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AI-Powered Approach to Data Science: Understanding and Important Factors

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Abstract

The explosive growth in analytics, artificial intelligence, and cognitive computing has had a profound impact on organizations and businesses. It is even became much easier to find what is not impacted than what is impacted. These impacts have been categorized into areas such as organizations, work, and jobs, as well as potential unintended consequences. Consequently, mitigating such undesirable impact concerns for AI-powered data science, that merged data science initiatives with new developments in AI, applications become interested topic. The study aimed at understanding the current status of AI-powered data science and identifying important factors that affect the meeting of motivations behind the aim. The main motivation behind this aim is the need to mitigate these undesirable impact concerns from multidisciplinary perspectives. The study adopted literatures review and thematic analysis as main research methods. The study's findings showed that creation of data science department, people analytics; incomplete or inaccurate data and decision-making; privacy, biased or diminished human agency on decision-making- are major impact concerns for AI-powered approach applications. Also, a generalized human-mediated framework for AI and deep learning–based enterprise-level analytics solutions, synthetic data, complexity domains, master slave relationship were important factors that had effects meeting the motivations behind the aim.

Keywords
Data Science, Privacy, Synthetic Data, Complexity Domains and Master Slave relationship.

1. Introduction
The Section introduces the research's problem, aim, motivations behind the aim, and the objectives that the study follows. Finally, the Section concludes with paper organization.

According to Sharda et al. (2021), "There will be a tremendous influence on future businesses from the rapid growth and implementation of analytics, artificial intelligence (AI), and cognitive computing. The use of AI, analytics and cognitive computing can be categorized into three high-level areas that encompass the impact of computers and intelligent systems, (1) Society, (2) Individuals, and (3) Organizations." As intelligent systems, AI-powered data science applications are associated with undesirable technological, organizational, and societal impact concerns on stakeholders (data and artificial intelligence's users and scientists) such security, integration with other systems; incomplete, inaccurate, or biased decision-making; as well as, stakeholders retrain and train, or privacy impacts.

The study aims at understanding these undesirable impact concerns and at identifying important factors that affect the motivations behind the aim meeting, from multidisciplinary perspectives.
On the other hand, the study is motivated by the mitigation of such undesirable impact concerns.

1.1 Objectives

To understand the undesirable impact concerns of AI-powered data science and to identify important factors that affect the meeting of motivations behind aim; that is, the mitigation of such concerns, the study follows the following three objectives:

- selecting questions,
- highlighting literatures analysis, and
- identifying important factors.

Finally, the study is organized as follow. Section (2) views literature review, Section (3) presents methods, Section (4)) discusses results, and Section (5) presents the conclusion.

2. Literature Review

The Section addresses study's literature review building blocks that aims at understanding the undesirable impact concerns for AI-powered data science and the mitigations of such undesirable impact concerns. It identifies key concepts and investigates how key concepts, motivation, and aim related to each other, that is; concluding theorical framework and illustrating the AI-powered data science's ecosystem.

Mainly, data science and AI are the key concepts that are central to the study along with their relationships to mitigate undesirable impact concerns. "According to Cady (2024), "Data Science is Analysis-focused tasks that require a significant Software Engineering background, mainly for various reasons." Essentially, data science refers to the process of finding data or discovering underlying patterns (i.e., Complex behaviours, Trends, Insights, etc.) contained in data." Tyagi (2021). According to Kumari et al. (2024), the data science is "a special area where people who know a lot about data work with experts in other fields, using things like AI, stats, and tech to handle and make sense of information".
On other hand, analytics is woven into data science. Sharda et al. put answer for 'ANALYTICS OR DATA SCIENCE?' this way:

> Data science differs from traditional analytics primarily in technical depth and analytical sophistication. While data analysts focus on cleaning and visualizing historical data, data scientists employ predictive models and advanced algorithms to identify patterns and make forecasts. This requires skills in programming languages such as Python, R, or Java, as well as knowledge of machine learning and data mining. Various academic fields, including computer science and statistics, use the term "data science," while business sectors typically refer to it as analytics. (Sharda et al. 2021). ,

Alos, comparisons have been made between business intelligence and data science. Dietrich et al. put 'BI Versus Data Science' this way:

> Business Intelligence (BI) focuses on generating reports and dashboards regarding past and present business performance, answering closed-ended questions about revenues, goals, and sales. It compiles historical data into categories for retrospective analysis but lacks the ability to explain the reasons behind past events or their future implications. Conversely, Data Science employs disaggregated data proactively, analyzing current trends to forecast future outcomes. It utilizes techniques like time series analysis and predictive analytics to estimate future sales and revenue based on historical data. Additionally, Data Science includes exploratory techniques to optimize scenarios, addressing more complex and uncertain questions that BI cannot solve. (Dietrich et al. 2015)

Based on above definitions, a comparison of data science, analytics, and BI shown in Table 1.

Table 1. Comparison of Data science, analytics, and BI

Dimension	BI	Analytics	Data Science
Analytical Orientation	Descriptive and retrospective	Predictive with limited prescriptive scope	Predictive and prescriptive, forward-looking
Primary Function	Summarization and reporting of business performance	Statistical analysis and model-based explanation	Advanced modeling, forecasting, and decision optimization
Disciplinary Alignment	Business and management disciplines	Business analytics and applied statistics	Computer science, statistics, applied mathematics
Decision Support Role	Provides hindsight and limited insight	Enables informed prediction	Supports optimized and prescriptive decision-making

Another key concept is AI. Russel and Norvig put AI and intelligent machines this way:

> Artificial Intelligence (AI) involves agents that perceive and act within environments through connections between sensing and action. Various structures, like reactive and deep learning models, are used to tailor behavior to specific situations. Learning agents are notable for improving their internal components over time, enhancing action quality. This adaptability helps them cope with new environments. The quest for initiatory learning mechanisms has driven AI research since Turing's concept of "learning machines," establishing the foundation for modern AI and its focus on independent learning for smart adaptability. (Russel and Norvig 2021).

Furthermore, generative AI is a branch of AI that uses generative models (a large class of deep neural networks), in which the deep belief networks (DBNs) are considered a type of it. According to Sharda et al. (2021), "What deep learning has added to the classic machine-learning methods is in fact the ability to automatically acquire the knowledge required to accomplish such informal tasks and consequently extract some advanced features that contribute to the superior system performance." Figure 1 illustrates deep learning as a part of performing informal tasks' environment, in which the machine-learning method (via deep learning algorithms) is able to automatically (not human-mediated) acquire the knowledge required to accomplish such informal tasks and consequently extract some advanced features that contribute to the superior system performance. In addition, Tucker puts the birth of Generative AI this way:

Over the past five decades, the interconnection of computers for information sharing led to the creation of the Internet, while advances in hardware transformed bulky machines into portable, networked smartphones that revolutionized global communication. As data generation accelerated, researchers developed machine learning to detect patterns and extract insights from vast datasets. A major breakthrough came with the ability to reverse this process, enabling systems not only to analyze but also to create new data—marking the emergence of Generative Artificial Intelligence (Generative AI), capable of producing creative and autonomous outputs (Tucker 2025).

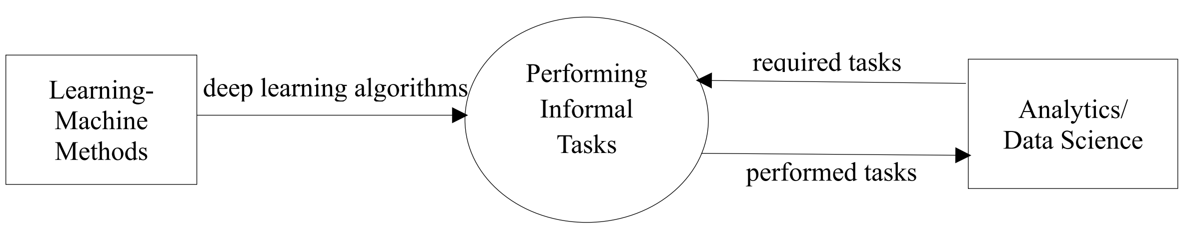

Figure 1. Performing Informal Task Dataflow Diagram

Now, the Section draws connections between data science and AI. As Tyagi (2021) states, "the vast realm of data science uses different approaches, methodology, algorithms and technology in order to analyze and gain knowledge through structured (labelled) and non-structured (unlabelled) data (i.e., data without assigned categories). Thus, as AI continues to advance, it will play an increasingly important role in helping to build a better and more efficient future on Earth." Papp. et al. put the generative AI emergence this way: The arrival of Generative Artificial Intelligence (GenAI) and its increased use within business intelligence (BI) and data science will completely change how BI is done (most importantly the nature of work performed) by providing access to relevant information in an easy-to-understand way (i.e., through natural language). In addition, GenAI speeds up the daily analysis of data and automates many routine tasks including cleaning and preparing data. By freeing up time, it enables analysts and data scientists to focus on more complex business issues while providing users enhanced access to data so they can make informed choices and take action based on it. (Papp et al. 2024).

According to SAS (2024), a major analytical and AI vendor, "modern data management is coupled with AI and machine learning. AI and generative AI (GenAI) will continue to push data management boundaries – not just now, but in the future." Data science, according to Sharda et al. (2021), "is rapidly adopting its initiatives and even integrating them with new advancements in artificial intelligence". In addition, and according to Kumar et al. (2024), "The specific topics of computer science within Data Science are already addressed by Artificial Intelligence (AI), Graphics and Interactive Techniques (GIT), Data Management (DM), and Mathematical and Statistical Foundations (MSF)". Moreover, according to Kumari et al. (2024), "to effectively analyze large volumes of data, engaging in data science requires the application of concepts and frameworks from various fields, including computer science, information theory, and mathematics", and as a result, an interdisciplinary field that emerged from data science and AI has been formed, AI-powered data science. Figure 2 illustrates AI and data science interdisciplinarity.

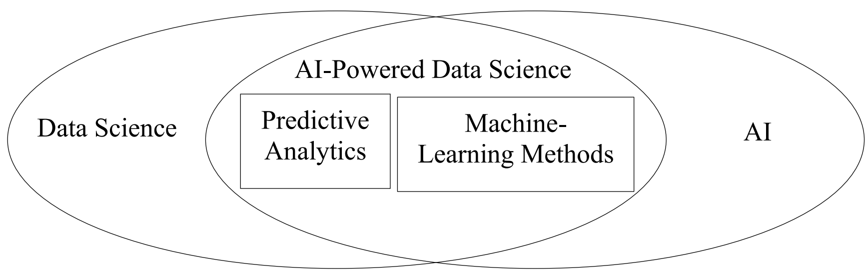

Figure 2. Data Science and AI Interdisciplinarity

Now, the Section moves to the second building block; the motivations behind the aim. The presence of AI-powered data science applications trigger the motivations behind the study's aim; that is, the need to mitigate undesirable technological, organizational, or societal impact concerns those arise when embracing AI-powered data science. In sum, the section is going to address the caveats of AI-powered data science.
According to Sharda et al. (2022), "Smart technologies have changed many parts of our lives and many companies. The factors that affect us are much easier to list than the factors that do not affect us. To classify the effects of smart technology, we separate them into three categories: Those relating to the way Organizations operate, the way people Work and the way Jobs are created; The potential for unforeseen consequences." Sharda et al. put legal, privacy, and ethical issues for AI, data science, and analytics this way:

As data science, analytics, cognitive computing, and AI develop, their impact on individuals raises ethical, legal, and privacy concerns. Technology's capabilities do not guarantee ethical use; thus professionals in these fields must address associated issues. The legal implications include liability for adverse consequences resulting from intelligent machine recommendations, and mismanagement leading to injury. Privacy concerns arise from using Business Analytics tools to expose fraudulent activities, such as tax evasion or hiring undocumented workers. This raises questions about the cost of privacy in preventing crime, as breaches can signal illegal activities. Ethical practices in developing intelligent systems require careful consideration, including how information is accessed and used. There is also a pressing need to ensure neutrality and equity in intelligent systems and to develop processes for eliminating biases in their creation. Finally, mechanisms must be established to maintain user control over intelligent systems while adhering to both legal and ethical standards in information gathering (Sharda et al. 2022).

According to Sharda et al. (2022), "intellectual property protection, ethics, security, privacy, connectivity, integration, strategy, and top management roles are issues that are related to the implementation of intelligent systems". Sharda et al. put from ethics and privacy to organizational and societal impacts for intelligent systems this way:

As technology continues to advance at breakneck speed, it's essential for people to continually learn and adapt. The influence of data science, analytics, cognitive computing, and artificial intelligence is growing, and it's going to touch everyone's lives in some way. However, just because technology has the capability to do something doesn't mean it's always ethical, legal, or the right course of action. This is something that managers and professionals in data science and AI need to keep in mind. The rise of intelligent technologies brings with it a host of legal, ethical, and privacy challenges that are closely intertwined. According to a study by the McKinsey Global Institute, as highlighted by Thusoo in 2017, we could face a shortage of around 250,000 data scientists by 2024. This means many professionals will need to be retrained or educated in order to effectively navigate the realm of intelligent technologies, advancements in data science, and the real-world challenges that arise. Education must evolve to meet these shifting needs. The requirements for data scientists are already changing, and to develop practical systems like the Internet of Things (IoT), they will need to be well-versed in intelligent technologies and machine learning. As data platforms adapt to new demands, innovative algorithms are enhancing operations and security, making it all the more important for professionals to stay ahead of the curve. (Sharda et al. 2021).
NASEM puts impact concerns of data on data science and AI this way:

Although data are critical components of numerous computing research sub-domains (e.g., artificial intelligence; data science; and human-computer interaction), computing researchers typically have no formal training or exposure to basic principles and practices concerning proper data management and manipulation. Access to specific types (e.g., individual-level data, as well as published research data) of 'found' or shared data has been made increasingly easier through open science initiatives and the Internet. However, the existence of these shared data/making them available to researchers has created many ethical, social, and other issues critical to good computing research practice for which researchers will bear some level of responsibility. (NASEM 2022).

Also, NASEM puts the source of societal problems that arise when designing solutions to computational problems this way:

The use of computation is based on simplifications of the problem in order to allow for a formal representation and/or the application of mathematics to facilitate a solution. However, this abstracting and simplifying process is a fundamental tool for development of solutions for problems in computation and poses a risk to society because it may discard important elements or emphasize the wrong things in situations that it is intended to solve. (NASEM 2022).
In short, Sharda et al. put The O'Neil Claim of Potential Analytics' Dangers this way:

Cathy O'Neil, a PhD math graduate from Harvard who has worked in both finance and data science, shares her expertise about these tools with the world in "Weapons of Math Destruction," which discusses how using data to create models and algorithms has long-lasting, often negative impacts on society. It is essential for both managers and data science experts to understand this and take into consideration how their interactions with these tools could impact individuals and groups in disproportionate ways. (Sharda et al. 2022).

Figure 3. views the concerns within AI-powered data science data science ecosystem.

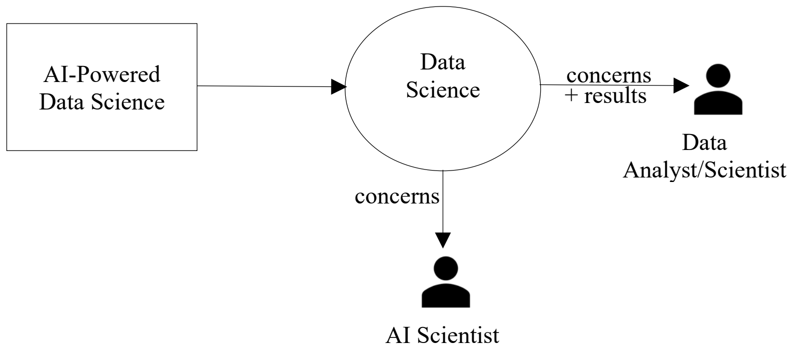

Figure 3. AI-Powered Data Science Concerns Ecosystem

The third building block is the aim itself. In this context, the study is considered one of evolved proper educations toward achieving the study's aim; investigating the current status of AI-powered data science and identifying important factors. This investigation provides answers to the study's selected questions and identifies the important factors. It addresses how data science and AI professionals and managers have to be very aware of legal and ethical concerns for AI-powered data science that may affect everyone, and how to retrain or train scientists so they can deal with intelligent technologies and the changes in data science and in solving related real-world problems.

As mentioned in first paragraph and after introducing the three building blocks of the study, investigating how these building blocks are related to each other can now take place. The ecosystem of AI-powered data science illustrates the relation among these three building blocks. The performing informal task process accepts required task from data science field, and then applies deep learning algorithms from machine learning field to provide data science field with performed task. The ecosystem must be featured rich interplay between data analysts and the machine learning method developers to retrain or train data science scientists to deal with AI-powered data science issues and achieving good results for people in general that are affected by those AI-powered data science applications. Figure 4. illustrates the ecosystem of AI-powered data science.

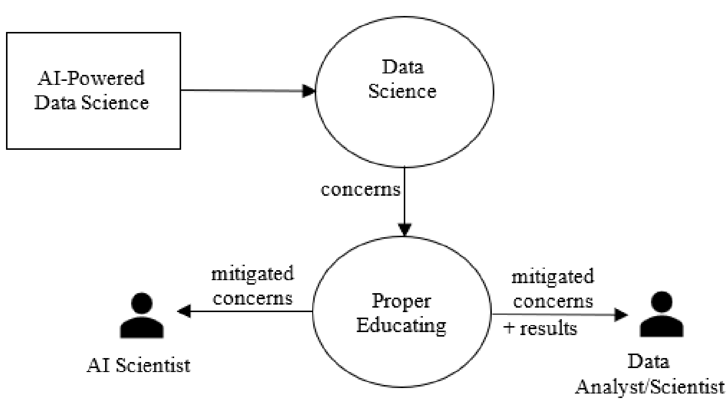

Figure 4. AI-Powered Data Science Ecosystem

3. Methods

The study adopts literature review and literature/thematic analysis research methods to meet its objectives that are stated in Section 1.1 above.

3.1. Selecting Questions

The reviewed literatures show that the research questions constitute the following major questions. *What are the major undesirable impact concerns for AI-powered data science application?* And *how to mitigate such concerns, from multidisciplinary perspectives?*
The problem, as mentioned above in Introduction section, is that AI-powered data sciences, as they AI applications, stakeholders are affected good or badly. Data science and AI scientists believe that data science and AI professionals have to be very aware of these concerns, and there will be a need to retrain or train scientists so they can deal properly with AI-powered data science problems. Thus, proper education must evolve. The main question of this research is *what is this proper education that must evolve to deal properly with AI-powered data science concerns?* This main research question involves several questions such as *how data science and AI professionals and managers have to be very aware of legal and ethical concerns for AI-powered data science that may affect everyone? how to retrain or train scientists so they can deal with intelligent technologies and the changes in data science and in solving related real-world problems? what are frameworks that embrace and merge data science initiatives with new developments in AI? How to retain and train scientists so they can deal properly with AI-powered data science issues? What are the caveats of Analytics and AI?*

There will be a need to How to retrain or train scientists so they can deal with intelligent technologies and the changes in data science and in solving related real-world problems?

3.2 Highlighting Literatures Analysis

In previous Section, the reviewing literatures showed the study's selected questions. On the other hand, this Section addresses answers to these selected questions through following the second study's objective; highlighting literatures analysis.

The proper education that must evolve for AI-powered data science professionals and everyone affected, to deal properly with AI-powered data science applications, focuses on two dimensions: 1) developing awareness of the existing legal and ethical concerns for AI-powered data science applications on professionals and everyone affected, and 2) training or retraining data scientists so they can deal with intelligent technologies and the changes in data science and in solving related real-world problems.

3.2.1 AI-powered Data Science Ethical Concerns

Of an interesting topics in AI fields are Ethical concerns. Alto (2023) states that, "AI experts warn about the direction that the pace of development of advanced technologies might take without critical safeguards and an understanding of the consequences. In this letter, they express the opinion that advanced artificial intelligence form a global catastrophe, and powerful impact adversely requires very careful planning and supervision. The letter starts by outlining the fact that AI research facilities are growing to develop strong AI that is far beyond human intelligence, and the activities are being conducted on a large scale than at any time before".

Ethical concerns regarding AI-powered data science in its research and applications. The NASEM's recommendations reflect this. NASEM, National Academies of Sciences, Engineering, and Medicine, puts its recommendations in this way:

> Recommendation 1 calls on scholars and the research community to rethink the field of computing research. The goal? Bring in the right ethical guidelines and pull in ideas from social and behavioral sciences—basically, do what it takes to make sure computing research gets done responsibly.
> Recommendation 2 turns to the people with the resources: funding agencies and research institutions. It pushes them to back researchers as they build this new framework, and to support fresh kinds of projects and collaborations that actually put this broader vision into action.
> Then there's Recommendation 4, which builds on Recommendation 3. It lays out clear ways for computing research institutions—working together with sponsors and professional groups—to give researchers real access to academic work in ethics and the social and behavioral sciences.
> Recommendations 5 and 6 put the spotlight on the two big players in computing: the research sponsors and the scholarly publishers. These groups have the job of judging research and making the call on whether

projects are really paying attention to ethical and societal issues.
Recommendation 7 speaks directly to researchers building systems. It's simple: stick to the best practices that have already been established.

Finally, Recommendation 8 asks everyone involved in computing research to work together to help the public really understand what computing research is and what it actually achieves (NASEM 2022).

On the other hand, UNESCO puts AI ethical concerns in this way:
Artificial intelligence brings a whole set of new ethical problems—some obvious, some not so much. It's not just about how AI changes decision-making or affects jobs. We're talking about its impact on how people interact, how healthcare works, who gets access to education, what shows up in your news feed, who can get online in the first place, and how your data gets used or misused. AI even touches on environmental issues, democracy, law, security, policing, and tricky things like when technology meant for good can be used for harm. And, of course, there are big questions about human rights, privacy, free speech, and making sure people aren't unfairly singled out or discriminated against. One of the tougher issues is how AI can actually make existing biases worse. When algorithms pick up on our prejudices and stereotypes, they don't just copy them—they can amplify them, making discrimination and unfair treatment even harder to shake. A lot of worries come from the fact that AI now does things only living beings—or even just humans—used to do. That shift gives AI a bigger role in our everyday lives and in how we interact with the world around us. For kids and young people especially, this changes the environment they grow up in. It affects how they figure out who they are, how they make sense of the world, how they learn to question what they see in the media, and how they pick up decision-making skills. Looking ahead, AI might even mess with what makes us human—our sense of experience and agency. This raises some pretty deep questions about how we see ourselves, how we connect with others and the environment, and what things like autonomy, dignity, and value really mean (UNESCO 2023).

3.2.2 AI-powered Data Science Techniques Training and Retraining
Data scientists and analysts need to retrain or train scientists so they can deal with intelligent technologies and the changes in data science and in solving related real-world problems (Sharda et al. 2021). NASEM states that "Recommendation 3 puts education front and center. It pushes schools to rethink and update their courses in several ways. Plus, it urges scientific and professional groups, as well as research funders, to step up and provide training so computing researchers really know how to do—and judge—responsible computing research (NASEM 2022)".
Shards et al. put the need for generic framework for AI and deep learning–based enterprise-level analytics solutions in this way:

Enterprise analytics is changing fast, with AI pushing it into new territory. For most companies, diving into deep learning and AI on their own isn't easy. Honestly, teaming up with experts who know how to get real results makes a huge difference. That's where a solid framework comes in—it keeps track of models running in production and makes sure they actually work. This whole setup runs on four main pillars: AI Strategy, AI Rapid Analytic Consulting Engagement (Race), AI Foundation, and AI as-a-Service (Sharda et al. 2021).

3.3. Important Factors
The Section follows the third study's objective; identifies the important factors that affect meeting the motivations behind the aim. The identified important factors include:

3.3.1 Synthetic Data
Synthetic data reduces AI ethical concerns. Synthetic data is artificial data designed to mimic real-world data. It's generated through statistical methods or by using artificial intelligence (AI) techniques like deep learning and generative AI (IBM 2025). IBM puts the acting of synthetic data in training AI models in this way:

Synthetic data isn't real, but it's built to look and behave just like the real thing. It keeps the same core patterns as the original data, so you can use it alongside real datasets—or even swap it in completely. A lot of people use synthetic data to test systems or train machine learning models, which is huge right now because finding enough good, real-world data is tough. You see this especially in fields like finance and healthcare. Data there is locked down—either it's hard to get, takes ages to collect, or gets tangled up in privacy rules and security laws. That's where synthetic data steps in and fills the gap. No wonder it's catching on fast. Gartner even says that by 2026, three out of four businesses will use generative AI to create their own synthetic customer data (IBM 2025).

3.3.2 Domain Complexity

According to Russel and Norvig (2021), "If the subsequent state of the environment is entirely dictated by the present state and the action taken by the agent(s), we refer to the environment as deterministic; otherwise, it is nondeterministic". Taking this into account, and analogy to Tucker (2025, October 10), "if AI-powered data science adoption is in the Clear or Complicated complexity (deterministic, predictable) domains, then data analysts or experts could do it themselves; they are writing instructions to handle the situation. If its adoption is in the Complex or Chaotic complexity (non-deterministic, non-predictable) domains, providing additional instructions will not be beneficial in this context, as we are unable to predict future outcomes in advance. Therefore, it becomes essential to engage in a cyclic process of experimentation followed by responsive actions.". AI-powered data science, according to Tucker (2025, October 12), "it does not execute the processes associated with non-deterministic and non-predictive scenarios, and at best, according to its capabilities, it offers incomplete solutions". Furthermore, and according to Tucker (2025, October 12), "determining the truth requires problem-solving, is fundamentally non-deterministic, and the methods for establishing the truth exceed the abilities of Generative AI; at present, this external assessment must be performed by humans".

3.2.3 Master/Slave Relationships

In case of AI-powered data science success in running all processes of deterministic and non-deterministic domain situations, is this a problem? In deterministic domain situations, this leads to device over human one of master/slave relationships between humans and devices, which in turns is described as very bad. In non-deterministic domain situations, how will the devices cope when the problem solving results in a negative answer? What does someone, or something, with no empathy do when they don't receive the expected result?
The relationship between AI-powered data science should be of kind human over device, which is described as good, in which master craftsman, expert with their tools.

5. Conclusion

The study followed three objectives. First, Selecting questions. it reviewed relevant literatures, and then posed the main question; what is the proper education that must evolve to deal properly with AI-powered data science issues? Second, highlighted relevant literatures and provided answers to selected questions. Data scientists and analysts need deep understanding and training on AI-powered data science. Finally, adopted thematic analysis and identified the important factors such as human master device relationship that ensures responsible and ethical implementation and application of AI-powered data science.

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