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The Influence of Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons on Artificial Intelligence for Clinical Decision-Making Among Physicians

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Abstract

This study investigated the perspectives of physicians regarding the influence of Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons on Clinical Decision Making in Malaysian Healthcare. In particular, this study addressed the mediating effect of artificial intelligence (AI) on the relationship between these health data concepts and Clinical Decision Making. A descriptive, analytical, cross-sectional study was conducted in public and private hospitals in Malaysia. The research population entails physicians with experience handling EMR. The sample included 160 participants. The data were collected using a researcher-made questionnaire and analyzed using the SPSS software using descriptive and Pearson Correlation tests). Health Data Spaces, Data Natives, Data Collectives, and Data Commons showed a significant fair correlation with clinical decision-making, while Data Repositories showed a moderate correlation. Additionally, when AI is introduced as a mediator, the correlation coefficients generally increase, indicating a stronger relationship between the health data variables and clinical decision-making. The study emphasizes the importance of policymakers investing in AI-driven platforms for collaboration between healthcare organizations and technology developers, offering crucial insights to empower healthcare providers in leveraging AI for improved patient care, streamlined processes, and enhanced clinical decision-making. This research holds significance in steering the advancement of health data and AI initiatives focused on enhancing patient care and outcomes. It stands out as one of the limited endeavours that investigate the impacts of novel concepts, such as Health Data Spaces and artificial intelligence, on clinical decision-making within the Malaysian healthcare system.

Keywords: health data spaces, data repositories, data collectives, data natives, data commons, artificial intelligence, clinical decision-making

1. Introduction

The digitization of healthcare has ushered in transformative advancements, yet the interoperability of Electronic Medical Records (EMR) remains a persistent challenge (Li et al., 2023; Fennelly et al., 2020). The seamless exchange and accessibility of patient data across disparate systems are critical for effective care coordination and informed clinical decisions (Elvas et al., 2023). Furthermore, recent studies on the complexities of data exchange in healthcare underscore the need for standardized data formats and improved data-sharing practices (Khalid et al., 2023; Takeshita et al., 2022; Schwalbe et al., 2020; Sarkar, 2022). As the industry grapples with EMR interoperability concerns, innovative concepts such as Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons have gained prominence. These interconnected notions hold the promise to not only alleviate EMR interoperability issues but also revolutionize the healthcare landscape. By fostering collaborative data sharing, standardizing formats, and enabling comprehensive access to diverse datasets, these concepts pave the way for enhanced clinical insights, improved patient outcomes, and a more cohesive healthcare ecosystem (Quinn et al., 2018; Panagopoulos et al., 2022). Artificial intelligence (AI) can play a significant role in integrating these concepts and improving the interoperability of EMR.

In this context, health data spaces emerge as a promising solution to address the issue of scattered medical information. These spaces offer a single platform to gather and study healthcare data from various sources. According to Marelli et al. (2023), data spaces play a crucial role in bringing together patient information from different medical areas and settings. They ensure data security and allow AI programs to access diverse patient details, leading to more accurate and personalized clinical insights. Similarly, data repositories act as central hubs for storing extensive healthcare data, including patient records, medical images, and genomic data. These repositories play a key role in research, analysis, and supporting clinical decisions by offering a complete view of patients' medical histories. Research by Raja &

Asghar (2020), underscored the importance of data repositories in combining patient data from various sources, fostering data-centric research efforts and clinical insights. The significance of data repositories extends to AI-powered clinical decisions. These repositories accommodate large datasets, enabling AI models to conduct complex analyses that offer practical insights. By leveraging these abundant datasets, AI algorithms are trained with diverse patient information, increasing their effectiveness within decision-support tools used by doctors. This notion is supported by recent findings by Jwa & Poldrack (2022), which demonstrate how AI algorithms trained on comprehensive data repositories enhance diagnostic precision, particularly within the realm of neuroimaging.

On the other hand, Data Collectives and Data Commons are both concepts related to collaborative data sharing, but with distinct characteristics and purposes. Data Collective refers to a collaborative effort pooling diverse datasets from various sources, including patient records, research data, and medical images. These initiatives aim to create comprehensive datasets from different healthcare settings, enabling cross-disciplinary research and promoting data-driven clinical insights (Kariotis et al., 2020). Whereas a Data Commons refers to a shared platform or repository where standardized and accessible datasets are made available for collaborative research. Data Commons expedites the development, validation, and refinement of AI models while adhering to principles of open data sharing and collaboration (Asiimwe et al., 2021). A fundamental underpinning of the AI healthcare narrative lies in the emergence of a new generation that is comfortable with sharing personal health data and engaging with digital health tools. They generate a wealth of data through wearable devices, mobile apps, and other digital health technologies. This data provides insights into modern patient behaviours and preferences, enabling more personalized healthcare interventions. Previous research emphasized the importance of data natives within the digital health ecosystem producing valuable health-related data using wearable devices and health applications (Shin et al., 2020; Aggarwal et al., 2021).

The relationship between AI and healthcare is complex and multifaceted. AI has the potential to handle the vast amounts of data inherent to medicine, including electronic health records, medical images, genomics data, and patient-generated information from wearables (Shandhi & Dunn, 2022). This data can be used to create a tapestry of medical insights, but it must be integrated, stored, and analysed in a unified platform. However, health data integration and clinical decision-making encounter significant challenges. These include the fragmentation of health data across disparate healthcare systems, a lack of standardized formats and interoperability, and limited technical infrastructure for seamless data sharing (Aggarwal et al., 2021; Fennelly et al., 2020).

There is notable empirical research that investigates the perceptions of physicians regarding the utilization of these concepts to enhance their decision-making practices (Samhammer et al., 2022). However, to the best of our knowledge, no study has comprehensively assessed all Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons on AI-assisted clinical decisions. Previous studies have examined this construct independently (Jwa & Poldrack,2022; Shin et al., 2020; Panagopoulos et al., 2022; Hussein et al., 2023). Therefore, this research is particularly significant as it focuses on a rapidly developing country in Southeast Asia, namely Malaysia. Developing countries, such as Malaysia, encounter more challenges compared to developed countries concerning physician awareness and contextual adaptation to data-centric concepts (Mollura et al., 2020; Koumamba et al., 2021; Kaewkungwal et al., 2020).

Thus, the present study aims to empirically explore the perspectives of physicians regarding the influence of Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons on Artificial Intelligence for Clinical Decision Making. Moreover, we tested the following hypotheses:

H1: There is a significant relationship between Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons and Clinical Decision Making.

H2: There is a mediating effect of Artificial Intelligence on the relationship between Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons and Clinical Decision Making.

2. Method

The Method section describes in detail how the study was conducted, including conceptual and operational definitions of the variables used in the study, Different types of studies will rely on different methodologies; however, a complete description of the methods used enables the reader to evaluate the appropriateness of your methods and the reliability and the validity of your results, It also permits experienced investigators to replicate the study, If your manuscript is an update of an ongoing or earlier study and the method has been published in detail elsewhere, you may refer the reader to that source and simply give a brief synopsis of the method in this section.

2.1 Study Design and Setting

This descriptive, cross-sectional study was conducted from August 2023 to September 2023, among physicians in 20 public and private healthcare in Malaysia. The survey method was designed to collect data from physicians who had used or were using EMR.

2.2 Study Population and Sample

The research population consisted of physicians working in public and private healthcare in Malaysia. In this study, the respondents were recruited by purposive sampling. Since this study intended to assess the perspectives of physicians regarding the influence of Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Common on AI for Clinical Decision Making, only physicians were purposively recruited from both public and private healthcare.

The inclusion criteria were physicians who willingly consented to participate in this study as well as those with exposure to the EMR system. The sample size was determined using G*Power version 3.1.9.7, employing an F test to generate statistical reliability for a multiple linear regression statistical technique. In this regard, the anticipated effect size was set at 0.15, the desired alpha level was established at 0.05, and the number of predictors was fixed at six. Furthermore, to meet the recommended minimum power as suggested by Cohen, (1988), the desired statistical power was also set at 0.80. As a result, the minimum sample size required for this study was determined as 98 samples. Based on the above criteria and literature arguments, we have selected the respondents and collected the data from 20 Malaysian hospitals.

2.3 Data Collection Tool

This research used a self-administered questionnaire via Google Forms to collect data. This approach was chosen as it is the lowest cost option and requires minimal staff to collect data. Moreover, this method allows the research to expand the geographical coverage (Bougie & Sekaran, 2016). The questionnaire consisted of two main sections. The first part is on the demographic characteristics of the participants, such as age, gender, and work experience as well as their involvement within the EMR system. The second section entails a total of 51 items related to Data Spaces (7 questions), Data Repositories (7 questions), Data Collectives (7 questions), Data Natives (6 questions), Data Commons (8 questions), AI (8 questions), and Clinical Decision Making (8 questions). A five-point Likert scale from 1 (very high) to 5 (very low) was used to answer all the questions. Before conducting the main survey, a pilot test was performed involving 25 physicians to validate the instrument. The internal reliability of the research instruments was evaluated using Cronbach's alpha coefficient, utilizing SPSS version 25. All the variables reported a high alpha coefficient of more than 0.60 (Data Space at 0.726, Data Repositories at 0.807, Data Collectives at 0.808, Data Natives at 0.757, Data Commons at 0.861, AI at 0.878, Clinical Decision Making at 0.871), thus indicating that all the constructs demonstrated acceptable internal consistency (Malhotra, 2004).

2.4 Data Analysis

The data underwent analysis using Statistical Package for Social Sciences (SPSS) version 22.0. This study employed a Pearson correlational design, involving the computation of correlations between various dimensions. Additionally, an examination of the mediating influence of Artificial Intelligence on the connection between Health Data Spaces, Data Repositories, Data Collectives, Data Natives, Data Commons, and Clinical Decision-Making was performed using an interaction method. The interpretation of the resulting correlation (r) values followed the guidelines for correlation coefficients in medicine outlined by Akoglu (2018).

3. Results

3.1 Participants' Demographic Characteristics

Out of the 250 questionnaires distributed, 160 were completed and returned, resulting in a response rate of 64%. Therefore, the final sample size included 160 participants who had properly completed the questionnaire. Among these participants, approximately half of them (86 individuals, accounting for 53.8%) were female, while the remaining (74 individuals, representing 46.2%) were male. Most of the respondents are aged between 36-40 years old, followed by those in the age groups of 31-35 years old, with 35 individuals (21.9%); 41-45 years old, with 31 individuals (19.4%); and more than 50 years old, with 20 individuals (12.5%). The smallest groups consist of respondents aged less than 31 years old and those aged 46-50 years old, each comprising 9 respondents (5.6%). All of the respondents are medical doctors. In this study, the included respondents comprise 127 individuals (79.4%) from the public healthcare sector and 33 individuals (20.6%) from the private healthcare sector. Based on the respondents' experience levels, the majority of them have between 11 and 20 years of experience, accounting for 50.6% or 81 individuals. This is followed by respondents with less than 10 years of experience (28.8% or 46 individuals), those with 21 to 30 years of experience (11.3% or 18 individuals), and those with 31 years of experience or more (9.4% or 15 individuals). In terms of experience with handling EMR Systems, all the respondents indicated that they have the relevant experience. The demographic details of the respondents are presented in Table 1.

Table 1. Demographic Characteristics (n = 160)

Characteristics	Category	Frequency	(%)
Gender	Male	74	46.2
	Female	86	53.8
Age	Less than 31 years old	9	5.6
	31-35 years old	35	21.9
	36-40 years old	56	35.0
	41-45 years old	31	19.4
	46-50 years old	9	5.6
	More than 50 years old	20	12.5
Medical Doctor	Yes	160	100.0
Type of Healthcare	Public Healthcare	127	79.4
	Private Healthcare	33	20.6
Experience	10 years and less	46	28.8
	11- 20 years	81	50.6
	21 - 30 years	18	11.3
	31 years and above	15	9.4
Experience handling Electronic Medical Record System	Yes	160	100.0
	No	0	0

Abbreviations: None

3.2 Correlation of Evaluated Factors

Our results showed a significant moderate correlation between data repositories and clinical decision-making (r = 0.613, P<0.01). However, there was a significant fair correlation between four types of data (data spaces, data collectives, data natives, data commons) and clinical decision-making, with correlation coefficients ranging from r = 0.398 to 0.587, P<0.01. (Table 2)

Table 2. The Correlation Between Health Data Spaces, Data Repositories, Data Collectives, Data Natives, And Data Commons and Clinical Decision Making

Variables		1	2	3	4	5	6
1	D. Space	1					
2	D. Repositories	.816*	1				
3	D. Collectives	.739*	.894*	1			
4	D. Natives	.617*	.663*	.620*	1		
5	D. Commons	.708*	.798*	.794*	.575*	1	
6	CDM	.542*	.613*	.587*	.398*	.572*	1

Abbreviations: D.Space, Data Spaces; D.Repositories, Data Repositories; D.Collectives, Data Collectives; D.Natives, Data Natives; D.Commons, Data Commons; CDM, Clinical Decision Making.* Correlation is significant at the P- value <0.01.

Table 3 reports the correlation between health data spaces, data repositories, data collectives, data natives, data commons, and the interaction effect of AI on clinical decision-making. Using an interaction helps in understanding the effect of AI on the relationships between the different data variables and CDM. The results show that the interactions between Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons with CDM have varying degrees of positive correlations. When AI was introduced into the analysis, the correlation coefficients generally increased: health data spaces* AI and clinical decision making (r = 0.611), health data repositories*AI and clinical decision making (r = 0.642), health data collectives*AI and clinical decision making (r = 0.628), health data natives*AI and clinical decision making (r = 0.518) and), health data commons*AI and clinical decision making (r = 0.607).

Table 3. The Interaction Effect of Artificial Intelligence on The Relationship Between Health Data Spaces, Data Repositories, Data Collectives, Data Natives, And Data Commons and Clinical Decision Making.

Variables	CDM (r)	Variables	CDM (r)
D.Spaces	0.542	D.Spaces*AI	0.611
D.Repositories	0.613	D.Repositories* AI	0.642
D.Collectives	0.587	D.Collectives* AI	0.628
D.Natives	0.398	D.Natives* AI	0.518
D.Commons	0.572	D.Commons* AI	0.607

Abbreviations: D.Space, Data Spaces; D.Repositories, Data Repositories; D.Collectives, Data Collectives; D. Natives, Data Natives; D.Commons, Data Commons; CDM, Clinical Decision Making; AI, Artificial Intelligence

4. Discussion

Given the rapid changes in the field of healthcare research, it is crucial to explore the influence of data-driven and artificial intelligence on clinical decision-making among physicians. Currently, there is a limited number of studies that investigate the relationship between these data-driven infrastructures (Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons) and clinical decision-making. This represents a substantial gap in understanding the potential benefits and challenges that arise from the integration of artificial intelligence in the healthcare domain.

In the research conducted, a robust positive fair correlation (correlation coefficient: 0.542) was identified between data spaces and clinical decision-making. This implies that physicians recognize data spaces as influential in shaping their decision-making processes positively. These findings are aligned with the study by Tommel et al., (2023), from a Dutch and Belgian perspective. The healthcare professionals acknowledged the benefits of data sharing for better healthcare but worries about misuse, privacy, and false assumptions in clinical visits existed. Data spaces provide a comprehensive platform for managing and analyzing health data, allowing for more efficient collaboration and research (Marelli et al., 2023). However, there are also some potential drawbacks to data spaces. One issue is that data spaces can be expensive to develop and maintain. Another issue is that data spaces can be vulnerable to data breaches and other security threats (Hussein et al., 2023). Despite these concerns, data spaces remain an invaluable tool for researchers, clinicians, and other stakeholders in the healthcare field.

The correlation coefficient of 0.613 between data repositories and clinical decision-making suggests a moderately strong positive relationship. This positive correlation indicates that as the utilization or presence of data repositories increases, there is a tendency for an enhancement or influence on clinical decision-making processes. In practical terms, this could imply that healthcare organizations or practitioners leveraging data repositories are more likely to experience improvements or changes in their decision-making strategies (Maher et al., 2023). However, Tendedez et al., (2022) study highlights that despite the potential of data repositories to support timely and informed decision-making among clinicians, the trustworthiness and awareness of data sources play a crucial role in influencing the decision-making process. As such, organizations must invest time and resources into ensuring their data sources are accurate and reliable, or else risk making poor decisions that could negatively impact patient outcomes.

Health Data Collectives represent collaborative initiatives across diverse healthcare settings aimed at gathering, exchanging, and consolidating healthcare data to derive data-driven clinical insights. The correlation coefficient of 0.581 observed between data collectives and clinical decision-making underscores the favourable perspectives held by healthcare practitioners regarding this approach to clinical decision-making. A study by Ivankovic et al.,(2023) investigates data-driven collaboration between hospitals and healthcare organizations in Europe during 2021, the second year of the COVID-19 pandemic. The research highlights the positive impact of data-driven practices, which aim to enhance governance, organizational models, and data infrastructure. This often involves the reconfiguration of care delivery and the establishment of new partnerships. This underscores the critical role Health Data Collectives play in advancing integrated healthcare systems, especially in the face of unprecedented challenges such as the global pandemic.

At present, a wealth of research and clinical data is scattered across isolated repositories, managed and controlled by individual researchers adhering to diverse standards and governance frameworks. By establishing a centralized repository of patient health data, data commons offer a comprehensive source of information for training and validating AI algorithms, thereby laying the foundation for personalized treatment approaches and enhanced patient outcomes (O'Hara et al., 2022). Our results indicate a significant fair correlation between data commons and clinical decision-making. This suggests that health data commons benefit healthcare practitioners in making clinical decisions. In a study by Afshar et al., 2023 it was found that existing health data overlap across different data sources; and that data commons can integrate these data into one single platform to provide a comprehensive resource for clinicians and policymakers. Health data commons also provide a platform for healthcare professionals to collaborate and share information, leading to better patient outcomes.

A noteworthy, yet fair correlation was identified between data natives and clinical decision-making ($r = 0.398$, $P<0.01$). This implies that although the relationship between data natives and clinical decision-making may not be very strong, there is still a noticeable association between the two variables. Consistent with previous literature (Aggarwal et al., 2021; Schaarup et al., 2023), there were significant variations in the patient perceptions, levels of support, and understanding of health data sharing to help clinical decision-making. Data natives, who have grown up in the digital age, tend to have higher levels of trust in sharing their health data for clinical decision-making. However, concerns regarding security and privacy issues still exist, highlighting the need for robust data protection measures. Further research is needed to explore the factors that contribute to this relationship and to determine if any other variables could strengthen or weaken the correlation.

Our study reveals a significant increase in the correlation coefficient when artificial intelligence (AI) is integrated as a mediator between data-driven infrastructure (Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons) and clinical decision-making. Hence, by harnessing the power of AI, health data-driven platforms can provide valuable insights and recommendations to clinicians, enabling them to make more accurate and informed decisions for patient care (Polevikov, 2023; Čartolovni et al., 2022). Additionally, AI can assist in identifying patterns and trends within large datasets that may not be easily visible to human clinicians. However, recent work by (Samhammer et al., 2022) found that healthcare professionals generally have a positive attitude towards AI - Decision Support Systems (AI-DSS) but expressed concerns about the potential loss of expertise and autonomy. They further highlighted that AI-DSS should be designed to support and enhance the expertise and autonomy of physicians, rather than replacing them. Thus, AI technology should be implemented in a way that preserves physicians' authority and autonomy, while enabling them to benefit from its capabilities (Wysocki et al., 2023).

5. Study Limitation

The study focuses on healthcare organizations in Malaysia with regard to the perception of Health Data Platforms in the healthcare sector. While the findings can be broadly applied to other developing countries, further research is imperative to assess the applicability of these insights across diverse cultural contexts. A noteworthy limitation stems from the cross-sectional nature of the data, which provides only one perspective and does not accurately represent complex relationships. Additionally, the use of a generic survey for data collection, although effective for quantitative data, constrains the depth of inquiry into the studied issue. Moreover, the small sample size was also a limitation which owes itself to a small number of individuals' willingness to participate. Therefore, future investigations are recommended to adopt a mixed-methods approach, allowing for a comprehensive exploration of both subjective and objective aspects of Health Data Platforms, thereby enriching the understanding of these concepts in various cultural and organizational contexts.

6. Practical Implications

This quantitative nonexperimental correlational research study addresses a notable gap in existing peer-reviewed literature by investigating the influencers of innovative concepts like Health Data Spaces, Data Natives, Data Collectives, Data Commons, and Data Repositories, combined with artificial intelligence (AI), and their impact on clinical decision-making within the Malaysian healthcare landscape. The study underscores the potential for transformative advancements in healthcare practices resulting from the positive correlation observed. Policymakers are strongly encouraged to allocate investments towards the development and implementation of AI-driven platforms, aligning with physicians' expressed openness to incorporating health data-driven tools in decision-making. To effectively harness these emerging concepts, targeted training and education programs for physicians are deemed crucial to ensure proficiency in navigating these sophisticated platforms. Collaborative efforts between healthcare organizations and technology developers are vital for creating standardized and interoperable systems. Policymakers should advocate for robust data privacy and security measures to allay concerns related to health data sharing. Ongoing research and development initiatives are recommended to refine and enhance the effectiveness of AI-driven healthcare platforms, and public awareness campaigns are essential to educate patients and the public about the benefits and ethical considerations of these technologies, fostering a supportive environment for the integration of innovative healthcare concepts. Moreover, the findings of this research can assist clinicians and healthcare practitioners in integrating these tools to gain a more comprehensive view of patient data, thereby facilitating more accurate diagnoses and personalized treatment plans. Clinicians and practitioners can also play a vital role in advocating for robust data security measures, addressing patient concerns about privacy, and fostering trust in these emerging technologies. The integration of AI and data-centric systems thus offers clinicians an invaluable resource for elevating clinical outcomes and advancing patient care.

7. Conclusion

This study aimed to delve into the perspectives of Malaysian physicians regarding the influence of Health Data Spaces, Data Repositories, Data Collectives, Data Natives, and Data Commons on the integration of AI for Clinical Decision Making. The results of this study show a significant positive correlation, highlighting that Malaysian physicians' are open to using health data-driven platforms for making clinical decision-making. As the application of AI and collaborative data-driven approaches is still in its early stages in Malaysia, the outcomes of this study signify the country's potential to fully embrace these cutting-edge technologies.

The results not only affirm Malaysian physicians' willingness to incorporate health data-driven platforms into their clinical decision-making processes but also underscore the broader implications for the country's healthcare landscape. The study demonstrates that Malaysia is poised to leverage AI and data-driven collaboration to enhance healthcare practices, marking a promising trajectory for advancements in patient care. Additionally, the research reveals a positive outlook among physicians regarding the potential of AI and data-driven collaboration to yield improved patient outcomes, indicating a collective recognition of the transformative power of these technologies in the medical field.

Given the affirmative stance of Malaysian physicians and the optimistic perceptions surrounding the impact on patient outcomes, this study emphasizes the imperative for policymakers to sustain and augment their investments in the development and implementation of these platforms. The positive inclination toward utilizing health data-driven approaches implies a strategic opportunity for the government and policymakers to further nurture and optimize the integration of data-driven collaboration in healthcare. This study underscores the need for continued support, research, and infrastructure development to harness the full potential of these data-driven platforms as instrumental tools for informed clinical decision-making, ultimately contributing to the enhancement of overall patient outcomes in the Malaysian healthcare landscape.

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Authors contributions

Thelagavathy Naidu Ramasamy were responsible for study design, data collection and drafted the manuscript. Assoc. Prof. Dr. Shathees Baskaran revised and approved the final manuscript.

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Data sharing statement

No additional data are available.

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