

Introduction

Artificial intelligence (AI) was formally founded as an academic discipline at a conference in 1956, long before workforce management (WFM) systems became a staple in the contact center. In the years since, AI initiatives and enthusiasm have ebbed and flowed, but there's been a recent surge in interest and investment due to advancements in computing power, an explosion of data collection and the business need to seek increased productivity and profitability through technology.

Writing in Harvard Business Review, MIT researchers Erik Brynjolfsson and Andrew McAfee called Al and machine learning "the most important general-purpose technology of our era."

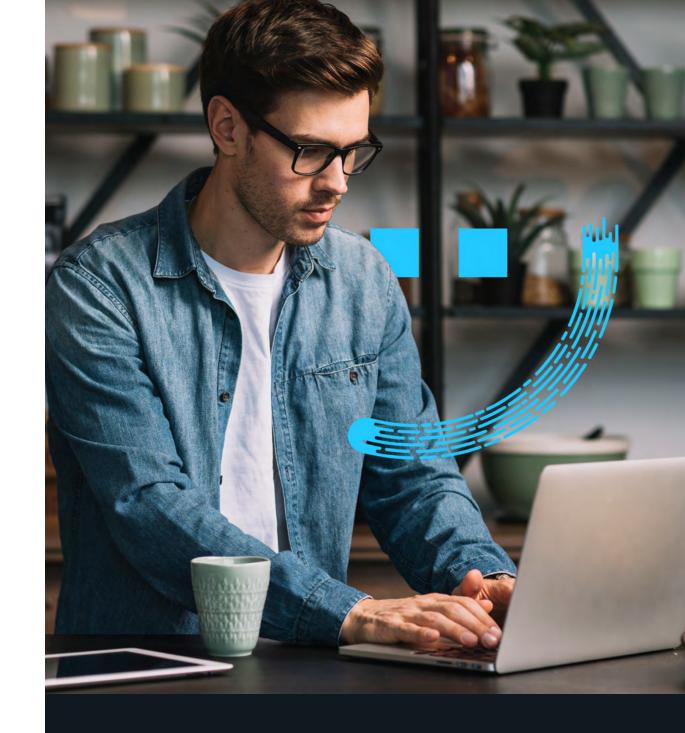
The field of Al is broad, covering many perspectives such as reasoning, knowledge representation, planning, natural language processing, perception and object manipulation. Its toolbox includes search and mathematical optimization, artificial neural networks, statistical evaluation and probability analysis.

Machine learning (ML) is a subset of AI. The term was coined in 1959 to describe a process whereby algorithms can learn from and make predictions on data. It's the "science of getting computers to act without being explicitly programmed," writes Andrew Ng, an adjunct professor at Stanford University and former head of Baidu AI Group/Google Brain.

The discipline of AI has made significant advances since its inception. Early machine learning models specified all possible choices to enable the computer to make decisions. The "decision tree" had to be preprogramed to account for all eventualities.

Today, however, machine learning uses flexible models that enable the computer to make choices that include options not explicitly defined. The machine learns by being "fed" large amounts of information (input data), and initial decisions are "guessed" by the machine.

These initial "guesses" are then fine-tuned by comparing them to the "correct" answer or a specified expected outcome (output data). The primary goal is to generalize beyond the instances in the input or output data — often called the training data — so that new information that arrives can be readily analyzed and acted upon without human intervention.



Machine learning occurs in two general forms:

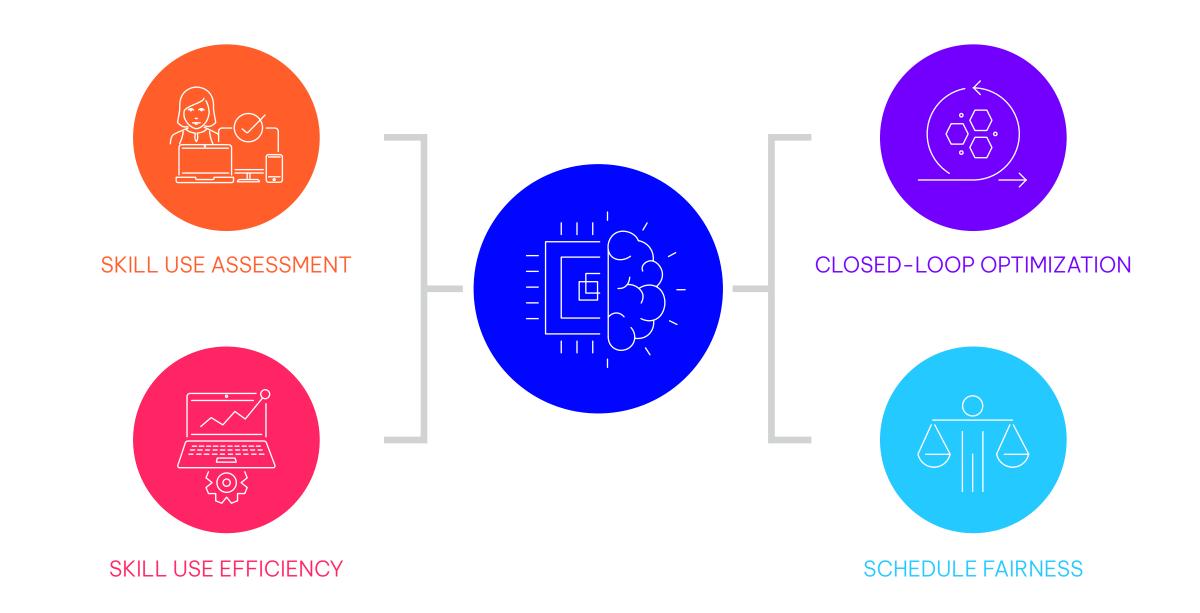
- Supervised learning: The computer is given examples of inputs and the resulting outputs from those inputs. The goal is to derive a rule or routine that processes the inputs to automatically predict the expected outputs.
- Unsupervised learning: The computer finds structure or patterns in the input data with no foreknowledge of the resulting outputs. The goal is to analyze raw data to find hidden patterns.

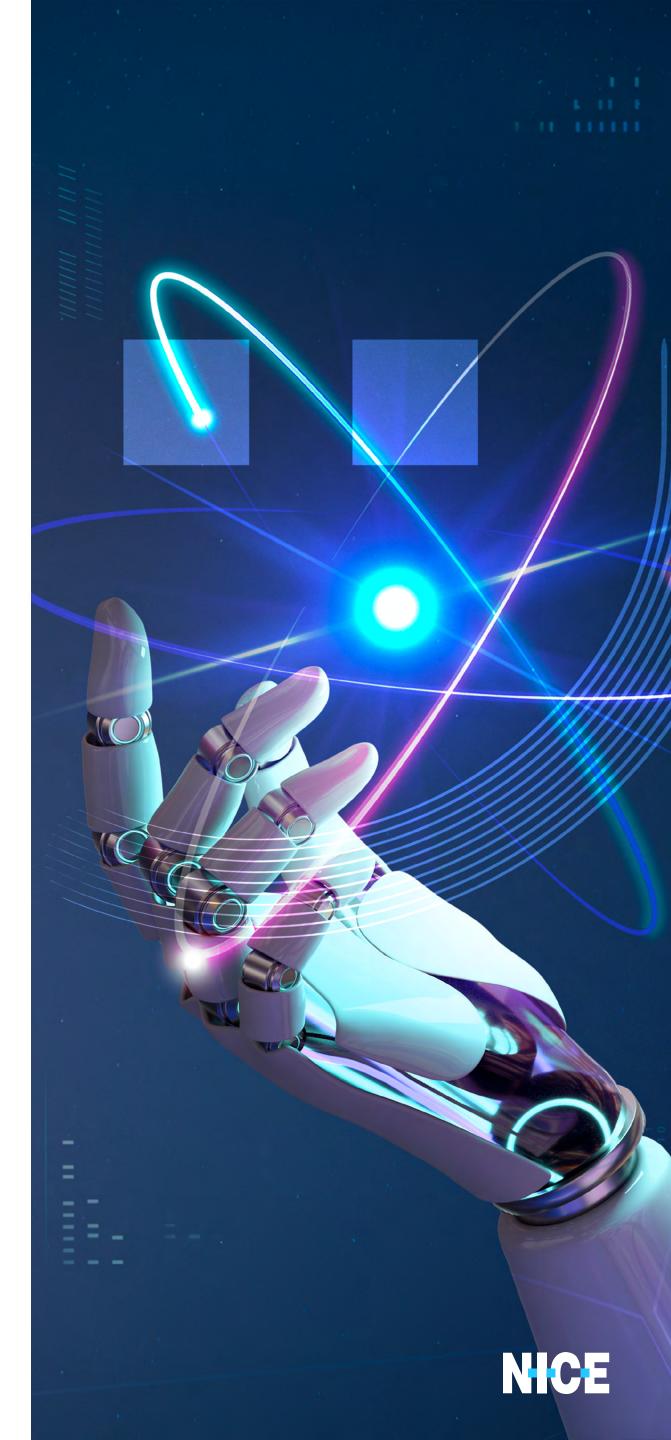


How NICE WFM Uses AI and ML

NICE has made a significant investment into AI and ML techniques that are embedded into its core workforce management solution, NICE WFM. Recent advancements include learning models that find hidden patterns in the historical data used to generate forecasts for volume and work time. NICE WFM also has an AI tool that determines, from a series of more than 40 models, which single model will produce the best results for each work type being forecasted.

These are just the newest applications of AI and ML in NICE WFM – NICE began leveraging AI and ML in the solution as a matter of practice long before artificial intelligence became the marketing buzzword de jour. **Here's how:**







Skill Use Assessment Intelligence

Determining optimal schedules and efficiency gains when using multi-skilled employees is highly dependent on a significant challenge in today's omnichannel work centers: the ability to accurately estimate when and to what extent an employee needs to be shared across multiple work streams.

Accurate schedule generation is a challenge in and of itself given today's creative scheduling concepts, but it is further complicated by the need to accurately split an employee's productive time across two or more work queues. Without a reliable understanding and prediction of the time an employee will contribute to each work area, the use of multiskilled employees can lead to poor decisions... and poor customer service.

Both factors demand fluidity in a multi-skill environment – fluidity that requires some level of artificial learning to fully comprehend. Most WFM systems, however, lack the ability to accurately assess and predict this most important element of skill usage estimation. Some systems simply split an agent 50–50 or in thirds, depending on the number of assigned skills.

Other systems consume an employee's productive time using a most-to-least-skilled hierarchy and "hope" there is spare capacity to allocate the employee to lower-skilled work streams. "Hope" is a poor planning method, as it disregards the specific conditions that warrant sharing an employee between multiple work streams. Other systems attempt to eliminate the "hope" approach by assuming that history is a good predictor of skill usage. While prescriptive for root cause analysis, historical skill usage data is a poor predictor of future intent, because it is rare that the schedules, work volume, work times and queuing conditions of the future are the same as they have been in the past.

The NICE WFM skill usage assessment is based on predictive analysis embedded in the discrete event simulator. Using this approach, no historical data is analyzed, no forced hierarchy of skill consumption is required, and no assumptions or user input is needed. The learning of skill usage estimates occurs through the analysis of unstructured data as the data is processed through a predictive model that is created by the end user to mimic work flows. The model represents a basic decision tree, without needing to account for all eventualities of how employees of various skill profiles might be used in any given interval on any given day.

The model predicts if, when and to what extent a particular skill of a particular employee should be used. This flexible machine modeling is a form of unsupervised learning that allows the system to find patterns of skill usage in the input data with no foreknowledge of the resulting outputs. The result is a highly accurate assessment of skill usage, which is the foundation for determining multi-skill efficiencies and optimal schedules.

What makes this skill usage assessment so hard to achieve? Two factors are at play:

- The time Employee A spends using his skills is dependent on the time Employee B spends using her skills – the actions of one person affects everyone else.
- Conditional queuing: ("If...Then... Else" logic in the routing constructs) and automated "reskilling" of employees (using features such as reserve skills or precision queuing) hinder predictability from one interval to the next.





Skill Use Efficiency Intelligence

One of the primary challenges in modern WFM practices is understanding the impact of multi-skilled employees on "required lines." "Required lines" represent the number of full-time equivalent workers (FTEs) needed in a productive state to meet service objectives (ASA, Service Level, Maximum Occupancy, etc.). Most WFM systems rely on a calculation method called "Erlang" to determine the FTE value for each interval of the planning horizon.

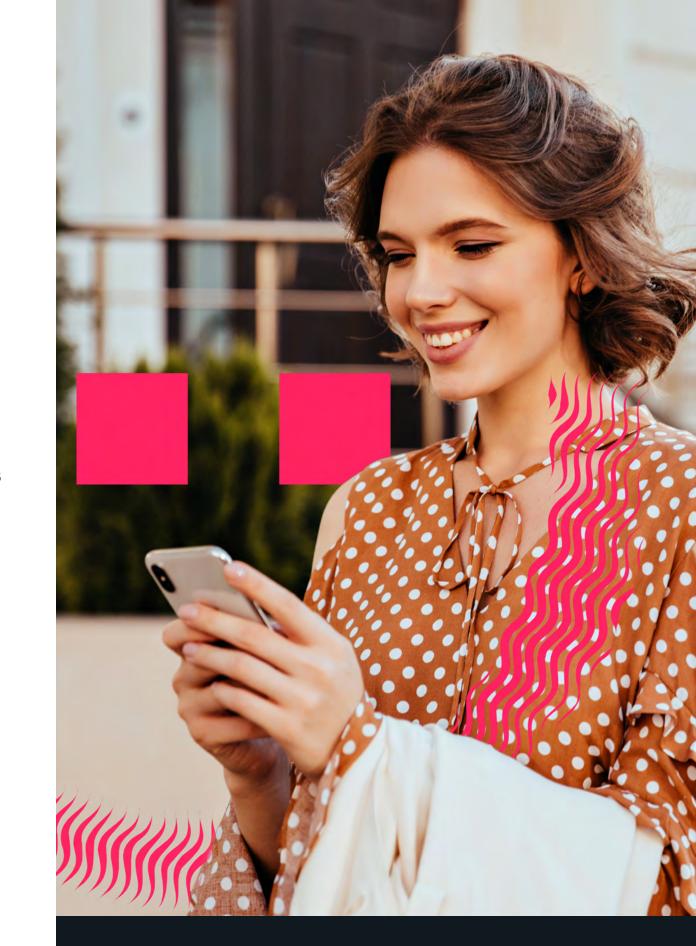
Unfortunately, Erlang has two significant assumptions that are not valid in today's modern work center. Specifically, it assumes that all employees share a homogenous skill assignment and that work items queue to a single skill profile. This is rarely true in today's work center. The net effect of these assumptions is to overstate the required lines.

Other WFM systems attempt to apply an adjustment factor, but the end user must provide the value of the adjustment factor. Some WFM systems perform a rudimentary estimation of an adjustment factor but do not perform the estimation uniquely for each interval or for ever-changing queuing scenarios.

NICE WFM solved this FTE overstatement by adding intelligence directly to the required line calculation.

The intelligence automatically learns the efficiencies that are inherent in each unique work center. This learning process occurs uniquely for every interval of every day for each work stream. The system is given each interval's inputs of work volume, work time and staffing information as well as the expected output from those inputs. When the derived output does not match the expected output, the NICE WFM system automatically learns the underlying efficiencies.

This patented algorithm, which is a form of supervised learning embedded with the discrete event simulator, provides the intelligence to artificially "deflate" the Erlang-derived FTE to a value that is trustworthy with no human interaction required. As schedules are modified to account for shrinkage, a simulation launches the relearning of the efficiencies. As skills are assigned (or reassigned) manually (or automatically), a simulation launches the relearning of the efficiencies. As forecast values are updated to account for unexpected shifts in demand, a simulation launches the relearning of the efficiencies. Basically, whenever an underlying planning element changes, the NICE WFM system is smart enough to understand the gain (or loss) of efficiencies when using multiskilled employees.



Many WFM systems simply ignore the impact of multi-skilled workers and present the user with overstated required lines that must be manually "re-interpreted" by the end user.



Closed-Loop Optimization Intelligence

NICE has also invested in artificial learning in the form of "closed-loop schedule optimization." This application leverages the form of machine learning in which the machine learns by being fed large amounts of information, with initial decisions are "guessed" by the machine.

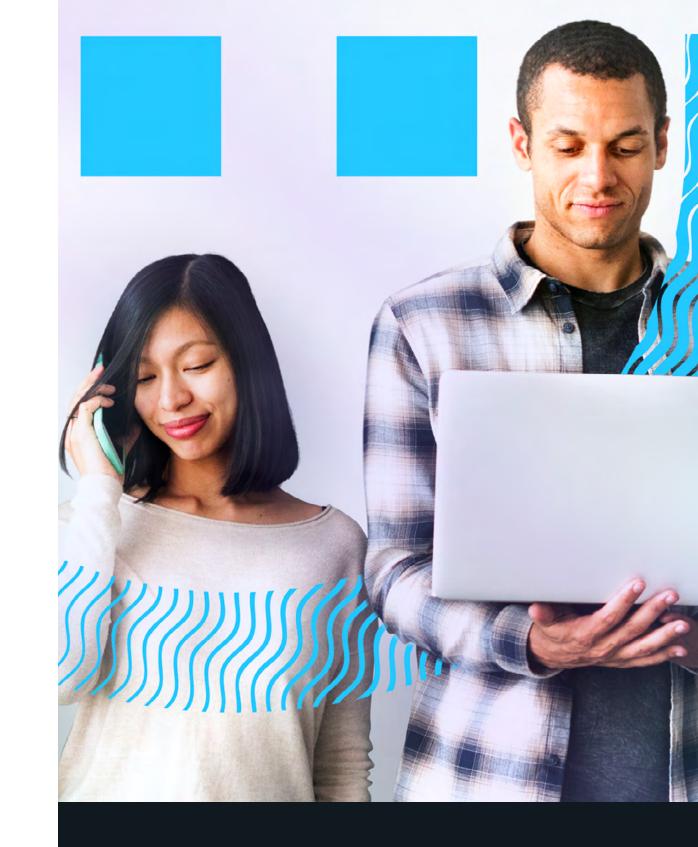
These initial "guesses" are then fine-tuned through a process of comparison to the expected outcome.

By employing a closed-loop feedback process, the system starts with some self-educated "guesses," then learns and fine tunes information with each successive iteration of a planning and scheduling "pass." The user can determine how many passes and how much time to allow the system to run through this learning process. This gives the user the option to give the machine more opportunities to learn from the outputs of multiple iterations. Environments with highly flexible scheduling rules usually allow more time and more passes than environments with fixed scheduling rules.

With each pass, the system learns and refines skill usage estimates as it analyzes output data related to the previous pass (such as service levels, ASA, occupancy and net staffing). It can sense where coverage is suffering and modify break time, lunch length, shift start, shift length or other parameter it is allowed to adjust (while constrained by work rules defined for each employee). After schedule adjustments are made, the system performs another round of analysis to ensure that the changes had the intended effect. If new opportunities for improvement arise, additional adjustments are made and the process continues.

Note that this process is a closed-loop one. The end user simply configures the general model and the iteration parameters, and the system performs the iterative learning without human intervention.

At no point must the user interject himself into the decision-making the machine is performing as it learns about the operating environment unique to each interval on each day.



This is generally how NICE WFM solves the schedule optimization challenge when faced with several unknowns inherent in an omni-channel environment. Although it may seem counter-intuitive, NICE WFM does not need to know the exact skill usage estimates or efficiencies before it can start optimizing schedules.



Schedule Fairness Intelligence

WFM practitioners have recently turned their focus to employee engagement, which has been shown to boost productivity and increase performance. Of particular interest is how schedule assignment and schedule management can be used to engage employees. NICE has made significant inroads with its recent Employee Engagement Manager solution, which has multiple capabilities designed to include employees in the complex process of managing schedules to meet customer needs. This is an area that is a prime target for additional artificial intelligence capabilities.

In addition, schedule assignment has long benefited from machines able to learn the unique needs of the business and desires of the employees. With NICE WFM, multiple machine algorithms are designed to create a fair workplace that replaces or enhances traditional seniority-based assignment processes.

Some examples of this in action include:



Adaptive Assignment

When NICE WFM is integrated with NICE Performance Management's adaptive intelligence capabilities (NICE AWFO), work schedules can be assigned using uniquely identifiable metrics, attributes and preferences of each employee. (see https://www.nice.com/websites/adaptiveWFO/ for more information)



Preference Persona Assignment

Even without the advanced Al available in NICE AWFO, NICE WFM offers a robust persona that each employee selfmanages. The capabilities include selfidentified work time availability, which is guided by the machine to ensure that basic coverage is provided by each employee. Employees may also define a customized preference persona that reflects not only the desire for preferred shift elements (such as start time, stop time, days off, lunch length, work day patterns, shift length, lunch times, etc.), but also the relative priority of each element as perceived by the employee. The machine constantly monitors for changes in preference personas and adjusts assignments accordingly.



Fairness Assignment

Some people want to volunteer to work certain days of the week, weekends or holidays, while others want to be rotated through the assignments fairly. NICE WFM fairness intelligence monitors assignment history, fairness credits (which can be tied to NICE AWFO), volunteerism, work rules and business need to manage the work day assignments fairly.



Policy Assignment

No one likes being repeatedly assigned to shifts that are considered less desirable. To help create a fair workplace, NICE WFM has integrated intelligent policies that manage schedule creation and schedule assignment fairly while meeting customer needs. For example, a policy may state that every employee must work a late afternoon shift at least once every three weeks, subject to fluctuating customer demand. Or, alternatively, certain sequences of shifts may be monitored by the machine to ensure that employees are fairly assigned to back-toback shift types. These machine algorithms are designed to balance the needs of the business with the needs of the employee while eliminating the human intervention often required to keep things fair.





Conclusion

Artificial intelligence is enjoying a resurgence in news and marketing arenas, with renewed focus on its applications for business. Its utility and promise, however, are nothing new for NICE, which for years has continuously invested in AI and ML to help omnichannel contact centers, back-office operations and branch environments benefit from "the science of getting computers to act without being explicitly programmed." With NICE WFM, the machine takes on the herculean tasks of learning the uniqueness of each environment and applying intelligence that exceeds the human capacity to process. In doing so, it frees humans to focus on those activities and thought processes that require a human touch.

Reference >



About NICE

With NICE (Nasdaq: NICE), it's never been easier for organizations of all sizes around the globe to create extraordinary customer experiences while meeting key business metrics. Featuring the world's #1 cloud native customer experience platform, CXone, NICE is a worldwide leader in Al-powered self-service and agent-assisted CX software for the contact center - and beyond. Over 25,000 organizations in more than 150 countries, including over 85 of the Fortune 100 companies, partner with NICE to transform - and elevate - every customer interaction.

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