research

2024

TDWI AI Readiness

Assessment Guide

By Fern Halper, Ph.D.

Licensed to:

Informatica

tdwi
Transforming Data
With Intelligence™

research

2024

TDWI AI Readiness

Assessment Guide

Table of Contents

About the Author

FERN HALPER, PH.D., is vice president and senior director of TDWI Research for advanced analytics. She is well known in the analytics community, having been published hundreds of times on data mining and information technology over the past 20 years. Halper is also coauthor of several Dummies books on cloud computing and big data. She focuses on advanced analytics, including predictive analytics, machine learning, AI, cognitive computing, and big data analytics approaches. She has been a partner at industry analyst firm Hurwitz & Associates and a lead data analyst for Bell Labs. She has taught at both Colgate University and Bentley University. Her Ph.D. is from Texas A&M University.

You can reach her by email, on X/Twitter, and on LinkedIn.

About TDWI Research

TDWI Research provides research and advice for data professionals worldwide. TDWI Research focuses exclusively on data management and analytics issues and teams up with industry thought leaders and practitioners to deliver both broad and deep understanding of the business and technical challenges surrounding the deployment and use of data management and analytics solutions. TDWI Research offers in-depth research reports, commentary, inquiry services, and topical conferences as well as strategic planning services to user and vendor organizations.

Foreword from the Author

This is an exciting time for AI. Organizations are looking to advanced analytics technologies such as machine learning (ML) to help them gain insights, build applications, become more competitive, and digitally transform. AI technologies are being used across a wide variety of use cases, including churn analysis, fraud analysis, situational analysis, preventive maintenance, improved understanding of customers, and so much more. We often see organizations enhancing their infrastructure, typically involving a move to cloud platforms, to support advanced analytics. They are appointing chief data officers (CDOs) and chief analytics officers (CAOs) to support the effort. Vendors are also working hard in this ecosystem to infuse AI into their tools to make them easier to use.

Of course, the introduction of generative AI—systems trained on vast amounts of data to be able to generate output such as music, text, images, or audio—has taken the world by storm. Generative AI has, in many ways, put pressure on some organizations to advance more quickly. We see that generative AI is an executive mandate in some organizations. Others are viewing it as a path on their AI journey. It comes with a huge opportunity to transform how organizations do business, but there are also challenges organizations must address.

Although some organizations manage to advance in AI, others are stuck. The reality is that if organizations were adopting AI technologies at the rate they claimed in TDWI research, more than 75% of respondents to our surveys would be using ML and other AI technology today. In 2024 TDWI research, only about a quarter of the respondents are starting to build machine learning models and another quarter are already utilizing advanced AI technologies such as ML and natural language processing (NLP). Many admit they are struggling.

There are many reasons why organizations struggle to move forward, including culture, funding, skills, and tools. Yet, most organizations we survey do want to move forward, especially with AI and now generative AI. In fact, in a recent TDWI survey, generative AI was ranked higher than machine learning as a priority for analytics in 2024. Is it wise to effectively "jump" over the analytics tools and skills that go into developing machine learning models and move straight to generative AI? That remains to be seen.

There are several prerequisites for undertaking any AI program. TDWI developed this AI readiness assessment based on conversations with enterprises and vendors, as well as our own research into AI success. We are excited to offer this readiness assessment for AI.

Fern Halper

Fern Halper,
TDWI VP Research, Sr. Director Research for
Advanced Analytics

Trends and Opportunities in AI

What Is AI and Why Is It Important?

The idea that machines can act intelligently has been around since the ancient Greeks, yet there has been no real consensus about what the term artificial intelligence means. Back in the 1950s, when John McCarthy used the term, he described it as "Making a machine behave in ways that would be called intelligent if a human were so behaving."[1] There has been debate about the term ever since.

From a technology perspective, AI is an umbrella term that includes numerous methodologies and techniques. AI makes use of technologies in the fields of mathematics, computer science, computational linguistics, cognitive sciences, and robotics, to name a few. Popular technologies include:

MACHINE LEARNING (ML): Systems that learn from data to identify patterns with minimal human intervention. Machine learning originated in the field of computer science. Popular machine learning algorithms include decision trees, neural networks, and Naïve Bayes classification.

DEEP LEARNING: A subfield of machine learning in which algorithms learn functions that can classify complex patterns such as images. Often uses deep neural networks.

NATURAL LANGUAGE PROCESSING (NLP): Systems that can read, analyze, and understand human language with the goal of human/computer interaction.

COMPUTER VISION: A field of computer science in which computers can obtain information from images or other multidimensional data.

GENERATIVE AI: Like much of AI, generative AI is not a new concept. It goes back to the 1950s and 1960s when researchers were trying to use computers to generate content. Recent advances in algorithms such as generative adversarial networks, variational encoders, and now transformer models (such as GPT-4) have moved the field ahead. These foundation models are often trained on billions of parameters. For text data they are known as large language models (LLMs); these are able to predict which words statistically come next within the response to a user-entered text prompt. This kind of application is familiar to many people. It appears you're having a conversation with the AI system, but in reality, the algorithm is putting words together.

At TDWI, we see AI being used for many customer-focused, operational, and vertical use cases. For instance, AI is used to predict which customers will churn and to better understand customer behavior. AI is used in operations to predict when maintenance will be needed for equipment or to help optimize supply chains. It is used in vertical applications such as disease detection, fraud analysis, and network optimization. Additionally, AI is being employed in applications such as recommendation engines, smart cities, chatbots, personal assistants, employee onboarding, document summarization, and precision agriculture. AI is being embedded into processes for call centers, supply chains, marketing, and sales. Some organizations even consider AI models a data product they can buy and sell on marketplaces and exchanges.

There is clear value to be gained from AI. It can help improve decision-making, productivity, and efficiency and has clear top-line impact. In fact, at TDWI we consistently see that organizations that become more sophisticated with analytics are more likely to measure top- or bottom-line impact. In many ways, the use of advanced analytics is part of a success cycle: As organizations see success with their analytics program, they start to do more. As they do more and as they gain more experience,

[1] See *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*

they tend to see positive results. This success builds on itself and is perhaps one reason why enterprises that are more analytically advanced tend to be more satisfied and measure impact. In other words, there is tangible value to having a mature program.

Evolving Trends in AI

AI is not simply about building models, although the skills to do so are obviously important. It is also not simply about using a public generative AI system to help write marketing copy or develop a simple chatbot. It is about putting AI models into production and operationalizing the AI. At TDWI, we're seeing the following associated trends:

- **EMBEDDING AI IN BUSINESS PROCESSES.** An evolving trend in AI is the ability to put AI models into production as part of a business process. For instance, AI is being used to tailor interactions, recommendations, and services to individual preferences and behaviors. It is being used to automate routine actions. AI algorithms are being deployed directly on devices (such as smartphones, IoT devices, and edge servers).
- **DEVELOPING GENERATIVE AI APPLICATIONS.** At TDWI, we see organizations planning to build numerous types of generative AI applications. These include simple chatbots as well as applications that utilize company information. This may be as simple as using generative AI to summarize call center notes, or it may be more complex, such as using generative AI to create personalized marketing messages by working in conjunction with traditional machine learning models. Often, this involves using newer techniques such as converting each word in a sentence into a vector using a pretrained word embedding model and storing it in a vector database for use by the generative AI model. This may also include retrieval-augmented generation, where the vector embedding might be combined with a prompt and sent to the generative AI system that uses it to generate an in-context response. Building these applications often calls for development expertise.
- **OPS TEAMS TO SUPPORT AI IN PRODUCTION.** TDWI also sees the emergence of MLOps and AIOps teams to help put models into production. These teams work with data scientists and ML engineers to streamline the process of model development, including feature engineering, model training, and validation. They are responsible for establishing CI/CD pipelines for ML projects to automate the testing, validation, and deployment of ML models and their updates. They move models into production environments so they can be easily accessed by other systems or end users. They are responsible for monitoring the models in production to ensure that, when they become stale, they are retrained.
- **RESPONSIBLE AI**. Responsible AI considers the ethical, societal, compliance, legal, and environmental ramifications of using data in a wide variety of applications and processes. It examines the business, legal, and societal risks associated with AI. For example, ethical data practices include protecting privacy, reducing bias, boosting fairness and equity, improving diversity and inclusion, and engaging in ethical business conduct. Organizations are starting to understand that responsible AI will become very important to their businesses. This is, in no small part, driven by regulations. Regulations such as the EU AI Act are already in place; TDWI expects the U.S. to pass AI legislation in 2024. Canada is also considering legislation.

The AI Readiness Assessment

With these trends and opportunities in mind, TDWI created the TDWI AI Readiness Assessment. The assessment has approximately 75 questions across the five categories that form the dimensions of the TDWI AI Readiness Model (see Figure 1). These dimensions are:

Organizational Readiness	Data Readiness	Skills Readiness	Operational Readiness	Governance Readiness
• Leadership • Strategy • Funding • Culture	• Data diversity • Data integrity • Data platforms • Data architecture	• Scope • Roles and responsibilities • Skills, knowledge, and upskilling • Data and AI literacy • Tools	• Production readiness • Development • Process integration • Model management	• Data governance • Model governance • Governance roles • Security and privacy • Responsible AI

Figure 1. *TDWI AI Readiness Model dimensions.*

- **ORGANIZATIONAL READINESS.** To what extent do your organizational goals, strategy, culture, data and analytics leadership, and funding support AI? This dimension assesses several factors key to organizational readiness. It looks at whether leaders are on board with a realistic expectation of what AI can achieve and what is involved. It examines whether a strategy is being developed to support AI that includes not only AI technology but other important factors such as a solid data foundation and the right skills and talent. It looks at whether the resources and funding are available for AI success. It also examines whether your organization is culturally ready to utilize AI.
- **DATA READINESS.** AI makes use of diverse data. This may include structured data as well as text data, image data, or voice data. Organizations have been trying to modernize their architectures to support more modern analytics such as AI. This dimension examines whether your data infrastructure is ready for AI. It looks at factors including whether your platforms are scalable, how they support diverse data, and data quality and integrity. How coherent is your architecture in support of an AI initiative?
- **SKILLS READINESS.** This dimension assesses how your organization will support the technical skills needed for AI. It examines the skills already in place for data science, data engineering, and operations as well as plans for putting these in place. It also looks at how your organization will support AI literacy efforts to help others in the organization better understand AI and use tools that incorporate AI or the output from AI. It also examines what tools are in place that can support AI in the future, such as pipelines. What analytics and development skills currently exist in your organization? How does your organization believe it will obtain advanced analytics and data science skills? How will it build data science and other teams?
- **OPERATIONAL READINESS.** When many organizations embark on AI, they are thinking only of building AI models, not actually productionizing them. Yet, that is where the value lies. This dimension examines how ready your organization is to operationalize AI. It examines capabilities such as production readiness, pipeline readiness, process integration, and developer readiness.
- **GOVERNANCE READINESS**. Organizations rely on a range of processes, people, and tools to help with data and analytics governance. This dimension tracks the availability and adoption of tools for data and analytics governance. This looks at how advanced your organization is in its data governance as well as how it is positioned to support AI governance and responsible AI.

How the Readiness Assessment Tool Quantifies Metrics and Dimensions

The goal of the AI Readiness Assessment is to determine whether your organization has the experience, tools, and processes needed to leverage AI. Leveraging AI might include building a model using machine learning to predict customer actions, leveraging machine learning models in applications, or building generative AI applications. Note that this assessment is not a *generative* AI readiness assessment. Although generative AI has become popular, it is but one of the AI approaches outlined earlier. In this assessment we are looking at what you need to put AI and AI models into production to gain value and grow from there.

When you select answers to questions in the AI Readiness Assessment tool, the score for each dimension is calculated. The largest score for each single dimension is 20. Multiplying 20 by the five dimensions yields 100, which is the highest possible total score. At the end of the assessment, you will see scores for each dimension (out of a possible 20 points) and overall score (out of a possible 100).

If your organization is completely prepared to leverage AI today (and may be doing so), your score across all dimensions might total 100, but that's rare for someone taking the assessment; most overall assessment scores will fall between 40 and 70.

An overall score of 50 is a reliable watershed benchmark. Above that, users should proceed with their AI projects and further preparation may be successfully executed concurrently during the implementation. Below that, there are likely improvements that should be made to use-case commitments, data management, and skills before you undertake an AI implementation.

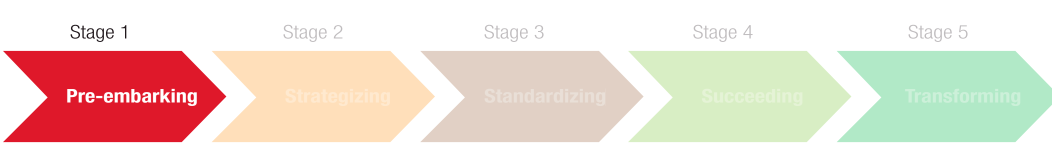
Stages of Readiness

The TDWI AI Readiness Model consists of five stages: Pre-embarking, Strategizing, Standardizing, Succeeding, and Transforming.

Figure 2. *Stages of readiness for AI.*

This guide provides a brief overview of each of the stages of the TDWI AI Readiness Model. This description provides context for interpreting your scores when taking the assessment.

Stage 1: Pre-embarking

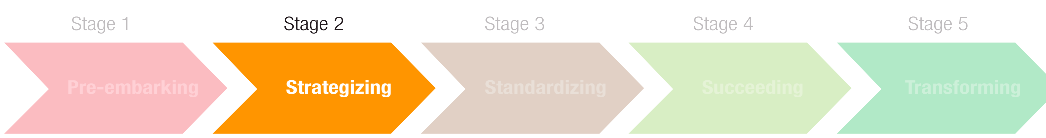


In this stage, organizations are often not ready for AI, but they have begun to sense the need for an AI journey and are looking for an on-ramp.

Typical scenario. Companies at this stage typically do not have leadership behind them to support an AI effort. The resources and talent are simply not in place to make AI happen, although there may be interest. Spreadsheets may still be the form in which these organizations build and share analytics. The organization may not have the data infrastructure in place to support more than spreadsheets; typically, these organizations are only working with structured data coming from diverse and siloed systems. They may not even govern this data. Although they may like the idea of doing analytics and analyze data via spreadsheets, they don't have the infrastructure, team, or the culture in place to make AI happen in the near term.

Recommendations. Organizations in this stage need to begin their data, analytics, and AI journey by determining what business problems they need to solve. From there, they need to start to build a data foundation to support business goals. This may involve a data warehouse, lake, data lakehouse, or other data platform. Consider the kinds of BI that may be needed and begin to look for tools and talent. Concurrent with this, the organization should start to put data governance measures in place. In this way, the organization can start to build the foundation it will need for analytics and, down the road, AI.

Stage 2: Strategizing



In this stage, leadership has embarked on the AI journey and realized they need a master plan or strategy to bring it coherence.

Typical scenario. In the strategizing stage, leadership has begun to understand how AI can be useful. The organization may already be using reports and dashboards to drive decision-making, so the culture is moving in the right direction. In this stage, organizations may not have a very solid data foundation in place for AI—such as a way to manage large volumes of diverse data in a unified way. They may not have the skills in place to start to address AI; this often means they will have to hire data scientists to build machine learning models or data engineers to build machine learning pipelines.

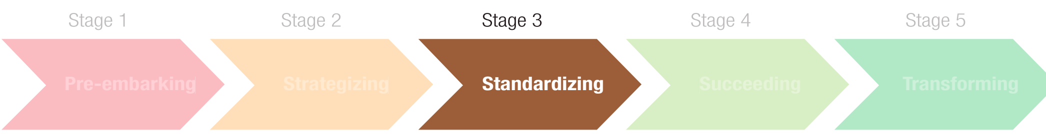
Typically, a strategizing organization may have started its analytics journey because it wants AI, but its analytics is not yet advanced.

Recommendations. In the AI strategizing stage, an executive sponsor may have emerged to drive the AI discussion in the company. Companies in this stage may score high in the organizational readiness dimension of this assessment. They may consider outsourcing an AI project. This may be because they are excited about AI and generative AI, but beware! An organization without the foundation for AI in place may have a difficult time implementing it, even with leadership support. At best, in the case of generative AI, they may begin to put disconnected AI systems in place for various use cases, such as chatbots that depend on website data or fine-tuning an LLM on company products or services. A company at this stage may have assembled data to build a machine learning model.

However, such a company may find that it starts to run into issues when it wants to add other company data to the application (such as client data) or when it wants to put a machine learning model into production. Although deploying a generative AI application may signal some type of AI readiness, an organization is only truly AI-ready when it has the capability, resources, and data foundation to deploy AI solutions. That is why it is still best for most companies to forge a path forward by building out a data and analytics foundation and starting to bring skills into the organization.

Some companies might hire a “tiger team” of external AI experts to get development done as fast as possible. However, it can be difficult to bring in the team if the data foundation is not ready, business leaders don’t completely understand what AI is going to do, and no change management is in place.

Stage 3: Standardizing

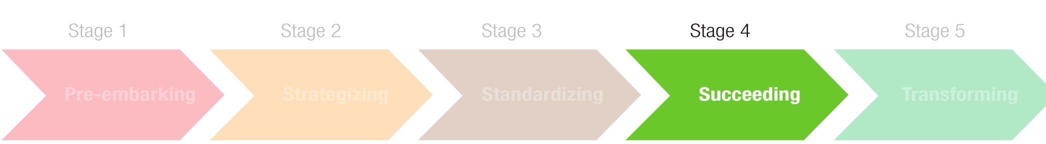


In this stage, organizations can leverage the lessons learned in their analytics journey to establish standards for platforms, tools, methodologies, roles, and processes to carry their journey forward.

Typical scenario. During the standardizing stage, there is a strategy and plan in place for AI. This may also include preliminary use cases the organization is looking to implement. Leadership is on board for some proofs of concept. The organization may have a data warehouse or other data platform in place that it can use to build a model against the (typically structured) data the company is managing. Such a company is often utilizing BI tools such as dashboards and even self-service BI. Some data governance practices are in place. Data analysts are on board, and some of them are interested in new techniques such as machine learning. This organization wants to take the next step in its analytics journey to technologies in the AI space.

Recommendations. For a company in this stage to continue in analytics and implement AI, it will be important to put the right skill set in place and manage expectations. This company should be hiring data scientists and data engineers. As these professionals start to build models, they will need to start thinking about how to put them into production and manage and monitor them there. This may require new team members such as MLOps who are responsible for operationalizing models and monitoring them in production. They will need to start considering how to scale their environments to support future endeavors. This may include utilizing new types of data such as text data. It may also involve understanding how to scale for the computationally intensive nature of certain AI models. If the company is outsourcing some of its AI development, it should begin to bring the talent in house.

Stage 4: Succeeding

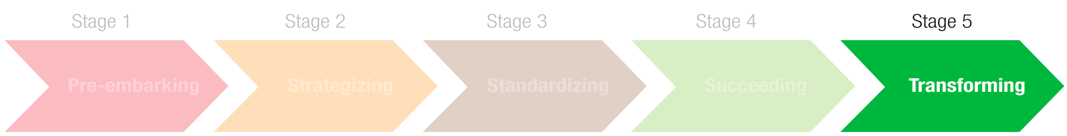


In this stage, organizations are starting to see clear ROI from AI. These enterprises are also considering how to broaden the metrics of success for AI to address all the responsible data analytics stakeholders and concerns such as managing bias and ensuring accountability.

Typical scenario. This is an exciting time for organizations: they are now implementing AI. During this stage, the organization is building machine learning models and starting to implement them in production environments. They have data scientists and data engineers on board. There may also be developers who are building AI applications, including generative AI. Data governance is in place, with mostly trusted data, and the organization is extending governance to manage and govern their models in production. They may even be thinking about responsible AI as they produce more models. During this stage, the organization is typically starting to see some ROI from AI which may feed the success cycle. They may even be thinking about how their models can be leveraged as data products and monetized.

Recommendations. Organizations in this stage should plan to put MLOps or even AIOps teams into place if they haven't already. These teams are responsible for operationalizing AI and caring for models in production. Additionally, now is the time to move beyond data governance to address responsible AI practices such as managing bias, fairness, and transparency as part of the overall governance efforts. Make sure to manage business risks associated with AI models.

Stage 5: Transforming



Some organizations will reach the transforming stage of AI readiness. These are often innovative companies that have the data infrastructure, talent, and tools to get the most from AI. They have developed a clear strategy that includes managing large amounts of high-quality data needed for training AI models. This often includes the use of cloud platforms. Enterprises in this stage invest in top talent who can work collaboratively to implement AI solutions. These team members also collaborate with others outside their organization and may be part of open source or other projects. These companies often foster a culture of continuous learning and experimentation and are quick to adopt new AI technologies.

These companies have a strong commitment to ethical AI practices and understand the importance of trust in AI applications. They have strong governance in place including using a CI/CD process to manage their AI models.

Evaluating Assessment Scores

The TDWI AI Readiness Assessment has approximately 75 questions across the five categories that form the dimensions of the Readiness Model. Of course, organizations can be at different stages of readiness in these five categories, and most are.

Scoring

Questions are weighted differently depending on their relative importance. Each dimension has a possible maximum score of 20 points. Because organizations can be at different levels of readiness in the five dimensions, we score each section separately and provide an overall score. The assessment output is a score in each dimension and the total score.

Interpretation

Once you complete the survey, you will see a report showing your score for each dimension and an overall score.

The breakdown of scores for each dimension is as follows:

SCORE	STAGE
5 or less	Pre-embarkation
6-10	Strategizing
11-14	Standardizing
15-18	Succeeding
19-20	Transforming

For instance, if you receive a score of 11 in the Organizational Readiness dimension of the assessment, you are in the Standardizing stage for that dimension. You should expect to see your scores vary across the different dimensions. AI efforts don't necessarily evolve at the same rate across all dimensions.

When you complete the assessment, you might see scores such as this:

DIMENSION	SCORE	STAGE
Organizational Readiness	11	Standardizing
Data Readiness	8	Strategizing
Skills Readiness	9	Strategizing
Operational Readiness	5	Pre-embarkation
Governance Readiness	15	Succeeding

This means that although your organization is ready in the organization and governance dimensions, it is not as ready in the others. Understanding your relative strengths and weaknesses will help you establish goals and, in turn, target your efforts and allocate resources.

Summary

The TDWI AI Readiness Assessment provides a quick way for organizations to assess their readiness for AI. The assessment is based on the TDWI AI Readiness Model, which consists of five stages.

The assessment serves as a relatively coarse measure of your AI readiness. The approximately 75 questions across five categories merely touch the surface of the complexities involved in building out an AI program. To gauge precisely where you are, it may also make sense to work with an independent source to validate your progress.

About the Sponsor

Informatica

Informatica (NYSE: INFA), a leader in enterprise AI-powered cloud data management, brings data and AI to life by empowering businesses to realize the transformative power of their most critical assets. We have pioneered a new category of software, the Informatica Intelligent Data Management Cloud™ (IDMC), powered by AI and an end-to-end data management platform that connects, manages, and unifies data across any multi-cloud, hybrid system, democratizing data to modernize their business strategies. Customers in approximately 100 countries including more than 80 of the *Fortune* 100 rely on Informatica to drive data-led digital transformation.

Connect with LinkedIn, X, and Facebook.

Informatica.
Where data and AI come to life.™

www.informatica.com

research

TDWI Research provides research and advice for data professionals worldwide. TDWI Research focuses exclusively on data management and analytics issues and teams up with industry thought leaders and practitioners to deliver both broad and deep understanding of the business and technical challenges surrounding the deployment and use of data management and analytics solutions. TDWI Research offers in-depth research reports, commentary, inquiry services, and topical conferences as well as strategic planning services to user and vendor organizations.

tdwi

Transforming Data With Intelligence™

A Division of 1105 Media
6300 Canoga Avenue, Suite 1150
Woodland Hills, CA 91367

E info@tdwi.org