly, this is an encouraging phenomenon for medical research because publishing more high-impact research implies that the possibility of sustainable development of the focal discipline increases. However, it is also noteworthy that the benefit of digital competitiveness is contingent upon different types of qualities, science-based research, and explorative research. Although this may not cause serious issues in the short term, it is noteworthy to draw the attention of researchers. In highlighting the role of digital competitiveness in improving the quality of medical research, our study draws attention to the importance of understanding the prerequisites for balanced advances in medical research.

Summary of Contributions

The remainder of this paper is organized as follows. In Section 2, we discuss how advances in digital technology have been linked to improvements in medical research. Section 3 introduces a synthesized framework for research quality based on a literature review. Section 4 presents our empirical analysis exploring the association between digital competitiveness and research quality and examines the variance across each field in vital areas. Section 5 demonstrates the results. Finally, Section 6 presents conclusions and implications.

2. Digital Technology, Clinical Trials, and Medical Research

Discussions on digital technologies in medical research generally include the Internet of Things (IoT) [4], Big Data analysis [5], deep learning artificial intelligence (AI) [6], and blockchains [14] as part of digital health systems in hospitals or clinics [1]. For example, the expansion of the IoT has enabled the real-time collection of large-scale, highly interconnected medical data that can be used to "train" AI to understand medical trends or models to forecast potential risks. Digital technologies can significantly improve monitoring, surveillance, detection, and prevention efforts vital for coping with pandemics. They also contribute significantly to epidemiology and pharmacology, including vaccine development and therapeutics [1].

Clinical trials are crucial in medical research. They provide researchers with the basic knowledge and data required to investigate causality and to verify the efficacy and safety of new therapies, drugs, and devices. Clinical trials are the central mechanisms for assessing or proposing preventive measures and diagnoses [12]. However, it is challenging to conduct efficient clinical trials. Inefficiencies could arise at many stages, including participant identification and recruitment, data collection, and analysis, lowering clinical trial participation rates. For example, only about 8% of cancer patients enroll in cancer-related clinical trials [15]. Other barriers to high participation rates in clinical trials include the physical distance between patients and hospitals, financial costs, and scheduling problems [16]. Unfortunately, the infrastructure and environment for clinical research have changed little over the years, and clinical trial logistics remains demanding and expensive.

Digital technology can provide a stepping stone for improving clinical trials both qualitatively and quantitatively. Conducting virtual clinical trials, whether wholly or partially, can mitigate some of the real-life limitations that depress trial participation [12]. This can enhance the quality of the clinical trials in two ways.

First, the adoption of digital technology can improve clinical trial accuracy by simplifying the key steps to make them more reliable. According to Inan et al. [10], digital clinical trials follow three steps: digital recruitment and retention (finding, enrolling, and managing participants); digital data collection (data mining and processing); and digital analytics (data analysis and modeling). Digital technology can improve participant recruitment and retention through social media engagement and online consenting. It can improve real-time data collection through wearable and mobile-sensing technologies. Finally, it can improve analysis and modeling using AI. Thus, digital clinical trials can minimize or eliminate many obstacles that constrain traditional clinical trials, enabling qualitative improvements and saving resources.

Second, digital technology can improve medical education, which is essential for nurturing high-quality medical research. Researchers' levels of medical knowledge decisively influence their ideas and clinical trials. Currently, there is a gap between the education provided by medical institutions and the knowledge required to conduct high-quality clinical trials [17]. It is difficult for researchers to practice all theoretically learned medical tests in real life. Digital technology can overcome this limitation by reproducing the clinical experience in a virtual space. Students can learn medical techniques, gain firsthand knowledge, and efficiently analyze data through virtual reality. For example, 3D surgery simulators using haptic technology enable students to practice surgical techniques without risking their lives or overburdening their resources. Quality medical knowledge can directly affect the innovativeness of clinical trials. Chen et al. [17] presented various application methods, such as medical education training, health and behavior tracking, operation playback and reproduction, and medical knowledge popularization when digital twin technology is used in medical education.

In summary, digital technology improves the quality of clinical trials and medical education—the basis of medical research—which improves medical research. Figure 1 shows a conceptual diagram of this process.

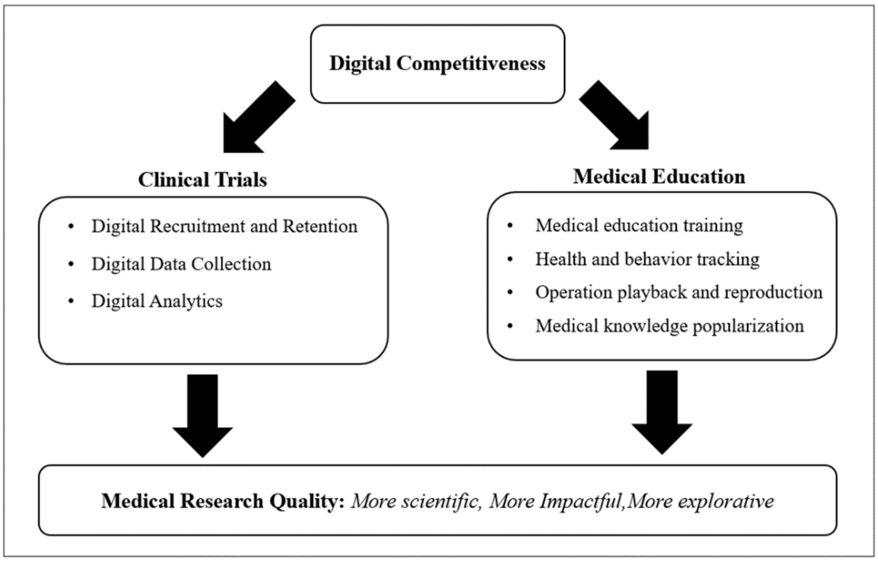

Figure 1. Effect of digital health technologies on medical research quality.

3. Synthesized Framework for Research Quality: Three Types of Research Quality

Academia depends on research to be sustainable and provide valuable insights. Therefore, understanding the nature and trajectory of research quality has received extensive attention from academia [18]. Perspectives are addressed separately in the literature to introduce a synthesized framework. Our framework explores the relationship between digital competitiveness and the quality of medical research using three indicators that represent different aspects of research quality, namely first-, second-, and third-order research.

3.1. First-Order Research Quality

This concerns whether a higher digital competitiveness leads to a more scientific approach to medical research. Numerous studies are published every year. However, knowing the document type is crucial for evaluating the quality of academic research [19], a widely acknowledged and used criterion in medical research is the distinction between citable and non-citable documents [20,21]. Citable documents are research articles and reviews based on scientific approaches; non-citable documents generally refer to other document types, such as editorials and letters. Accurately evaluating the academic quality of research requires distinguishing between the two [22]. Dong, Loh, and Mondry [23] argued that distinction between citable and non-citable documents is critical to evaluate the performance of research.

3.2. Second-Order Research Quality

This concerns whether higher digital competitiveness leads to more impactful medical research. The quality of citable published documents largely depends on how many researchers recognize and acknowledge the findings presented in the focal document. Despite some limitations and errors, forward citation count (the number of citations a focal document receives after publication) has been widely acknowledged and used as a proxy for the research quality of research groups and institutions in science and social science studies, including medical research [24–27].

3.3. Third-Order Research Quality

This concerns whether higher digital competitiveness leads to more explorative medical research. Similar to forward citations, citation behavior [28,29] is an important indicator of research quality. Self-citation (when authors cite their own work) is an exploitation-oriented citation behavior and narrows the deepened knowledge. Non-self-citation (when authors cite others' work) is exploration-oriented citation behavior that searches and absorbs external knowledge. Thus, high-quality explorative research is characterized by fewer self-citations than forward and external citations.

The ordinal number of research quality does not represent the hierarchy or superiority of the quality. Instead, it is discussed in chronological order of publication and citation, with each research quality representing distinct characteristics. Figure 2 illustrates the synthesized framework for research quality.

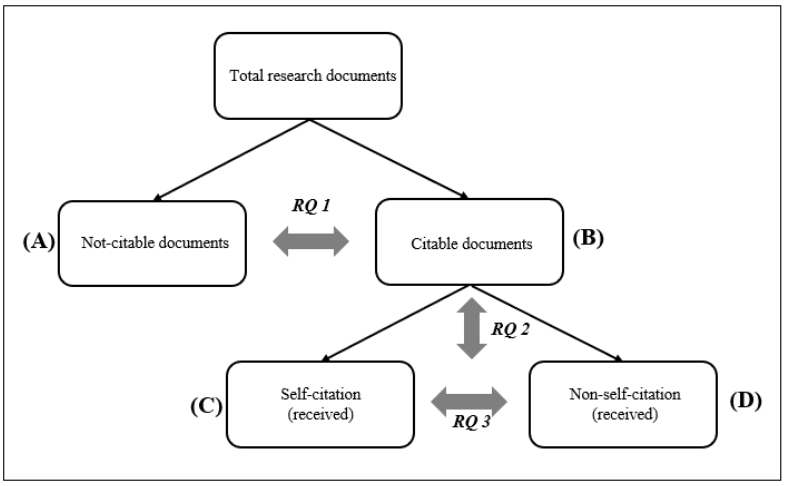

Figure 2. Synthesized framework for research quality.

4. Empirical Setting

Medical research is highly diversified. Therefore, in this study, we considered the effects of national digital competitiveness on research quality in only these vital areas in medicine: surgery, internal medicine, pediatrics, perinatology and child health, and obstetrics and gynecology, as they relate directly to mortality. Knowledge of these vital areas is especially critical during widespread health crises, such as the COVID-19 pandemic. Knowledge about how infectious diseases affect different body parts is critical in coping with unprecedented pandemics such as COVID-19. For instance, while the COVID-19 pandemic has tremendously impacted pediatric surgery, many patients have suffered from uncontrollable changes in the system [30]. Using regression analysis with country-level, unbalanced panel data, we examined the association between national digital competitiveness and three types of quality of research in each vital field.

4.1. Data and Sample

For our exploration of the impact of digital competitiveness on the diverse dimensions of medical research, we used several databases. Regarding national digital competitiveness (NDC), we used the World Digital Competitiveness data from the International Institute for Management Development (IMD), a top-tier global research institute in Switzerland. Since 1989, IMD's comprehensive annual report on national competitiveness with corresponding proxies has been widely acknowledged in various academic fields [31–34]. IMD provides a numerical value for each country based on 52 criteria covering knowledge, technology, and future readiness.

To estimate the diverse dimensions of medical research, we extracted data from the *SCImago Journal* and the *Country Rank* database. SCImago is an established data-mining and visualization group in Spain that provides a wide range of bibliometric data, including journals and citations. SCImago has been used in bibliometric research [20,21,35,36] and is well-regarded by top-tier journals, such as *Nature* and *Lancet* [37,38]. We obtained the raw numerical values of published medical documents and citation information for each country and constructed the relevant variables. Regarding control variables, drawing on multiple databases, we collected country-level data on gross domestic product (GDP), government protectionism, science research legislation, patent counts, health infrastructure, education expense, and innovation index. The details of this are discussed in the next section.

The final sample comprises 38 countries with 189 country-year observations between 2015 and 2020, which are unbalanced panel data. We used 2015 as the starting year because, interest in digital health has drastically increased owing to the emergence of digital transformation. We chose 2020 as the cutoff because of the truncation issue for research publication and citation information [39].

4.2. Variable Descriptions

Response variables. We constructed the different types of quality medical research using the number of published documents and citation information in surgery, pediatrics, perinatology and child health, obstetrics and gynecology, and internal medicine.

We measured the first-order research quality dimension, which is the ratio between non-citable documents and citable documents, as follows:

$$\textit{First order research quality}\ _{i,t,c} = \frac{\textit{Noncitable document}\ _{i,t,c}}{\textit{Citable document}_{i,t,c}}$$

where non-citable documents i, t, and c represent the number of non-citable documents published by country i in medical field c in year t; and citable documents i, t, and c represent the citable documents published by country i in medical field c in year t.

We measured the second-order research quality dimension as the ratio of total forward citations to citable documents as shown below:

$$\textit{Second order research quality}\ _{i,t,c} = \frac{\textit{Forward citations}\ _{i,t,c}}{\textit{Citable document}_{i,t,c}}$$

where total forward citations *i*, *t*, and *c* represent the number of forward citations; and citable documents *i*, *t*, and *c* represent the total number of citable documents published by country *i* in medical field *c* at time *t*.

We measured the third-order research quality dimension, which is the ratio of self-citations to non-self-citations received by the focal document after publication, as follows:

$$Third\ order\ \ research\ quality\ _{i,t,c} = \frac{Self\ citations\ _{i,t,c}}{Nonself\ citations_{i,t,c}}$$

where the total forward citations *i*, *t*, and *c* represent the number of self-citations; and non-self-citations *i*, *t*, and *c* represents the total number of citable documents published by country *i* in medical field *c* in year *t*.

Explanatory variables. We measured national digital competitiveness (NDC), using digital competitiveness ranking data from the IMD World Competitiveness Yearbook, which ranks digital competitiveness with scores from 0 to 10 and provides a comprehensive estimation of the digital and technological level of each country based on a combination of statistical and survey data. Digital initiatives for medical activities can be influenced by hospitals and public health systems [40].

We use the World Bank's gross domestic product (GDP) data as our control variable. Economic level has been cited as an indicator of digital technologies in healthcare [41]. We also controlled for policy instruments that might have influenced the quality and application of the research. Based on the IMD National Competitiveness Data, we controlled for the nations' government protectionism, scientific research legislation (laws relating to scientific research encourage innovation), and patent intensity that could influence the potential use of research knowledge and health infrastructure quality. Since the IMD measures health infrastructure based on relative criteria, the degree to which it meets the social needs of the focal society could be subjective. Hence, we also employed hospital density (measured as hospital beds per 1000 people) as an absolute criterion in the World Bank database.

As discussed, educational quality can influence the quality of medical research. To control for this effect, we used educational expenses (national spending per enrolled student) based on measures from the IMD World Competitiveness Data. The research can be affected by the overall innovation environment, including institutional competitiveness. Therefore, we used the innovation index of a nation from the global economy. We measured the global economy using data from Cornell University, INSEAD, and the World Intellectual Property Organization, which provide an innovation index that comprehensively captures each country's quality of institutions, human capital and research, infrastructure, and market and business sophistication.

4.3. Models

We employed a regression model to examine the association between national digital competitiveness and different types of qualities in medical research. Because we used panel data to control for unobserved heterogeneity, we employed a fixed-effects regression model instead of a random-effects model based on the Hausman test [42], as shown below. We considered the time lag (three years) between the explanatory and response variables because the bibliometric information (documents and citations) was based on the previous three years.

$$\mathrm{RQ_1\ (S, P, O, I)_{i,t+3}} = \alpha_{0i} + \alpha_1 \mathrm{Natioanl\ digital\ competitiveness\ (NDC)}_{\ i,t} + \alpha_2 \mathrm{Controls}_{\ i,t} + \mathrm{e}_{i,t} \tag{1}$$

$$\mathrm{RQ_2\ (S, P, O, I)_{i,t+3}} = \beta_{0i} + \beta_1 \mathrm{Natioanl\ digital\ competitiveness\ (NDC)}_{\ i,t} + \beta_2 \mathrm{Controls}_{\ i,t} + \mathrm{e}_{i,t} \tag{2}$$

$$\mathrm{RQ_3\ (S, P, O, I)_{i,t+3}} = \gamma_{0i} + \gamma_1 \mathrm{Natioanl\ digital\ competitiveness\ (NDC)}_{\ i,t} + \gamma_2 \mathrm{Controls}_{\ i,t} + \mathrm{e}_{i,t} \tag{3}$$

where α_{0i} represents country fixed effects, and $e_{i,t}$ is the random error. RQ (S), RQ (P), RQ (O), and RQ (I) refer to the quality of medical research in the vital areas of surgery, pediatrics, perinatology and child health, obstetrics and gynecology, and internal medicine, respectively. We investigated three indicators of research quality as response variables: RQ_1, RQ_2, and RQ_3, which refer to first-, second-, and third-order research quality, respectively.

5. Results

Table 1 presents the descriptive statistics and Table 2 shows correlation matrices for the main variables. Due to space limitations, we abbreviated each variable for the correlation matrix and took the logarithm of three variables: gross domestic product, education expense, and patent intensity. Table 2 indicates that national digital competitiveness (NDC) was positively correlated with second-order research quality (forward citations per document) in all the vital areas, including surgery ($\rho = 0.23$, $p < 0.01$), pediatrics, perinatology, child health ($\rho = 0.15$, $p < 0.05$), obstetrics and gynecology ($\rho = 0.12$, $p < 0.1$), and internal medicine ($\rho = 0.21$, $p < 0.01$). The relatively high correlation for second-order research quality in these areas could be attributed to their academic relatedness. Multicollinearity was not a major concern in our data because we tested these response variables separately in our regression analyses.

Table 1. Descriptive statistics.

Variables Description	Abbreviation	Mean	S.D.	Min	Max
Non-citable/Citable documents in surgery	NCDS	0.13	0.07	0.00	0.47
Non-citable/Citable documents in Pediatrics, Perinatology, and Child Health	NCDP	0.10	0.06	0.00	0.30
Non-citable/Citable documents in Obstetrics and Gynecology	NCDO	0.05	0.05	0.00	0.50
Non-citable/Citable documents in Internal Medicine	NCDI	0.17	0.11	0.00	0.67
Citations/document in surgery	CDS	6.03	4.89	0.32	29.6
Citations/document in Pediatrics, Perinatology, and Child Health	CDP	5.81	4.60	0.34	20.1
Citations/document in Obstetrics and Gynecology	CDO	7.06	6.50	0.00	37.5
Citations/document in Internal Medicine	CDI	10.5	9.24	0.44	63.6
Self-citations/Non-self-citations in surgery	SNS	0.22	0.20	0.00	1.15
Self-citations/Non-self-citations in Pediatrics, Perinatology, and Child Health	SNP	0.23	0.21	0.00	1.29
Self-citations/Non-self-citations in Obstetrics and Gynecology	SNO	0.23	0.18	0.00	1.09
Self-citations/Non-self-citations in Internal Medicine	SNI	0.20	0.16	0.00	0.92
National Digital Competitiveness	DC	7.54	0.96	4.67	9.47
Gross domestic product (GDP) [a]	NDC	6.18	1.56	2.83	9.88
Protectionism	PT	6.28	1.14	3.41	8.98
Science research legislation	SRP	5.61	1.44	2.94	8.43
Health infrastructure	HI	6.30	1.85	2.16	9.25
Public expense for student [a]	PES	8.68	0.88	6.13	10.2
Innovation index	II	50.0	8.82	29.1	68.3
Hospital density	HD	4.59	2.63	0.94	13.3
Patent intensity [a]	PI	7.56	2.39	3.04	14.0

N = 189; [a] logarithm.

Table 3 presents the results of our analyses during surgery. Models 1, 3, and 5 show the baseline regression results without controls, and models 2, 4, and 6 are the full models with all controls. The negative coefficients of NDC in models 1 ($\beta = -0.018$, $p < 0.05$) and 2 ($\beta = -0.017$, $p < 0.1$) indicate that NDC reduced the ratio of non-citable documents to citable documents. Thus, the NDC has led to more science-based research on surgery. The positive coefficients of NDC in models 3 ($\beta = 3.545$, $p < 0.001$) and 4 ($\beta = 3.501$, $p < 00.1$) show that NDC increased forward citation counts per document, implying that NDC led to more impactful research in surgery. The negative coefficients of NDC in models 5 ($\beta = -0.032$, $p < 0.01$) and 6 ($\beta = -0.035$, $p < 000.1$) show that NDC diminished the ratio of self-citations to non-self-citations, indicating that NDC encouraged more exploration-oriented research in surgery.

Table 2. Correlation.

	NCDS	NCDP	NCDO	NCDI	CDS	CDP	CDO	CDI	SNS	SNP
NCDS	1.00									
NCDP	0.43	1.00								
NCDO	0.10	0.13	1.00							
NCDI	0.23	0.33	0.11	1.00						
CDS	−0.22	−0.07	0.25	0.03	1.00					
CDP	−0.16	−0.07	0.28	0.05	0.84	1.00				
CDO	−0.16	−0.03	0.36	0.19	0.74	0.78	1.00			
CDI	−0.03	−0.01	0.44	−0.01	0.73	0.82	0.72	1.00		
SNS	0.10	0.20	−0.17	0.20	−0.23	−0.24	−0.21	−0.20	1.00	
SNP	0.06	0.15	−0.12	0.15	−0.17	−0.21	−0.19	−0.15	0.83	1.00
SNO	0.02	0.15	−0.14	0.13	−0.24	−0.25	−0.27	−0.23	0.85	0.86
SNI	0.06	0.22	−0.19	0.27	−0.16	−0.20	−0.18	−0.20	0.89	0.75
NDC	−0.05	−0.04	0.12	0.11	0.23	0.15	0.12	0.21	−0.06	−0.07
GDP	0.17	0.38	−0.21	0.25	−0.17	−0.17	−0.26	−0.17	0.75	0.62
PT	0.05	0.17	0.17	0.16	0.17	0.19	0.13	0.12	−0.11	−0.03
SRP	0.10	0.20	0.27	0.13	0.15	0.12	0.03	0.14	0.14	0.12
HI	0.08	0.30	0.18	0.18	0.13	0.11	0.06	0.13	0.01	−0.03
PES	0.23	0.32	0.31	0.30	0.23	0.21	0.14	0.22	−0.06	−0.18
II	0.12	0.28	0.29	0.20	0.20	0.16	0.10	0.14	0.14	0.00
HD	−0.20	−0.01	−0.19	0.08	0.00	−0.03	0.01	−0.09	0.07	−0.20
PI	0.05	0.27	−0.25	0.24	−0.15	−0.19	−0.22	−0.18	0.78	0.54
	SNO	**SNI**	**NDC**	**GDP**	**PT**	**SRP**	**HI**	**PES**	**II**	**HD**
SNO	1.00									
SNI	0.79	1.00								
NDC	−0.15	−0.01	1.00							
GDP	0.71	0.75	0.02	1.00						
PT	−0.07	−0.13	0.21	−0.04	1.00					
SRP	0.10	0.11	0.55	0.19	0.49	1.00				
HI	−0.09	−0.06	0.44	0.17	0.51	0.66	1.00			
PES	−0.22	−0.06	0.51	−0.02	0.48	0.75	0.73	1.00		
II	0.00	0.13	0.44	0.17	0.50	0.86	0.72	0.86	1.00	
HD	−0.15	0.10	0.02	0.05	−0.18	−0.03	0.21	0.22	0.18	1.00
PI	0.63	0.80	0.09	0.91	−0.12	0.18	0.18	0.03	0.23	0.31

All correlations with magnitude > |0.14| are significant at the 0.05 level.

Table 4 presents the results of our analyses of pediatric, perinatology, and child health. Models 1, 3, and 5 show the baseline regression results without controls, and models 2, 4, and 6 are full models with all controls. The negative coefficients of NDC in model 1 ($\beta = -0.016$, $p < 0.05$) and model 2 ($\beta = -0.019$, $p < 00.1$) illustrate that NDC reduced the ratio of non-citable to citable documents, indicating that NDC led to more science-based research in pediatrics, perinatology, and child health. The positive coefficients of NDC in models 3 ($\beta = 3.226$, $p < 0.001$) and 4 ($\beta = 3.287$, $p < 0.001$) show that NDC increased forward citation counts per document, implying that NDC led to more impactful research in pediatrics, perinatology, and child health. The coefficients of models 5 and 6 are insignificant although both show a negative sign.

Table 3. Fixed-effect regression of national digital competitiveness (NDC) on research quality in surgery.

	Research Quality in Surgery$_{t+3}$					
	Quantity 1		**Quality 2**		**Quality 3**	
	Non-citable documents /citable document (More scientific?)		Forward citations /documents (More impactful?)		Self-citations /non-self-citations (More explorative?)	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
NDC$_t$	−0.018 * 0.266	−0.017 + 0.009	3.545 *** 0.892	3.501 *** 0.817	−0.032 ** 0.010	−0.035 *** 0.010
Gross domestic product$_t$		−0.060 0.061		−5.811 5.557		−0.007 0.067
Protectionism$_t$		−0.009 0.007		1.110 + 0.668		0.006 0.008
Scientific research legislation$_t$		0.015 * 0.012		−2.309 * 1.063		0.022 + 0.013
Health infrastructure$_t$		0.003 0.010		−0.405 0.912		−0.002 0.011
Public expense for student$_t$		−0.043 0.043		0.963 3.903		−0.038 0.047
Innovations index$_t$		0.001 0.003		−0.289 0.268		0.004 0.003
Hospital density$_t$		−0.010 0.021		11.55 *** 1.884		−0.045 + 0.023
Patent intensity$_t$		0.013 0.022		−6.535 *** 2.017		0.169 0.024
R^2	0.002	0.04	0.05	0.01	0.004	0.649
F	4.53	1.63	15.79	9.20	9.38	7.60
N	189	189	189	189	189	189

We also conducted an analysis using a random-effect model, and the qualitative results remained the same. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Fixed-effect regression of national digital competitiveness (NDC) on research quality in pediatrics, perinatology, and child health.

	Research Quality in Pediatrics, Perinatology, and Child Health$_{t+3}$					
	Quantity 1		**Quality 2**		**Quality 3**	
	Non-citable documents /citable document (More scientific?)		Forward citations /documents (More impactful?)		Self-citations /non-self-citations (More explorative?)	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
NDC$_t$	−0.016 * 0.007	−0.019 ** 0.007	3.226 *** 0.85195	3.287 *** 0.789	−0.025 0.016	−0.029 + 0.016
Gross domestic product$_t$		−0.139 *** 0.048		8.249 5.370		−0.207 + 0.111
Protectionism$_t$		−0.002 0.006		0.912 0.645		0.012 0.013
Scientific research legislation$_t$		0.013 0.009		−2.738 ** 1.027		0.006 0.021
Health infrastructure$_t$		−0.004 0.008		0.061 0.882		0.002 0.018
Public expense for student$_t$		0.054 0.034		−0.726 3.772		−0.011 0.078

Table 4. *Cont.*

	Research Quality in Pediatrics, Perinatology, and Child Health$_{t+3}$					
	Quantity 1		**Quality 2**		**Quality 3**	
	Non-citable documents /citable document (More scientific?)		Forward citations /documents (More impactful?)		Self-citations /non-self-citations (More explorative?)	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Innovations index$_t$		0.001 0.002		−0.195 0.259		−0.001 0.005
Hospital density$_t$		0.036 * 0.016		9.170 *** 1.821		−0.015 0.038
Patent intensity$_t$		−0.013 0.017		−5.930 * 1.949		0.139 *** 0.040
R^2	0.001	0.077	0.021	0.0003	0.01	0.01
F	5.79	2.25	14.34	8.40	2.58	2.38
N	189	189	189	189	189	189

We also conducted an analysis using a random-effect model, and the qualitative results remained the same. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5 presents the results of our analyses of obstetrics and gynecology. The positive coefficients of NDC in models 3 (β = 3.922, $p < 0.05$) and 4 (β = 4.812, $p < 0.001$) show that NDC increased forward citation counts per document, implying that NDC led to more impactful research in obstetrics and gynecology. However, for the remaining models (1, 2, 5, and 6), the results were insignificant, indicating that NDC may not influence other types of research quality.

Table 5. Fixed-effect regression of national digital competitiveness (NDC) on research quality in obstetrics and gynecology.

	Research Quality in Obstetrics and Gynecology$_{t+3}$					
	Quantity 1		**Quality 2**		**Quality 3**	
	Non-citable documents /citable document (More scientific?)		Forward citations /documents (More impactful?)		Self-citations /non-self-citations (More explorative?)	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
NDC$_t$	−0.007 0.015	−0.009 0.017	3.922 * 1.700	4.812 *** 1.640	−0.011 0.011	−0.009 0.012
Gross domestic product$_t$		0.078 0.114		−3.380 11.161		−0.030 0.084
Protectionism$_t$		0.008 0.014		−1.357 1.341		−0.009 0.010
Scientific research legislation$_t$		−0.007 0.022		−4.029 + 2.134		0.013 0.016
Health infrastructure$_t$		0.007 0.019		0.563 1.833		−0.002 0.014
Public expense for student$_t$		−0.030 0.080		−1.974 7.839		−0.038 0.059

Table 5. *Cont.*

	Research Quality in Obstetrics and Gynecology$_{t+3}$					
	Quantity 1		**Quality 2**		**Quality 3**	
	Non-citable documents /citable document (More scientific?)		Forward citations /documents (More impactful?)		Self-citations /non-self-citations (More explorative?)	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Innovations index$_t$		−0.004 0.006		−1.060 + 0.538		0.000 0.004
Hospital density$_t$		0.014 0.039		20.54 *** 3.784		−0.008 0.028
Patent intensity$_t$		−0.038 0.042		−10.21 * 4.051		0.010 0.030
R^2	0.01	0.000	0.04	0.000	0.000	0.066
F	0.24	030	7.41	5.31	1.02	0.50
N	189	189	5.32	189	189	189

We also conducted an analysis using a random-effect model, and the qualitative results remained the same. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6 presents the results of our analysis in internal medicine analysis. The positive coefficients of NDC in models 3 (β = 3.192, $p < 0.01$) and 4 (β = 3.351, $p < 0.01$) show that NDC increased forward citation counts per document, implying that NDC led to more impactful research in internal medicine. The negative coefficients of NDC in models 5 (β = −0.036, $p < 0.05$) and 6 (β = −0.030, $p < 0.05$) show that NDC diminished the ratio of self-citations to non-self-citations, indicating that NDC encouraged more exploration-oriented research in internal medicine. However, the results of models 1 and 2 were insignificant, implying that NDC might have a limited effect on the ratio of non-citable documents to citable documents.

We found that, while digital competitiveness was positively associated with impactful research across fields in vital areas, the relationship between digital competitiveness and the other two types of research quality varied by field. For example, digital competitiveness benefitted all three types of research quality in surgery but only one type in obstetrics and gynecology. More specifically, obstetrics, gynecology, and internal medicine have quite limited benefits regarding the degree of scientific research and pediatrics, perinatology, and child health, and obstetrics and gynecology have restricted advantages regarding the degree of explorative research. Although this is a preliminary result of an exploratory study, it has implications for collaborative research, such as research by MDTs. Figure 3 shows a visual representation of how these associations vary in each field.

Table 6. Fixed-effect regression of national digital competitiveness (NDC) on research quality in internal medicine.

	Research Quality in Internal Medicine$_{t+3}$					
	Quantity 1		**Quality 2**		**Quality 3**	
	Non-citable documents /citable document (More scientific?)		Forward citations /documents (More impactful?)		Self-citations /non-self-citations (More explorative?)	
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
NDC$_t$	−0.003 0.007	−0.002 0.007	3.192 ** 1.173	3.351 ** 1.154	−0.036 * 0.016	−0.030 * 0.015
Gross domestic product$_t$		−0.089 0.051		−1.821 7.852	0.014	0.121 0.100
Protectionism$_t$		−0.005 0.006		0.750 0.944		0.014 0.012
Scientific research legislation$_t$		−0.009 0.010		−2.935 * 1.502		0.014 0.019
Health infrastructure$_t$		0.004 0.008		0.311 1.289		−0.035 * 0.016
Public expense for student$_t$		−0.050 0.036		−1.733 5.515		−0.018 0.070
Innovations index$_t$		0.000 0.002		−0.705 + 0.379		−0.001 0.005
Hospital density$_t$		0.038 * 0.017		12.664 *** 2.662		−0.087 * 0.034
Patent intensity$_t$		−0.024 0.018		−5.438 + 2.850		0.119 *** 0.036
R^2	0.013	0.001	0.015	0.01	0.02	0.57
F	0.26	2.17	7.41	4.75	6.27	3.27
N	189	189	189	189	189	189

We also conducted an analysis using a random-effect model, and the qualitative results remained the same. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

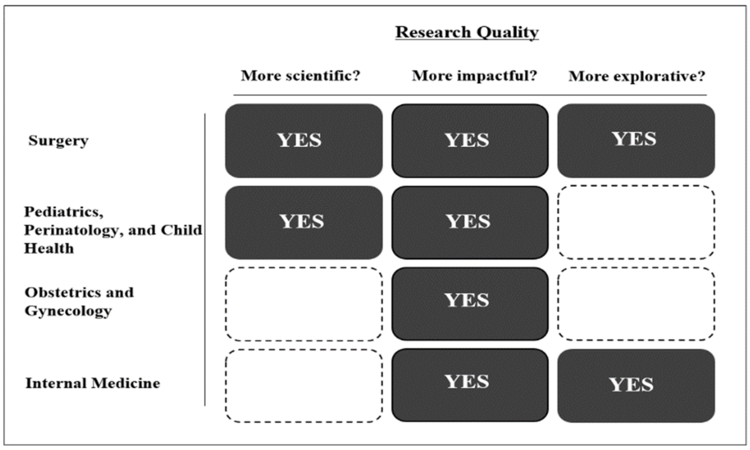

Figure 3. The impacts of digital competitiveness on research quality in vital area.

6. Discussion and Conclusions

6.1. Summary and Implications

In the medical field, the use of digital technology has become mainstream and is expected to continue to grow in the future. However, it takes time for a society or community to fully accept and understand the effects of rapidly developing technologies. This phenomenon is commonly observed in radical innovation. The development of digital technology has been accelerated by the COVID-19 pandemic and has presented us with tremendous benefits in advancing medical research. While digital technologies can be an instrument that dramatically improves performance for those who can effectively utilize them, the benefit may not be evenly distributed.

Our study discusses the intrinsic nature of digital technology in the context of medical research. We found that digital competitiveness is related to higher impact research in all four fields: surgery; pediatrics, perinatology, and child health; obstetrics and gynecology; and internal medicine. This is an encouraging phenomenon for medical research because publishing more high-impact research implies that the possibility of sustainable development of the focal discipline increases. However, it is also noteworthy that the benefit of digital competitiveness is contingent upon different types of qualities: science-based research and explorative research. Although this may not cause serious issues in the short term, researchers should pay attention to this possibility. By highlighting the role of digital competitiveness in improving the quality of medical research, our study draws attention to the importance of understanding the prerequisites for balanced advances in medical research.

During periods with complex challenges, such as COVID-19, doctors and researchers encounter various previously unknown problems [7], and the importance of collaboration across different fields in medicine is significantly augmented [8]. Balanced development across fields is essential for the sustainable growth of medical research through research collaboration. For instance, during the pandemic, the demand for enhanced recovery after surgery (ERAS) has drastically increased. To effectively manage ERAS during this challenging situation with various unpredictable medical risks, a consensus on research results is required between the surgery and anesthesiology departments. Considering economies of scale in the processes of introducing protocols for anesthesia, recovery, ward care, and purchase of necessary items for ERAS (i.e., carbohydrate beverage, which is a substitute for fasting), it is necessary to establish a balanced knowledge-sharing system. Therefore, it is very important to understand how interrelated medical research is adapting to macro-level external changes not only for academic reasons but also for the quality of actual medical services and the protection of patients' lives.

Our study provides an alternative perspective on differences in medical research advances by digital technologies. These differences may partially originate from the nature of the specific field of medicine. Traditionally, digital-based research support for the field of surgery has received less attention than oncology because of its own characteristics and real action-based practices including watching, feeling, and direct operation. However, it can be assumed that surgery researchers obtained immediate and massive data after robot surgery was introduced, whereas research on oncology requires more time to derive results due to trial-and-error-based experiments and simulations. Therefore, understanding the underlying reasons rather than superficially observing the differences in the progress of each field of medicine is important, especially when there is a decision regarding collaborative program investments.

The third important implication of our study is for policymakers and institutions. According to our analysis, scientific research legislation and legal support related to scientific research encourage innovation and are consistently and positively related to impactful research in all fields in vital areas. In order for new technology to be used in critical sectors such as medical research, adoption of technology is important. However, the institutions and social systems that enable a country to manage the utilization of such technology, such as a stable market system, transportation infrastructure, and high digital literacy, must be in place [40,43–45]. In other words, it is important to have a variety of institutional supports that enable effective and efficient use of knowledge throughout society.

In summary, our study showed that digital competitiveness is conducive to the qualitative advancement of medical research. However, by demonstrating differences in the degree or pattern of development by field in vital areas, several factors should be considered in the design of integrated medical service systems. Our study makes a unique contribution to the relationship between digital technology and medical research, which has recently received extensive attention from researchers. While the existing literature has mainly focused on the impact of digital technology on specific medical services, our research focuses on the quality of medical research that provides a basis for the long-term sustainable development of medicine.

6.2. Limitation and Suggestions for Future Research

Our study has several limitations. Although our study measured the quality of medical research using established variables, documents, and citations, because of the nature of medicine, where the role of experimentation and practice is important, it may have some limitations in accurately measuring the degree of knowledge progress based on published results. Future research should consider this point and also conduct a more in-depth analysis to investigate the mechanism by which digital capabilities are utilized in field studies.

Another limitation is the scope of the medical research field. Although the vital area is important because it is a field that is directly related to mortality, integrated medical practice requires cooperation with expertise in more fields, for example, anesthesiology or radiology. Further studies and comparative analyses can be conducted in a more extended range of fields in medicine.

Because each field in the vital area is not only academically but also practically related, the research quality of each field may also be highly related. Research on the design of a research collaboration model with high synergy can be conducted by studying this correlation.

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References

1. Ting, D.S.W.; Carin, L.; Dzau, V.; Wong, T.Y. Digital technology and COVID-19. *Nat. Med.* **2020**, *26*, 459–461. [CrossRef]
2. Tan, R.K.J.; Wu, D.; Day, S.; Zhao, Y.; Larson, H.J.; Sylvia, S.; Tang, W.; Tucker, J.D. Digital approaches to enhancing community engagement in clinical trials. *NPJ Digit. Med.* **2022**, *5*, 37. [CrossRef] [PubMed]
3. Portela, D.; Brito, D.V.; Monteiro, H. Using Digital Technologies in Response to the COVID-19 Pandemic in Portugal. *Port. J. Public Health* **2021**, *39*, 170–174. [CrossRef]
4. Ting, D.S.W.; Lin, H.; Ruamviboonsuk, P.; Wong, T.Y.; Sim, D.A. Artificial intelligence, the internet of things, and virtual clinics: Opthamology at the digital translation forefront. *Lancet Digital. Health* **2019**, *2*, E8–E9. [CrossRef]
5. Shilo, S.; Rossman, H.; Segal, E. Axes of a revolution: Challenges and promises of big data in healthcare. *Nat. Med.* **2020**, *26*, 29–38. [CrossRef] [PubMed]
6. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef] [PubMed]
7. Galluccio, F.; Ergonenc, T.; Garcia Martos, A.; Allam, A.E.S.; Pérez-Herrero, M.; Aguilar, R.; Emmi, G.; Spinicii, M.; Juan, I.T.; Fajardo-Pérez, M. Treatment algorithm for COVID-19: A multidisciplinary point of view. *Clin. Rheumatol.* **2020**, *39*, 2077–2084. [CrossRef]
8. Curigliano, G.; Banerjee, S.; Cervantes, A.; Garassino, M.C.; Garrido, P.; Girard, N.; Haanen, J.; Jordan, K.; Lordick, F.; Machiels, J.P.; et al. Managing cancer patients during the COVID-19 pandemic: An ESMO multidisciplinary expert consensus. *Ann. Oncol.* **2020**, *31*, 1320–1335. [CrossRef]
9. Price, S.J.; Joannides, A.; Plaha, P.; Afshari, F.T.; Albanese, E.; Barua, N.U.; Chen, H.W.; Critchley, G.; Flannery, T.; Fountain, D.M.; et al. Impact of COVID-19 pandemic on surgical neuro-oncology multi-disciplinary team decision making: A national survey (COVID-CNSMDT Study). *BMJ Open* **2020**, *10*, e040898. [CrossRef]

10. Inan, O.; Tenaerts, P.; Prindiville, S.; Reynolds, H.; Dizon, D.; Cooper-Arnold, K.; Turakhia, M.; Pletcher, J.J.; Preston, K.J.; Krumholz, H.M.; et al. Digitizing clinical trials. *NPJ Digit. Med.* **2020**, *3*, 1–7. [CrossRef]
11. Steinhubl, S.R.; Wolff-Hughes, D.L.; Nilsen, W.; Iturriaga, E.; Califf, R.M. Digital clinical trials: Creating a vision for the future. *NPJ Digit. Med.* **2019**, *2*, 126. [CrossRef] [PubMed]
12. Rosa, C.; Marsch, L.A.; Winstanley, E.L.; Brunner, M.; Campbell, A.N.C. Using digital technologies in clinical trials: Current and future applications. *Contemp. Clin. Trials* **2021**, *100*, 106219. [CrossRef] [PubMed]
13. Jenssen, B.P.; Mitra, N.; Shah, A.; Wan, F.; Grande, D. Using digital technology to engage and communicate with patients: A survey of patient attitudes. *J. Gen. Intern. Med.* **2016**, *31*, 85–92. [CrossRef] [PubMed]
14. Heaven, D. Bitcoin for the biological literature. *Nature* **2019**, *566*, 141–143. [CrossRef] [PubMed]
15. Murthy, V.H.; Krumholz, H.M.; Gross, C.P. Participation in cancer clinical trials: Race-, sex-, and age-based disparities. *JAMA* **2004**, *291*, 2720–2726. [CrossRef] [PubMed]
16. Anderson, D. Digital R&D: Four Ways to Maximize Patient Engagement in Clinical Trials. 25 June 2018. Available online: https://www2.deloitte.com/us/en/blog/health-care-blog/2018/digital-rd-four-ways-to-maximize-patient-engagement-in-clinical-trials.html (accessed on 24 August 2022).
17. Chen, M.; Wang, R.; Zhou, Y.; He, Z.; Liu, X.; He, M.; Liu, X.; He, M.; Wang, J.; Huang, C.; et al. Digital medical education empowered by intelligent fabric space. *Nat. Sci. Open* **2022**, *1*, 20220011. [CrossRef]
18. Aksnes, D.W.; Langfeldt, L.; Wouters, P. Citations, citation indicators, and research quality: An overview of basic concepts and theories. *Sage Open* **2019**, *9*, 215824401982957. [CrossRef]
19. Frandsen, T. On the ratio of citable versus non-citable items in economics journals. *Scientometrics* **2008**, *74*, 439–451. [CrossRef]
20. Ramin, S.; Shirazi, A.S. Comparison between impact factor, SCImago journal rank indicator and Eigenfactor score of nuclear medicine journals. *Nucl. Med. Rev.* **2012**, *15*, 132–136.
21. Kianifar, H.; Sadeghi, R.; Zarifmahmoudi, L. Comparison between impact factor, eigenfactor metrics, and Scimago journal rank indicator of pediatric neurology journals. *Acta Inform. Med.* **2014**, *22*, 103. [CrossRef]
22. Adam, D. Citation analysis: The counting house. *Nature* **2002**, *415*, 726–730. [CrossRef] [PubMed]
23. Dong, P.; Loh, M.; Mondry, A. The "impact factor" revisited. *Biomed. Digit. Libr.* **2005**, *2*, 7. [CrossRef] [PubMed]
24. Moed, H. Measuring China s research performance using the Science Citation Index. *Scientometrics* **2002**, *53*, 281–296. [CrossRef]
25. Mingers, J.; Yang, L. Evaluating journal quality: A review of journal citation indicators and ranking in business and management. *Eur. J. Oper. Res.* **2017**, *257*, 323–337. [CrossRef]
26. Gorraiz, J.; Gumpenberger, C.; Schlögl, C. Usage versus citation behaviours in four subject areas. *Scientometrics* **2014**, *101*, 1077–1095. [CrossRef]
27. Nieminen, P.; Carpenter, J.; Rucker, G.; Schumacher, M. The relationship between quality of research and citation frequency. *BMC Med. Res. Methodol.* **2006**, *6*, 42. [CrossRef]
28. Bonzi, S.; Snyder, H.W. Motivations for citation—A comparison of self citation and citation to others. *Scientometrics* **1991**, *21*, 245–254. [CrossRef]
29. Bornmann, L.; Daniel, H.D. What do citation counts measure? A review of studies on citing behavior. *J. Doc.* **2008**, *64*, 45–80. [CrossRef]
30. Dedeilia, A.; Esagian, S.M.; Ziogas, I.A.; Giannis, D.; Katsaros, I.; Tsoulfas, G. Pediatric surgery during the COVID-19 pandemic. *World J. Clin. Pediatrics* **2020**, *9*, 7. [CrossRef]
31. Cheung, H.Y.; Chan, A.W. Increasing the competitive positions of countries through employee training: The competitiveness motive across 33 countries. *Int J. Manpow.* **2012**, *33*, 144–158. [CrossRef]
32. Ciocanel, A.B.; Pavelescu, F.M. Innovation and competitiveness in European context. *Procedia Econ. Financ.* **2015**, *32*, 728–737. [CrossRef]
33. Fonseca, L.M.; Lima, V.M. Countries three wise men: Sustainability, innovation, and competitiveness. *J. Ind. Eng. Manag.* **2015**, *8*, 1288–1302. [CrossRef]
34. Ju, Y.; Sohn, S.Y. Development of a national competitiveness index based on a structural equation model. *Technol. Anal. Strateg. Manag.* **2014**, *26*, 565–579. [CrossRef]
35. Falagas, M.E.; Kouranos, V.D.; Arencibia-Jorge, R.; Karageorgopoulos, D.E. Comparison of SCImago journal rank indicator with journal impact factor. *FASEB J.* **2008**, *22*, 2623–2628. [CrossRef] [PubMed]
36. Roldan-Valadez, E.; Salazar-Ruiz, S.Y.; Ibarra-Contreras, R.; Rios, C. Current concepts on bibliometrics: A brief review about impact factor, Eigenfactor score, CiteScore, SCImago Journal Rank, Source-Normalised Impact per Paper, H-index, and alternative metrics. *Ir. J. Med. Sci.* **2019**, *188*, 939–951. [CrossRef] [PubMed]
37. Butler, D. Free journal-ranking tool enters citation market. *Nature* **2008**, *451*, 6. [CrossRef]
38. El-Azami-El-Idrissi, M.; Lakhdar-Idrissi, M.; Ouldim, K.; Bono, W.; Amarti-Riffi, A.; Hida, M.; Nejjari, C. Improving medical research in the Arab world. *Lancet* **2013**, *382*, 2066–2067. [CrossRef]
39. Choi, B.; Kumar, M.S.; Zambuto, F. Capital structure and innovation trajectory: The role of debt in balancing exploration and exploitation. *Organ. Sci.* **2016**, *27*, 1183–1201. [CrossRef]
40. Fagherazzi, G.; Goetzinger, C.; Rashid, M.A.; Aguayo, G.A.; Huiart, L. Digital health strategies to fight COVID-19 worldwide: Challenges, recommendations, and a call for papers. *J. Med. Internet Res.* **2020**, *22*, e19284. [CrossRef]

41. Yamin, C.K.; Emani, S.; Williams, D.H.; Lipsitz, S.R.; Karson, A.S.; Wald, J.S.; Bates, D.W. The digital divide in adoption and use of a personal health record. *Arch. Intern. Med.* **2011**, *171*, 568–574. [CrossRef]
42. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; MIT Press: Cambridge, MA, USA, 2010.
43. Kruse, C.; Betancourt, J.; Ortiz, S.; Luna, S.M.V.; Bamrah, I.K.; Segovia, N. Barriers to the use of mobile health in improving health outcomes in developing countries: Systematic review. *J. Med. Internet Res.* **2019**, *21*, e13263. [CrossRef] [PubMed]
44. Mahmood, S.; Hasan, K.; Carras, M.C.; Labrique, A. Global preparedness against COVID-19: We must leverage the power of digital health. *J. Public Health Surveill.* **2020**, *6*, e18980. [CrossRef] [PubMed]
45. Dadaczynski, K.; Okan, O.; Messer, M.; Leung, A.Y.; Rosário, R.; Darlington, E.; Rathmann, K. Digital health literacy and web-based information-seeking behaviors of university students in Germany during the COVID-19 pandemic: Cross-sectional survey study. *J. Med. Internet Res.* **2021**, *23*, e24097. [CrossRef] [PubMed]