Using Hyperautomation to Enhance Efficient Customer Engagement for United Airlines

Gary T. Leavens
 Computer Science
 University of Central Florida
Orlando, Florida, USA
Leavens@ucf.edu

Successful and timely resolution of customer’s problems currently relies on Robotic Process Automation (RPA) and on SMEs who can handle exceptional situations. RPA is cheap and always available, but inflexible in solving the complex problems affecting customers and SMEs are becoming hard to find and costly to train. Hyperautomation, which augments RPA with artificial intelligence (AI) in cases involving complex situations or fine judgments, can solve a higher percentage of customer problems with the same availability as RPA. Hyperautomation can thus augment the expertise of SMEs to handle more such complex cases faster.

KEYWORDS

Intelligent Automation (IA), Hyperautomation, Robotic Process Automation (RPA)

ACM Reference format:

Gary T. Leavens. 2022. Using Hyperautomation to Enhance Efficient Customer Engagement for United Airlines. In *Frontiers of IT (FIT’22). UCF Orlando, FL, USA, 2 pages.*

1 Introduction

When a customer has a serious problem, for example missing a flight, and if the airline can resolve the problem quickly, then the customer is more likely to be loyal. Conversely, a customer whose problem is not solved quickly may avoid the airline.

1.1 Background

United is the fourth largest commercial carrier in the US, with a 12.4% share of the US market [1]. United Airlines has the third largest revenue of any US carrier. United employed 9,272 people in “Passenger Service” roles in 2020 [2].

However, United fell from 6th to 8th place among US carriers in the JD Powers customer satisfaction for 2019 [3]. This indicates that there is room for improvement in United’s customer service.

1.2 The Problem

United’s overall problem is to increase customer satisfaction by quickly solving customer problems. These problems, such as missed or canceled flights, often require human judgment to decide on the level of compensation or accommodation to give to a customer. This judgment is difficult for our current Robotic Process Automation (RPA) system, and almost always requires human judgment from an agent who is a Subject Matter Expert (SME) in dealing with such issues. However, these SMEs are not as available as the RPA system, and so customers sometimes become frustrated with delays in solving their problems.

What is needed is a software system that can quickly solve most customer problems; the goal is to have 95% or more of customers report that their problem was solved within two hours. A long-range goal is to increase customer satisfaction, with at least 80% of customers reporting that they are “very satisfied” within 48 hours on a Likert scale, with United’s customer service.

1.3 Alternative Solutions

RPA is reliable and available, traits that are highly valued by customers (as reported in a study of banks [4]). However, RPA relies on if-then rules and needs structured data to make decisions, and so is inflexible and is not able to make fine judgments as required to solve complex customer problems or decide on appropriate compensation.

Currently the airline uses a combination of RPA and SMEs to handle customer problems, with a SME brought in by the rules whenever the customer’s situation does not fit one of the situations that the RPA can handle. However, these SMEs are not as available as the RPA, which causes delays in solving customer problems. Such service delays are a common occurrence when a large flight is cancelled or delayed. Furthermore, it is becoming harder to find qualified agents (SMEs) and their training is costly and lasts a long time.

2 Proposed Solution

The proposed solution is Hyperautomation, also known as Intelligent Automation (IA) [5]. IA is a combination of Machine Learning (ML) and RPA. The ML component can make decisions requiring fine judgments (such as the amount of compensation to give a customer) or that need to be based on unstructured data. The ML component would be trained using historical data and decisions made by agents while the system is running.

The architecture of the proposed customer service system is shown in Figure 1 below. Customers would contact the system using a phone or over the internet, and they would first interact with the rules in the RPA component. The RPA would be able to call various ML modules to make decisions requiring judgments or about unstructured data.



Figure 1 Proposed Customer Service System Architecture.

The RPA delegates to an agent when it comes across a situation that it cannot handle, as is currently the case. However, the new capability in this proposal is that the RPA could call ML modules to help make various decisions. The RPA, agent, and ML modules would all be able to access the flight database, which allows them to check on alternate flights and make reservations for customers.

2.1 ML Modules

We envision several ML modules to add intelligence to the customer support service system. The design and training data for these modules would need help from SMEs, so that the appropriate inputs and outputs could be used in training.

2.1.1 Compensation Module

The compensation module would have as its goal deciding on compensation for customers, depending on their circumstances. Currently this decision is made by agents. The history of such decisions made by agents would be used to train a module that would use a neural network to decide on appropriate compensation for customers, given their circumstances. To make such decisions, input from agents would be needed to understand what kind of circumstances are needed for the decision and what context is used for deciding on appropriate compensation, including what questions should be asked of the customer.

The circumstances to be considered might include: when the next appropriate flight is for the customer, the weather or other difficulties at the destination or airports on the route, how long the customer has been waiting for a resolution, customer (and family) health issues, and the time of day. The types of compensation might include: food credits, hotel accommodations, frequent flyer miles, refunds, suspending or eliminating penalties, and/or granting (free) future travel. Input from agents would undoubtedly be needed to complete these lists. Although some kinds of compensation are binary choices (such as whether to give hotel accommodation), others (such as those involving money or frequent flyer miles) can be given in fine increments.

2.1.3 Emotional Response Module

To allow for a more human-like interaction with customers (which was valued in the banking study mentioned earlier [4]), the RPA should consult an emotional response module frequently. This would allow the system to gauge the emotional state of the customer and produce an appropriate response if needed. In particular, this module should be able to decide if the customer is getting upset, impatient, or angry and should be able to generate some text that could help reassure or calm the customer.

There are some existing services (such as 0360 [6]) that can gauge the emotional state of a customer. It would be a straightforward problem to map these emotional states to responses, using the expertise of the airline’s agents.

2.1.4 Special Needs Requests

When a customer has special needs, such as a special diet or a wheelchair, this module should be able to decide the extent to which that request can be granted, given the circumstances. These circumstances might include: how far in advance the request is being made, what delays or cancellations the customer has faced, and the resources available at the airports involved.

This module would be trained on the history of agent interactions regarding such special needs requests.

2.1.2 Natural Language Understanding Module

Although outputs can be generated using templates, understanding written or spoken inputs from customers can benefit from using AI to understand the customer’s input. If an unambiguous meaning cannot be obtained by such a natural language understanding module, then the module should be able to use the uncertainty to produce clarifying questions to ask the customer.

The airline should purchase or subscribe to a service for this module, such as that provided by IBM Watson [7].

3 Consequences of the Proposal

This section describes the expected benefits and costs of the proposal.

3.1 Benefits

The main benefit for United Airlines would be improved customer satisfaction. The success of this proposal would mean that at least 95% of customer issues would be solved and that at least 80% of customers would be very satisfied with the airline’s customer service. This would help the company keep existing customers, and high customer satisfaction would translate into higher ratings in the JD Powers survey, which could help attract new customers. More loyal customers would allow the company to have slightly higher profit margins.

An additional important benefit would be that the agents (SMEs) would find their jobs more fulfilling, as they would be relieved of more routine work and could focus on those cases that are the most challenging and complex. This would help retain existing agents and lessen the need to recruit and train new agents. Having experienced agents working for the company would again result in loyal customers and improve relations with the agents.

3.2 Costs

Some customers might resent their loss of privacy when they learn that the customer support system is analyzing their emotions. The airline can reassure these customers by promising not to keep records of customer emotional states.

Some customers might also feel that the airline has lied to them if they discover that they are not talking to a human but instead to a RPA agent. This can be mitigated by designing the system to either inform the customer that they are talking to the RPA or by making some features of the interaction obviously non-human.

The costs of developing and maintaining the customer support system depend on the costs of developing the ML modules and the costs of integrating those modules into the existing RPA system. Development of the first three ML modules (compensation, emotions, and special requests) would be done using the airlines’ software development staff or external consultants, with help and consultation from the agents, for their expertise. [Need to estimate this cost.]

The natural language understanding module would be purchased or subscribed to, and thus would have a fixed cost determined by the vendor (such as IBM [7]). [Need to estimate or find this cost.]

As with any system using ML, the ML modules may make mistakes. These may have a negative impact on customer perceptions of the airline. Such mistakes can be addressed by introducing some bias towards the customer’s preferred outcome, so that such mistakes will only cost the airline some resources (money) instead of customer good will. Over time the ML modules can be tuned to reduce such mistakes as they are further trained.

The RPA system can be augmented with new ML modules as these modules are finished and tested, and the new system can be run alongside the old system with a smaller number of customers to test how well it works. After the new system has proven that it can meet the customer service goals and has had the bugs worked out, the new system can start taking over calls that come in, and thus there need be no downtime in switching to the new system. A similar process can be used to upgrade parts of the new system, such as new ML modules.

4 Conclusion

United Airlines has dropped from 6th to 8th place among US airlines in customer satisfaction [3]. Improving its customer satisfaction is thus an important goal. This goal can be achieved by resolving customer problems quickly and in a satisfactory manner. Intelligent Automation (IA, also called Hyperautomation) can solve this problem by providing reliable solutions at all hours.

Another problem that can be aided by IA is finding and retaining experienced customer service agents (SMEs). These SMEs are somewhat in short supply and are often called upon to do repetitive tasks in helping large groups of customers with the same problems. The combination of RPA and ML embodied in IA can help automate some of the customer service issues that would currently need help from these SMEs. This will allow the SMEs to focus their attention on more interesting, unique, and complex problems, to a larger extent than with the current system in which they are the backup to an inflexible RPA system.

Future work for the customer support system could involve making the system more autonomous, by creating new ML modules to deal with less frequent or more complex situations. This will increase availability of the system and allow the SMEs to focus more on the remaining interesting cases and on improving the accuracy of the new system.

# Works Cited

|  |  |
| --- | --- |
| [1]  | Statista, "Domestic market share of leading U.S. airlines from January to December 2020," Statista, 2021. |
| [2]  | United Airlines, "Annual Report for 2020," United Airlines, Chicago, IL, 2021. |
| [3]  | CNBC, "These are the worst (and best) airlines for 2019, based on mishandled luggage, delays and more," CNBC, 2020. |
| [4]  | K. N. Kumar and P. Rani, "Robotic process automation-a study of the impact on customer experience in retail banking industry," *Journal of Internet Banking and Commerce,* vol. 23, no. 3, pp. 1-27, 2018.  |
| [5]  | K. H. Ng, C.-H. Chen, C. K. M. Lee and J. (. Jiao, "A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives," *Advanced Engineering Informatics,* vol. 47, p. article 101246, Jan 2021.  |
| [6]  | O360, "Gauging customer emotions for improved brand engagement," O360, 2019. |
| [7]  | IBM, "Watson Natural Language Understanding," IBM, 2021. |