

AI IT Adoption

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The research study aims to explore the factors that impact the adoption of Artificial Intelligence (AI) in Information Technology (IT) departments. Specifically, the study will focus on organizational readiness, technological infrastructure, as well as the perceived benefits and risks. The goal is to gain insights into the barriers and facilitators of AI adoption in IT, ultimately enhancing our understanding of how AI can be seamlessly integrated into organizational processes.

Currently, original equipment manufacturers (OEM) and large first-tier manufacturing companies have recognized the necessity of embracing digitalization to remain competitive in the global economy. These entities possess the necessary resources, funding, and engineering expertise to assess and adopt Industry 4.0, including smart manufacturing and AI capabilities, to enhance their competitiveness and profitability. However, this is not the case for 90% of the supply chain, which comprises small- and medium-sized manufacturers (SMMs) (Harris & Yarbrough, 2024). This research aims to aid the 90 percent of businesses not currently utilizing AI by identifying the barriers they face.

The advancement of AI technologies, such as machine learning and business analytics (predictive and prescriptive), offers businesses unprecedented opportunities to optimize operations and refocus human efforts on innovative and creative work (Srivastava, Shneikat, Mendoza, Elrehail, & Afifi, 2024). AI is widely recognized as crucial for the modern workplace, and companies embracing AI are more likely to outperform their peers in terms of profitability and revenue growth (Stahl, 2024). Despite this, many organizations still feel hesitant about accepting and integrating AI. This research aims to investigate the relationship between AI

advancement and organizational adoption, focusing on identifying the factors that facilitate its adoption.

This research project aims to help small and medium-sized businesses identify the barriers preventing them from adopting AI into their organizations. The research will provide a database of similar industries and their unique barriers to adoption.

Database Design Process

The first step in the design process was to identify the key facets if an organization to adopt AI that needed to be captured. A facet is an atomic piece of metadata identified by its name. This means that emitting a new facet with the same name for the same entity replaces the previous facet instance for that entity entirely (OpenLineage, 2024). The key facets are the organization's readiness for AI adoption, the technology infrastructure that is currently in place, the customers' perceived benefits and risks of AI adoption, and the user feedback gathered.

Tables

In order to capture relevant data based on the identified facets, eight tables were created to store data. Each table is dedicated to a specific facet and contains fields to capture detailed information. The tables include Organizations, which stores basic information about each organization; Departments, which details specific departments within organizations; AI_Adoption, which tracks the level of AI adoption in various departments; Readiness_Factors, which measures factors influencing readiness for AI adoption; Infrastructure, which evaluates the IT infrastructure's capability to support AI; Perceived_Benefits, which records perceived advantages of AI adoption; Perceived_Risks, which lists potential risks associated with AI adoption; and User_Feedback, which collects qualitative feedback from users on AI implementation.

Fields and Data Types

Each table was designed to hold specific data fields relevant to its corresponding facet. A database field consists of a set of values organized in a table and shares the same data type. A field is also referred to as a column or attribute. These distinct fields preserve data accuracy and operational effectiveness (inetSoft, 2024).

Within the "Organizations" table, fields such as `org_id` (INT, Primary Key), `name` (VARCHAR), and `industry` (VARCHAR) store the unique identifier for each organization, the name of the organization, and the industry in which the organization operates, respectively. Meanwhile, the "Departments" table contains fields like `dept_id` (INT, Primary Key), `org_id` (INT, Foreign Key), and `name` (VARCHAR) to represent the unique identifier for each department, the linked organization, and the name of the department.

Furthermore, in the "AI_Adoption" table, fields including `adoption_id` (INT, Primary Key), `org_id` (INT, Foreign Key), `dept_id` (INT, Foreign Key), and `adoption_level` (VARCHAR) are used to uniquely identify each adoption record, establish links to the Organizations and Departments tables, and score the level of AI adoption (e.g., Low, Medium, High). Another table, "Readiness_Factors," incorporates fields such as `factor_id` (INT, Primary Key), `org_id` (INT, Foreign Key), `factor_name` (VARCHAR), and `score` (INT) to uniquely identify readiness factor records, establish links to the Organizations table, specify the name of the readiness factor (e.g., Training, Funding), and indicate the level of readiness.

Similarly, the "Infrastructure" table houses fields such as `infra_id` (INT, Primary Key), `org_id` (INT, Foreign Key), `infra_type` (VARCHAR), and `capability_score` (INT) that represent the unique identifier for each infrastructure record, link to the Organizations table, specify the type of infrastructure (e.g., On-Premises, Cloud Computing), and quantify the capability of the

infrastructure. Additionally, the "Perceived_Benefits" and "Perceived_Risks" tables store perceived benefits and risks, with fields such as benefit_id (INT, Primary Key), org_id (INT, Foreign Key), benefit_desc (VARCHAR), benefit_score (INT), risk_id (INT, Primary Key), org_id (INT, Foreign Key), risk_desc (VARCHAR), and risk_score (INT) fulfilling unique identification, organizational links, textual descriptions, and scoring functionalities.

Finally, the "User_Feedback" table includes fields like feedback_id (INT, Primary Key), org_id (INT, Foreign Key), feedback_text (TEXT), and feedback_date (DATE) to uniquely identify feedback records, establish links to the Organizations table, accommodate the textual feedback provided by users, and capture the date of the feedback submission.

Referential Integrity

Referential integrity pertains to the relationship between tables. In a database, each table must have a primary key, which can also appear in other tables due to its relationship to the data within those tables. When a primary key from one table appears in another table, it is referred to as a foreign key (IBM, 2022). In the case of the Adoption AI database, each table has a primary key, ensuring data consistency.

Furthermore, the Adoption AI database also enforces constraints. Database constraints are a crucial feature of database management systems, as they ensure that the rules defined at the data model's creation are enforced when data is manipulated (inserted, updated, or deleted) in a database (Fernigrini, 2022).

By implementing primary keys, foreign keys, and constraints, the AI Adoption database maintains referential integrity, essential for accurate and reliable data analysis, as shown in Figure 1. This design prevents data anomalies and ensures strong data consistency among table relationships.

Figure 1
AI Adoption Referential Integrity

The screenshot displays a database management interface with a schema tree on the left and a SQL editor on the right. The schema tree shows a database named 'AI_IT_Adoption' with tables including 'AI_Adoption', 'Departments', 'Infrastructure', 'Organizations', 'Perceived_Benefits', 'Perceived_Risks', 'Readiness_Factors', 'User_Feedback', 'Views', 'Stored Procedures', and 'Functions'. The SQL editor contains the following query:

```

1 SELECT
2   org.name AS organization_name,
3   dept.name AS department_name,
4   ai.adoption_level,
5   rf.factor_name,
6   rf.score AS readiness_score
7 FROM
8   Organizations org
9 JOIN
10  Departments dept ON org.org_id = dept.org_id
11 JOIN
12  AI_Adoption ai ON org.org_id = ai.org_id AND dept.dept_id = ai.dept_id
13 JOIN
14  Readiness_Factors rf ON org.org_id = rf.org_id
15 ORDER BY
16   org.name, dept.name, rf.factor_name;
17

```

Below the query editor, the 'Result Grid' shows the following data:

organization_name	department_na...	adoption_level	factor_name	readiness_score
FinCorp	IT	Low	Funding	4
FinCorp	IT	Low	Training	3
HealthInc	IT	Medium	Funding	4
TechCorp	IT	High	Training	5

Note. This query demonstrates how referential integrity ensures that related data across multiple tables can be combined to provide valuable insights into AI adoption levels and readiness factors across organizations.

Future Research

In order to advance future research in the field, it is crucial to focus on two additional areas. Firstly, understanding the financial impact of AI adoption on organizations, and secondly, examining the external effect of AI adoption on customer satisfaction and feedback. According to a research study by the McKinsey Global Institute, at the global average level of adoption and absorption, AI has the potential to generate additional global economic activity of around \$13 trillion by 2030, representing about a 16 percent increase in cumulative GDP compared with today (Bughin, Seong, Manyika, Chui, & Joshi, 2018). Example tables for financial performance could include the following fields: "Financial_Performance" with attributes such as org_id, year,

revenue, cost_savings, and ROI; and "Investment" to track AI-related investments with fields like org_id, investment_amount, and investment_date.

Additionally, it would be valuable for research to explore the external impact of AI adoption on customer satisfaction and feedback. In 2020, Brinks collaborated with OfferFit, an AI start-up, to conduct tests on thousands of message and offer combinations. Through the use of AI to optimize customer service and outreach, Brinks increased A/B testing and personalized every customer interaction. This led to significant increases in the company's direct-to-consumer(DTC) package size, DTC revenue per user, and overall revenue during the first half of 2021 (Edelman & Abraham, 2022). An example table for this could look like Customer_Feedback, which could contain fields such as org_id, customer_id, feedback_text, feedback_date, and satisfaction_score.

Assumptions or Limitations

This section will provide a detailed understanding of the assumptions and limitations impacting the database's design and functionality.

Assumptions

Uniform data quality is assumed, meaning that data collected from various organizations and departments is expected to be high quality, accurate, and consistent. Secondly, standardized measures for readiness factors, perceived benefits, and risks are assumed to be consistent across all organizations to enable meaningful comparisons and insights. Lastly, the assumption is that the user feedback collected represents a comprehensive and unbiased view of the AI adoption experience within organizations to accurately reflect the user experience and the real impact of AI adoption.

Limitations

The database has a few limitations that should be considered. First, the current schema may not encompass all aspects of AI adoption, such as regulatory considerations and cultural factors, and it may potentially be missing critical factors that influence AI adoption.

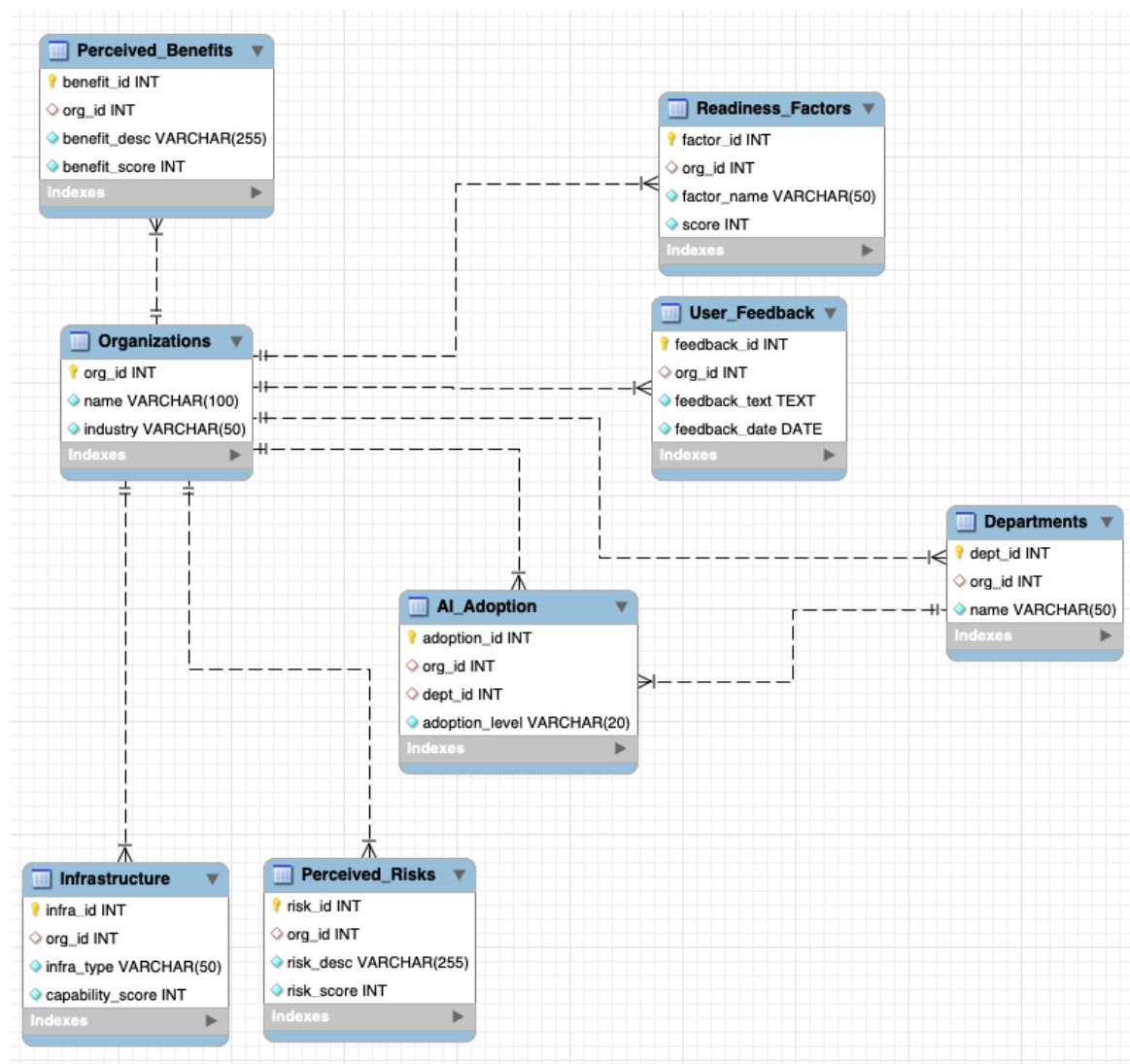
Additionally, the rapidly evolving nature of AI technology means that the data can quickly become outdated, requiring regular updates to remain relevant and accurate, as noted by Scientific America (Jones, 2024). This could lead to an inaccurate reflection of the current state or trends over time, highlighting the need to include time-based fields or tables.

While it is assumed there would be no bias when collecting data, there is a potential for bias in data collection, particularly in user feedback and perceived benefits and risks. If not addressed, this can skew results and lead to misleading insights. The schema assumes relatively independent relationships between factors such as readiness, infrastructure, benefits, and risks, although, in reality, these factors may be interdependent and require a more accurate model.

EER Diagram

The technical design of this database is structured with eight tables, each of which is related to at least one other table and contains more than two fields, as shown in Figure 2.

Figure 2
AI IT Adoption EER Diagram



Note. This was generated using MySQL Workbench.

Conclusion

The AI IT adoption database is a comprehensive tool designed to analyze various factors influencing the integration of AI within IT departments across different organizations. This research captures data on organizational readiness, infrastructure capability, perceived benefits and risks, and user feedback, providing valuable insights into the challenges and opportunities of

AI adoption. The design process ensures referential integrity while acknowledging certain assumptions and limitations that may impact the analysis. This framework will support current research and lay the groundwork for future studies that can extend its scope by incorporating additional data sources. Overall, this database significantly contributes to understanding and advancing AI adoption in small to medium businesses.

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