

● CX OPERATIONS · PEAK HOLIDAY STAFFING

Proactive Dashboards & ML-Based Forecasting

Reduced CX Backlog Tickets by 85% and Achieved 90%+ SLA Compliance for Faherty, an apparel brand during BFCM Holiday

CUSTOMER
Faherty

INDUSTRY
Omnichannel Apparel

USE CASE
CX Peak Staffing

SEASON
BFCM & Holiday 2025

EXECUTIVE SUMMARY

A reactive staffing model became a forecast-driven one and peak season stopped being a fire drill.

Faherty is an omnichannel apparel brand operating across eCommerce and roughly **75–78 retail locations** nationwide. During BFCM and the holidays, support volume surges alongside order inflows, carrier variability and promotional activity, and those surges were compounding year over year.

By the 2024 holiday season, peak-week SLA had dropped to around 50–60%, and ticket backlogs exceeded 1,000 open items. The root cause wasn't headcount it was the absence of a forward-looking signal: no reliable way to see demand coming before it arrived.

Partnering with Saras, Faherty unified order data, promotional calendars, carrier performance and CX history into a single layer, then built an ML model that produced **day-level staffing recommendations weeks ahead of peak**.



We saw strong success this year with CX staffing guided by Saras recommendations. After a stretched holiday season last year, we planned peak capacity far more effectively and supported demand.

T Tess CX Manager, Faherty

90%+

Peak holiday SLA compliance

up from ~50–60% the prior year

85%

Backlog reduction vs prior year

from 1,000+ to ~150 open tickets

2–8%

Monthly forecast variance

predicted vs actual CX demand

Company snapshot

COMPANY Faherty	INDUSTRY Omnichannel & DTC Apparel
SCALE eCommerce + ~75–78 retail locations	USE CASE CX Operations · Peak Holiday Staffing
2026 AGENDA PILLAR Data Foundation · CX Intelligence (ML)	PEAK WINDOW November 2025 – January 2026

01

THE PROBLEM

3 Operational Gaps That Cost Faherty SLA Compliance Every Peak Season

Each year, BFCM and the holidays concentrated Faherty's highest order volumes, promotional intensity and customer expectations into a compressed multi-week window. And each year, the CX team entered it with the same planning method: historical ticket averages, adjusted by judgment.

01

SLA compliance fell to 50–60% in the highest-volume weeks

That approach worked at lower scale. But as order volumes grew and fulfilment complexity increased across carriers and geographies, the gap between staffing plans and actual demand widened well below the targets the CX team was accountable for.

02

Backlogs exceeded 1,000 open tickets, with no early warning

There was no system to trigger staffing adjustments before a backlog had already accumulated. By the time the size of the problem was visible, the highest-stakes days of the season were already underway.

03

Corrective staffing actions arrived too late

The team was responding to volume that had already materialized, not anticipating volume about to arrive so every adjustment chased a peak that had already passed its breaking point.

There was no connection between the promotional calendar, carrier performance trends, and the CX staffing model. Each was tracked separately. None informed the other.

02 THE BUSINESS RISK & THE DECISION

Without Forward-Looking Data, Both Understaffing and Overstaffing Are Equally Likely

For an omnichannel brand, the holiday period is not just high-volume it is high-stakes. Customers placing gift orders have fixed expectations around delivery timing and immediate support when something goes wrong. A backlog of 1,000+ unresolved tickets in December is not an internal ops metric; it is a customer experience failure in the weeks that matter most to revenue and loyalty.

The risk compounded in both directions. Understaffing surge windows meant SLA breaches and frustration. Overstaffing quieter windows meant cost and capacity in the wrong places. Without a forward-looking signal, both mistakes were equally likely.

The decision: change the model, not the headcount

In 2025, Faherty committed to a planning model grounded in forward-looking data. The objective was specific day-level staffing recommendations, produced weeks ahead of peak, that could be acted on before demand arrived rather than in response to it. The data existed; it just lived in separate systems with no common layer to read it together.

Reactive in 2024 → proactive in 2025

2024 · REACTIVE CYCLE

Responding after the spike

- 1 **Ticket volume spikes**
Orders, promos and carrier issues hit at once.
- 2 **Backlog accumulates**
Open items climb past 1,000 before anyone reacts.
- 3 **Late staffing response**
Headcount added only after SLA breaches appear.
- 4 **SLA failure**
50–60% SLA

2025 · PROACTIVE CYCLE

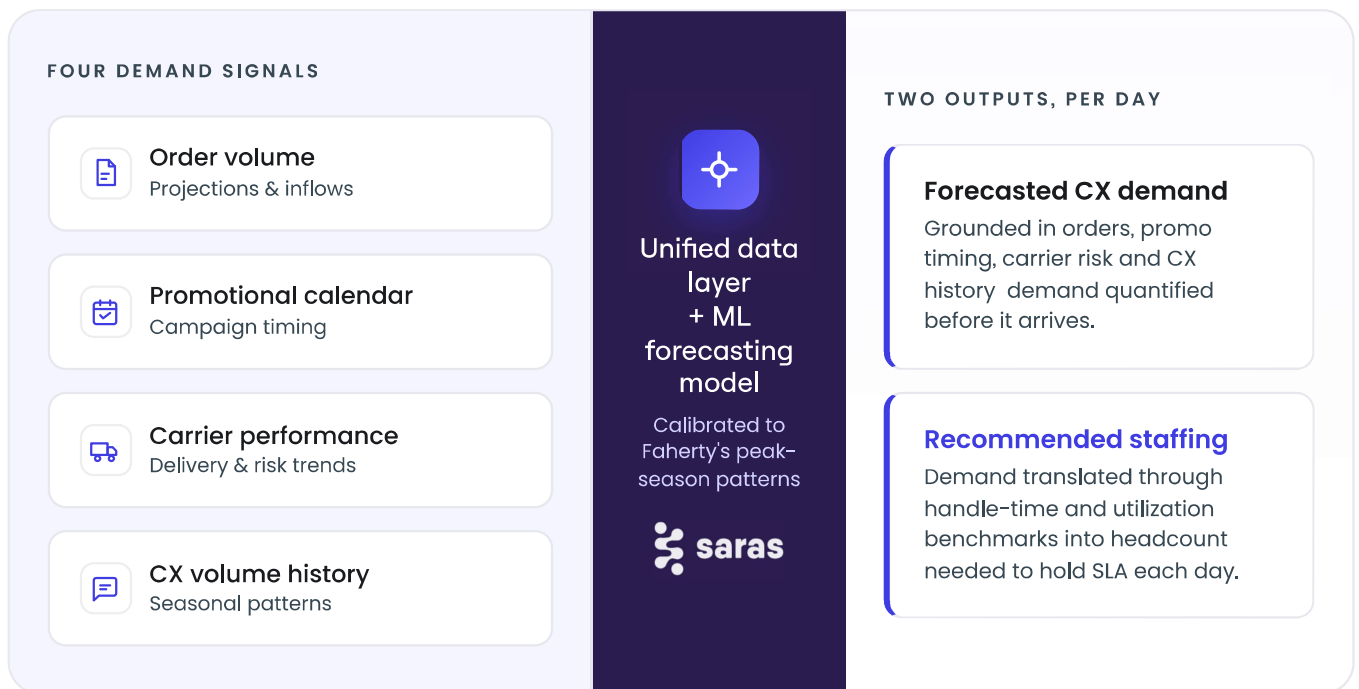
Acting before demand arrives

- 1 **ML demand forecast**
Day-level demand projected weeks ahead of peak.
- 2 **Day-level staffing plan**
Forecast translated into required headcount per day.
- 3 **Pre-peak deployment**
Capacity committed and resourced before volume lands.
- 4 **Service held at peak**
90%+ SLA

03 HOW SARAS MADE IT POSSIBLE

One Unified Data Layer, One ML Model: Day-Level Staffing Plans Built Weeks Ahead

Saras unified Faherty's order, promotional, carrier and CX history data into a single connected layer letting four demand signals that had previously been tracked in isolation be read together for the first time. On top of it, Saras built an ML forecasting model calibrated to Faherty's specific peak-season patterns.



Four signals that lived in separate systems, read together for the first time, and turned into a daily staffing plan.

- ◆ A distinction that changed deployment. The model separates genuine understaffing that needs headcount from backlog accumulating within naturally recoverable bounds, avoiding both over-hiring in low-risk windows and under-hiring during true surges.
- ◆ A recalibration loop that improved through the season. Weekly reviews of forecast versus actual refined the model's assumptions as conditions shifted, so accuracy improved rather than degraded, ending the season within 2–8% monthly variance.

04 FROM DATA TO DECISIONS

3 Staffing Decisions Now Made Weeks Earlier, Grounded in Data

Before the model, peak-staffing discussions were qualitative based on last year's outcomes, adjusted by instinct, and validated only after backlogs had already appeared. With day-level forecasts in place weeks ahead, those same conversations became grounded in data. Three categories of decision shifted.

01 Proactive capacity commitments

Staffing plans confirmed and resourced ahead of peak windows, with day-level specificity rather than reactive headcount additions triggered by SLA breaches already in progress.

02 Precision deployment across the season

Clear differentiation between days requiring surge capacity and days where standard coverage was sufficient efficient allocation with no trade-off on service level.

03 Fact-based escalation conversations

When volume events shifted, the model provided the data to validate or challenge escalation requests in real time replacing anecdotal signals with a shared factual basis for decisions.

The planning infrastructure built for 2025 is reusable. The same data connections, model architecture and review cadence support future peaks reducing annual planning overhead and compounding in accuracy with each season of data.

05 THE OUTCOMES

The Results: 90%+ SLA, 85% Fewer Backlog Tickets, 2–8% Forecast Variance

The 2025 holiday season (November through January) delivered improvement across every dimension of CX performance compared to the prior year.

90%+

PEAK SLA COMPLIANCE

Service levels held through the highest-volume weeks

Up from approximately 50–60% in the prior year, sustained throughout the most demanding period in Faherty's calendar.

85%

BACKLOG REDUCTION

Average open backlog fell from 1,000+ to ~150 tickets

Customers received faster resolutions during the weeks when expectations and order values are highest.

2–8%

FORECAST VARIANCE

Monthly predicted vs actual demand stayed within 2–8%

Confirming the model performed accurately under live conditions and providing a reliable foundation for future planning cycles.

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The forecasting solution helped us set the right targets for acquisition and retention teams.

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Alex Faherty Co-Founder & CEO, Faherty Brand

06

KEY TAKEAWAYS

5 Operational Lessons for Any Omnichannel Brand Running CX at Scale

Faherty's 2025 results point to specific, repeatable actions. Here is what the data says for any brand facing growing CX volume during peak.

01

Reactive staffing is a structural risk, not a resourcing problem.

More headcount doesn't solve a planning gap. What changed Faherty's outcomes wasn't additional staff it was earlier, more accurate signal about when and where staff were needed.

02

Your CX model is probably missing fulfilment data.

A significant share of peak CX volume is driven by delivery timing and shipment status. Connecting carrier performance to your staffing forecast is a high-leverage integration most teams haven't made.

03

Proactive planning compounds in value.

The recalibration loop means each peak season improves on the last. Manual planning approaches cannot replicate this compounding accuracy advantage.

04

Precision reduces cost and improves service simultaneously.

Distinguishing genuine understaffing from recoverable backlog let Faherty avoid overstaffing low-risk windows while fully protecting SLA during true surge days.

05

The data connection is the prerequisite.

The ML model was only possible because order, promotional, carrier and CX data were unified into one trusted layer first. The model is the activation; the connected data is the foundation it runs on.

FORECAST BEFORE IT HAPPENS

Forecast your next BFCM peak, before it happens

Forecast customer demand, allocate resources proactively, and maintain service levels when volume spikes. Talk to a Saras data consultant about the connected data layer and ML forecasting behind Faherty's best holiday peak.

Talk to a Data Consultant →

WEBSITE

sarasanalytics.com

TALK TO AN EXPERT

</talk-to-data-consultants>

WHAT POWERED THIS STORY

Unified data layer · ML forecasting