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AI lifecycle from a data-driven perspective: a systematic review

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Abstract

Introduction. Revising AI lifecycle models has drawn the attention of scholars from different areas because of the advances in AI technology. Many AI lifecycle models have been proposed. However, no systematic review of current AI lifecycle models has been found. This study aims to review and synthesize AI lifecycle models in current literature from a data-driven perspective and recognize the roles of data in different stages of the lifecycle.

Method. This study used the Preferred Reporting Items for systematic review and meta-analyses (PRISMA) protocol to systematically review AI lifecycle models from research papers, reports, and acts published between 2020 and 2024.

Analysis. A qualitative approach was applied with a pre-specified categorization framework. Open coding, axial coding, and selective coding were used.

Results. Twenty AI lifecycle models were identified. Stages and contents varied with overlaps and confused use of stage names. These models were proposed from the perspective of business objectives, AI model development, or a combination of implementing scenarios. Great importance has been attached to ethical issues for the whole AI lifecycle.

Conclusion. A double-layer AI lifecycle model with three phases and ten stages is synthesized. Six roles of data are identified. Data documentation in the AI lifecycle has not been fully valued.

Introduction

The fast development of big data, computing power, and large language models have brought the era of artificial intelligence (AI) (Rzepka & Berger, 2018), which is defined as '*the ability of a machine to perform cognitive functions that we associate with human minds*'(Rai et al., 2019, p. iii). Many countries treated AI as '*an area of strategic importance*' and '*a penitential key driver of economic development*'(Samoili et al., 2020, p. 6). Recent breakthroughs in AI technology are being embraced by scholars, governments, and tech-led companies (Allam, 2020). Because of AI's capabilities in autonomy (Rieder et al., 2020) and human task performance (Maedche et al., 2019), it has gained pervasive applications in various working and living scenarios (Heyder et al., 2023).

AI differs from previous technologies and information systems. AI systems can now be assigned complex tasks with vague requirements, rather than passively waiting to be utilized. Ethical and security concerns arose with the changes in AI technology, including distributive justice (Gabriel, 2022), bias and discrimination (Ferrer et al., 2021), and explainability and transparency (Endsley, 2023). As a result, flaws were noticed with information system lifecycle models when being implemented in the AI industry (Allam, 2020). Thus, New processes must be included in developing AI systems to ensure they can satisfy all requirements (Zancul et al., 2019).

Revising AI lifecycle models has drawn the attention of scholars from different areas(Allam, 2020), because of the advances in technology and changes in AI applications. According to the U.S. General Services Administration, the AI lifecycle can be treated as the iterative process of moving from a certain problem to a solution by applying AI technology (Centers of Excellence, 2024). Many AI lifecycle models have been proposed from various aspects. Until now, no systematic review of current AI lifecycle models has been found. Besides, many lifecycle models were revised based on business processes, which concentrated more on algorithm development but ignored the role of data in different stages of the AI lifecycle. Considering the above research gap, this study aims to recognize and compare the current AI lifecycle models from a data-driven perspective. It can provide a groundwork for future studies of AI in the field of information and benefit the application of AI lifecycle models in aspects besides product development. Three research questions guided this systematic review:

RQ1: What are the AI lifecycle models in the literature?

RQ2: Which stages of the AI lifecycle models are identified in the literature?

RQ3: What are the roles of data in different stages of the AI lifecycle?

Methodology

This study used the Preferred Reporting Items for systematic review and meta-analyses (PRISMA) protocol to carry out the systematic review. By creating concise summaries of existing research and evidence with a pre-determined process (Cooper, 2015), a systematic review with PRISMA can provide reliable, transparent, and reproducible findings for both communities of research and practice (Snyder, 2019).

Data collection

Following the steps of Lefebvre et al. (2019) and Davis et al. (2014), a four-stage strategy was used to build a comprehensive literature sample, namely identification, screening, eligibility, and included (Figure 1). Materials were obtained from three kinds of resources: databases (including Scopus and Web of Science), Google Scholar as a supporting database, and websites of related organizations for reports and acts. A keyword search was conducted in databases and Google Scholar. The search terms consisted of '*artificial intelligence lifecycle*' or 'AI *lifecycle*'. They were used to search for each study's title, abstract, and the listed keywords in databases. Google search engine was used to search websites for reports and acts. The search terms consisted of '*artificial* *intelligence lifecycle*' or 'AI *lifecycle*' and all combinations of '*report/regulation/act/strategy*'. This study focused on English literature published between 2020 and 2024.

In total, 22,116 publications were identified to be relevant to AI lifecycles. They were scanned by title, abstract, and keywords to include those that have proposed or implemented AI lifecycle models. Both theoretical and empirical studies were included because it is important to comprehensively review how AI lifecycles have been revised and updated and how it has been applied in product development, especially given that the evolvement of AI lifecycle models is relatively immature. After the assessment, 86 studies were included as the final literature sample.

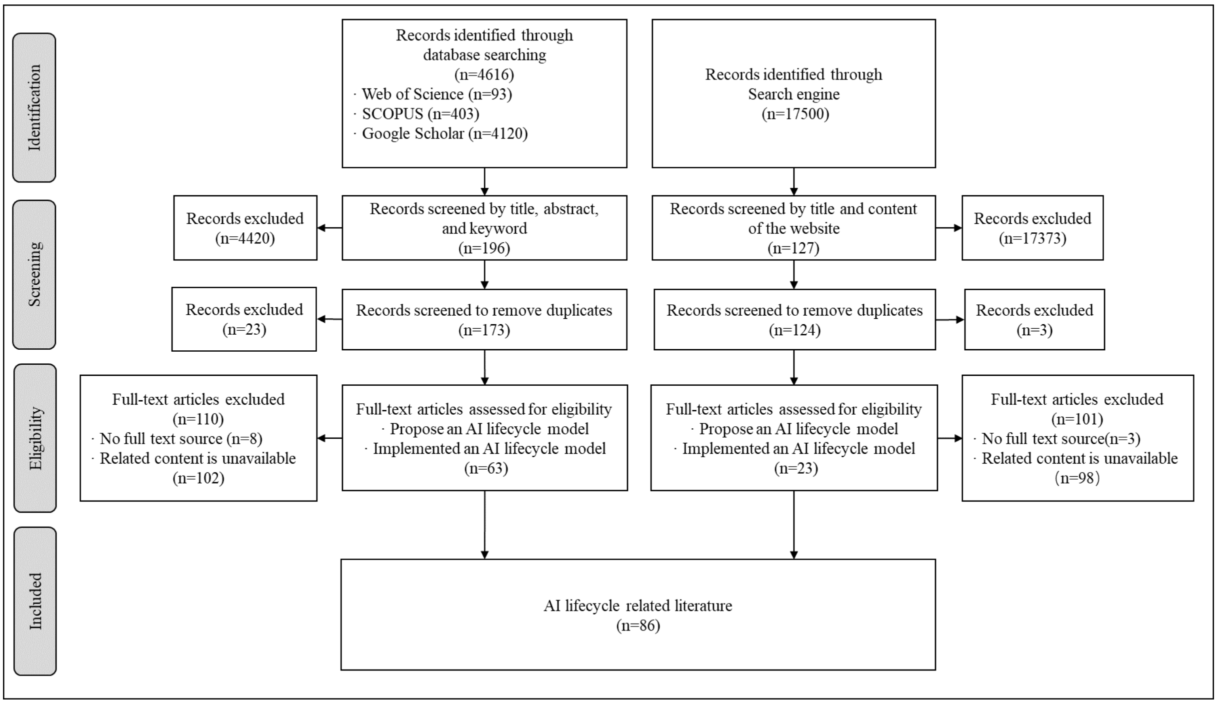

Figure 1. PRISMA flowchart

Data analysis

The study applied a qualitative approach to analyse AI lifecycle models of the literature sample. It is an effective approach for assessing and comparing articles from different areas and perspectives (Snyder, 2019). The software MaxQDA was used to facilitate the analysis. For the coding process of AI lifecycles, a pre-specified categorization framework was used to guide the process, which included three aspects: AI lifecycle types (the name of the proposed or implemented AI lifecycle model), AI lifecycle stages (the names and definitions of the stages included in the AI lifecycle model), stakeholders (related to AI lifecycle stages), and roles of data. Three coding techniques were used in the analysis, which are open coding, axial coding, and selective coding (Corbin & Strauss, 2008). The constant comparison method was used to distinguish different types of coding and to synthesize key concepts (Douglas, 2003).

AI lifecycle models overview

To answer RQ1, twenty AI lifecycle models were identified from the current literature (Table 1). More than half of the models were proposed in the years 2024 and 2022, indicating AI lifecycles' increasing attraction for scholars and the industry. The cross-industry standard process for data mining (CRISP-DM) is the most influential one, which has been '*the de facto standard for developing data mining and knowledge discovery projects*' for more than twenty years (Haakman et al., 2021, p. 94). Many new models were refined or extended based on CRISP-DM.

For the structure of AI lifecycle models, most of them have one layer with a range of stages. Five lifecycle models have two layers, which gather stages into phases. The end-to-end AI lifecycle was the only one with three layers. It separates the lifecycle into two parts: the data science lifecycle and the AI operations lifecycle (Arnold et al., 2020). They each include phases and stages. For the number of stages, six of the AI lifecycle models have 7 stages. The CDAC life cycle is the most detailed one with 19 stages, while the Team Data Science Process (TDSP) and AI ethics lifecycle are the most concise ones with four stages.

AI lifecycle model	Structure	Structure Details	Application scenario	Origin	Year	Reference
TDSP	One layer	Four stages	Machine learning		2017	(Ericson et al., 2017; Haakman et al., 2021)
CRISP-DM	One layer	Six stages	Machine learning		2019	(Haakman et al., 2021; Martínez-Plumed et al., 2017)
Microsoft model	One layer	Nine stages	Machine learning		2019	(Amershi et al., 2019; Haakman et al., 2021)
Allam's AI lifecycle	One layer	Five stages	All kinds of AI		2020	(Allam, 2020)
End-to-end AI lifecycle	Three layers	Two cycles Three phases Nine stages	All kinds of AI		2020	(Arnold et al., 2020)
AI application project lifecycle	One layer	Seven stages	All kinds of AI		2021	(Zhou & Chen, 2021)
Refined CRISP-DM	One layer	Nine stages	Fintech	CRISP-DM	2021	(Haakman et al., 2021)
AI lifecycle in clinical AI	One layer	Five stages	Clinical AI		2022	(Singh, 2022)
CDAC AI life cycle	Two layers	Three phases Nineteen stages	All kinds of AI		2022	(De Silva & Alahakoon, 2022)
Extended CRISP-DM	Two layers	Three phases Seven stages	Manufacturing	CRISP-DM	2022	(Rauh et al., 2022)
Isom's AI lifecycle	One layer	Five stages	All kinds of AI		2022	(Isom, 2022)
Moley's AI lifecycle	One layer	Seven stages	Machine learning		2022	(Georgieva et al., 2022)
Fairness intervention AI lifecycle	Two layers	Three phases Eleven stages	All kinds of AI		2023	(Calegari et al., 2023)
AI development lifecycle	One layer	Seven stages	Supply chain		2024	(Xia et al., 2024)
AI Ethics Lifecycle	One layer	Four stages	Energy systems		2024	(El-Haber et al., 2024)
AI-enabled system lifecycle	Two layers	Three phases Twelve stages	Clinical AI		2024	(Kaas et al., 2024)
Edge-to-cloud AI lifecycle	One layer	Seven stages	Industry 5.0		2024	(Alberti et al., 2024)
HEAAL	Two layers	Four phases Eight stages	Healthcare		2024	(Kim et al., 2024)
ODD & BC driven AI lifecycle	One layer	Six stages	All kinds of AI		2024	(Stettinger et al., 2024)
Seven-layer model	One layer	Seven stages	All kinds of AI	CRISP-DM KDD SEMMA	2024	(Agarwal & Agarwal, 2024)

Table 1. Details of the identified AI lifecycle models

For the application scenario of the identified models, about half of them are suitable for all kinds of AI products. Early lifecycle models were mainly proposed for machine learning, such as TDSP, CRISP-DM, and the Microsoft model. The variety of application scenarios increased with time. In

2024, the implementation of AI in the industry and healthcare has become the focus of many studies, including Industry 5.0, the supply chain, and the energy systems.

The identified AI lifecycle models were proposed from three different aspects, which may be the main cause for their differences. The majority of them were synthesized based on the process of AI product development, including CRISP-DM, the Microsoft model, the CDAD AI life cycle, Moley's AI lifecycle, etc. These lifecycles started with an analysis and understanding of business objectives and included a process of data preparation and analysis before training the AI models. Scholars treated such a kind of lifecycle as a data-driven AI development approach (Georgieva et al., 2022). The second aspect focused on AI model development, such as the operational design domain (ODD) and behaviour competencies (BC) driven AI lifecycle, AI ethics lifecycle, and Allam's AI lifecycle. These lifecycles were simple with key stages related to building AI models. The third aspect is the combination of AI development with specific scenarios or purposes. These lifecycles usually have complex structures with several layers and inserted stages related to the implemented scenarios. For example, the Health Equity Across the AI Lifecycle (HEAAL) includes a phase of clinical integration to execute AI solutions (Kim et al., 2024). AI-enabled system lifecycle includes a user training stage to teach expert users to operate and interact with the clinical diagnose support system (CDSS) (Kaas et al., 2024).

Stages of AI lifecycle

To answer RQ2, this study compared the stages of the identified AI lifecycle models (Table 2). In total, 16 stages were classified from these models. Three issues were noticed based on the comparison. First, many stages have no agreed names. Different names were used for stages of similar contents. For example, both data acquisition and data collection mean collecting data from a variety of sources for training AI models (Amershi et al., 2019; Singh, 2022). Second, though the names of the stages look the same, the meanings differ between the authors. For example, model evaluation is commonly used in many AI lifecycle models. Some authors put it before the model deployment stage (Alberti et al., 2024), indicating it to evaluate the performances of different AI models to choose a proper one for later deployment. Some authors put it after the model deployment or operational use stage, indicating it to be an evaluation of the whole AI project (Stettinger et al., 2024). Third, overlaps were recognized between stages. For example, some lifecycles included a design stage for designing the AI model (Georgieva et al., 2022), while others treated the design process as a phase including several stages from identifying the problem to preparing the data for training the AI model (De Silva & Alahakoon, 2022; Kaas et al., 2024).

After reducing the overlaps and conflicts of current AI lifecycle models, we synthesized a double-layer AI lifecycle model with three phases (design, develop, and deploy) and ten stages (Figure 2). It follows the data-driven approach by including a process of data preparation and analysis. The stages are not entirely sequential, with room for iterations and loops between stages. Details of each stage are as follows:

Problem identification is the initial stage of the AI lifecycle, where the problem is identified, elucidated, and formulated (Deck et al., 2024). This involves understanding the problem's typology, environment, expected objectives, stakeholders, systems, processes, and data (De Silva & Alahakoon, 2022). There are four types of typologies: strategic, tactical, operational, and research (De Silva & Alahakoon, 2022). Strategic typology addresses high-level challenges in specific domains, such as healthcare or energy. Tactical typology focuses on improving current methods to enhance productivity or quality. Operational typology involves applying validated AI capabilities to similar problems. Research typology aims at algorithmic innovations. The problem's setting influences objectives, whether commercial, industrial, or research-focused (Agarwal & Agarwal, 2024).

Project planning is crucial for building a fair and unbiased AI system. It focuses on creating '*the multi-granular matrix of ethics principles and paradigms for tuples of subject, requester, and temporality*' (El-Haber et al., 2024, p. 3). The subject is AI system, and the operators and output generated by the system. The requester encompasses various stakeholders, from operators seeking transparency and safety to managers and owners desiring accountability. Temporality refers to the duration of ethical considerations, from the start of a function to the system's operational life.

AI lifecycle model	Business understanding	Project planning	Data creation	Data collection	Data preparation	Data exploration	Data understanding	Model design
TDSP	O			O				
CRISP-DM	O				O		O	
Microsoft model	O			O	O			O
Allam's AI lifecycle								
End-to-end AI lifecycle				O	O			O
AI application project lifecycle	O			O				O
Refined CRISP-DM	O			O	O		O	
AI lifecycle in clinical AI			O	O				
CDAC AI life cycle	O			O	O	O		
Extended CRISP-DM	O				O		O	
Isom's AI lifecycle				O				
Moley's AI lifecycle	O							O
Fairness intervention AI lifecycle	O			O		O		
AI development lifecycle				O		O		O
AI Ethics Lifecycle								O
AI-enabled system lifecycle	O	O			O	O		
Edge-to-cloud AI lifecycle	O			O	O			
HEAAL	O	O						O
ODD & BC driven AI lifecycle								O
Seven-layer model	O			O	O			O
AI lifecycle model	**Model development**	**Model evaluation**	**Model testing**	**Model deployment**	**Model operation**	**Model monitoring**	**Model maintenance**	**Model documentation**
TDSP	O			O				
CRISP-DM	O	O		O				
Microsoft model	O	O		O		O		

Allam's AI lifecycle	O		O	O		O		
End-to-end AI lifecycle	O			O		O	O	
AI application project lifecycle	O		O	O		O		
Refined CRISP-DM	O	O		O		O		O
AI lifecycle in clinical AI	O	O		O				
CDAC AI life cycle		O		O	O	O		
Extended CRISP-DM	O	O		O		O	O	
Isom's AI lifecycle	O	O		O				
Moley's AI lifecycle	O		O	O		O		
Fairness intervention AI lifecycle		O		O				
AI development lifecycle	O	O		O		O		
AI Ethics Lifecycle	O	O			O			
AI-enabled system lifecycle	O		O			O	O	O
Edge-to-cloud AI lifecycle	O	O		O		O	O	
HEAAL				O		O	O	
ODD & BC driven AI lifecycle	O	O		O	O	O		
Seven-layer model	O		O	O				

Table 2. Comparison of stages of AI lifecycle models

Data acquisition aims to obtain data suitable for AI model development. Stakeholders must be aware of data acquisition methods, use privileges, and regulations to make informed decisions. Cybersecurity precautions and import/export policies are necessary when integrating datasets from the open market (Isom, 2022).

Data preparation involves processing and cleaning the acquired data to ensure they are suitable for analysis and model training (Alberti et al., 2024; Haakman et al., 2021). Special attention needs to be taken to avoid biases during the preparation steps, as they can affect the AI model's fairness and accuracy (Agarwal & Agarwal, 2024).

Model design begins with 'a comparison with industry benchmarks and algorithmic baselines' where similar problems have been addressed (De Silva & Alahakoon, 2022, p. 5). It demands a clear definition of the AI algorithm's purpose (Singh, 2022). It then includes, excludes, transforms, or aggregates features for effective and efficient handling of training models (Deck et al., 2024).

Model building involves training suitable AI algorithms that align with the intended application (Alberti et al., 2024). The maturity of AI technologies and the agility of programming languages have contributed to the capability and time efficiency of building several AI models by reimplementing algorithms, which ensures the integrity of AI models (De Silva & Alahakoon, 2022).

Model evaluation indicates models built in the last stage should be evaluated '*using the metrics designed for the type of AI capability and the algorithm*' (De Silva & Alahakoon, 2022), such as the benchmarks set in the model design stage. When the required capability is not achieved, new algorithms need to be developed based on novel research.

Model deployment involves integrating the AI model into a scenario for operational use (Singh, 2022), setting up necessary interfaces, and ensuring scalability, reliability, and security (Alberti et al., 2024). The best practice to reduce risk is to use safe deployment techniques, including A/B tests and canary releases (Arnold et al., 2020).

Model monitoring is crucial to ensure AI models' accuracy, explainability, and unbiasedness (Isom, 2022) by tracking key performance metrics. Monitoring tools are essential to understand AI actions and mitigate risks, enhancing user confidence through advanced traceability (Alberti et al., 2024).

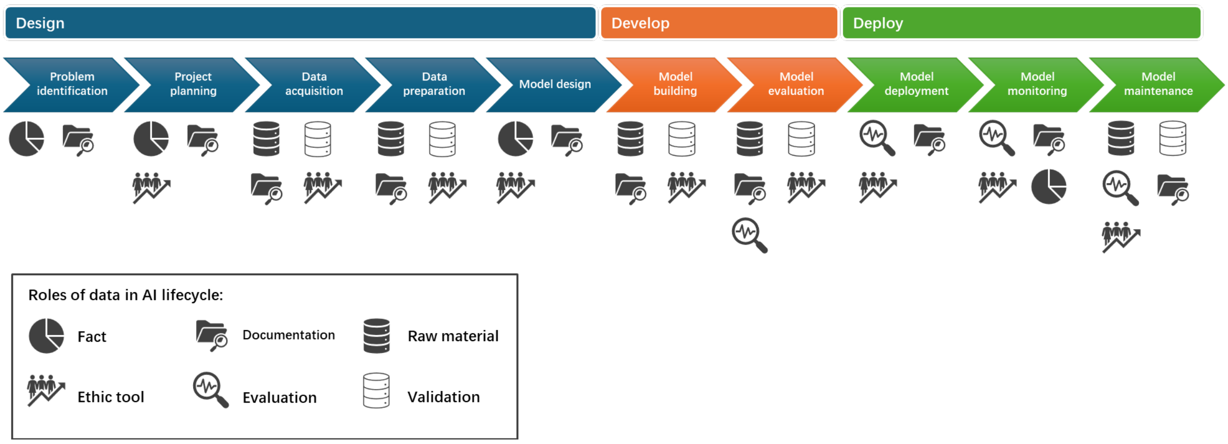

Figure 2. AI lifecycle model with the roles of data

Model maintenance is a stage commonly alternated with the model monitoring stage. It includes handling model drift and addressing issues, which are challenging tasks requiring skills and expertise (Alberti et al., 2024). Many methods can be used to improve AI models, including '*feature engineering, model architecture selection, hyperparameter tuning, and the addition of more training data using techniques such as active learning*' (Arnold et al., 2020, p. 4).

Discussion

To answer RQ3, based on the stages of the AI lifecycle model in the last section, this study identified six roles of data in the whole lifecycle of AI, which are facts, raw materials, validation, evaluation, ethic tools, and documentation. In different stages of the AI lifecycle, data plays different roles (Figure 2). These roles highlight the importance of high-quality, diverse, and well-managed data throughout the AI lifecycle.

Facts mean data describing the environment connected to the AI project. It can help stakeholders understand the problem, thus in problem identification, project planning, model design, and model monitoring stages, stakeholders collect data reflecting the facts to support decisions.

Raw materials mean the data for training AI models, allowing algorithms to learn patterns and make predictions or decisions based on new inputs. It is closely related to *Validation*, which means separating datasets to validate and test the model, ensuring it performs well on unseen data and generalizes effectively. The datasets for training and validating AI models usually are collected and processed together (Singh, 2022), thus datasets play these two roles in data acquisition, data preparation, model building, and model evaluation stages of the AI lifecycle. For model maintenance, sometimes additional datasets are used for the evolvement of AI models (Arnold et al., 2020), as explained in the last section.

Evaluation means data used to reflect the model's performance with various metrics and benchmarks, helping to refine and improve the AI model. AI models are not only evaluated in the development phase to select better-performed ones for the deployment phase (Haakman et al., 2021). They are managed in the deployment, monitoring, and maintenance stages with regular evaluations of their functions (De Silva & Alahakoon, 2022; Isom, 2022).

Ethic tools mean data to be diverse and representative to help in identifying and mitigating ethical issues, including biases (Kim et al., 2024), fairness (Agarwal & Agarwal, 2024), explainability (Singh, 2022), trustworthiness (Solanki et al., 2023), etc. Scholars have been extensively working to address AI ethics issues by inserting bias detection and fairness assessment in all stages of the AI lifecycle (Agarwal & Agarwal, 2024; Calegari et al., 2023), especially for the training datasets and evaluation metrics.

Documentation means the whole lifecycle to be properly documented (Kaas et al., 2024). This includes the evaluation metrics in model evaluation, deployment, monitoring, and maintenance stages, as well as data about the design and the model itself (Kaas et al., 2024). It enables reproducibility and a trail of actions and decisions (Haakman et al., 2021). Sufficient historical data will also help to build a more accurate model with fewer bias issues (Kim et al., 2024). However, data documentation in the AI lifecycle has not yet drawn enough attention. Only two current lifecycles included details of documentation (See Table 2).

Conclusion

This study reviewed 20 AI lifecycle models identified from the current literature. Overlaps of stage contents and confused use of stage names were noticed in these models. A double-layer AI lifecycle model was synthesized from the data-driven perspective, which provides a canonical overview of multiple stages that fit business objectives, AI model development, and various implementing scenarios. We anticipate this AI lifecycle model to address commercial, scholarly, and social interests and contribute to future AI studies. Six roles of data in the AI lifecycle were identified to increase the awareness and emphasis of high-quality, diverse, and well-managed data to support AI model development. This study also shows the documentation function of data in the AI lifecycle has not been fully valued. The key limitation of this study is that the proposed AI lifecycle model with data roles has not been validated with empirical research or practical applications, which calls for future studies to examine the model in real-world settings.

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