PREPARED FOR

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AI Transformation Roadmap

SPARK™ Executive Readout · The Holistyx Group · July 2026

20	7	$622.54M – $1,037.76M
Use Cases Evaluated	Use Cases Shortlisted	3-Year Value Range

About This Report

This report was produced via SPARKle - The Holistyx Group's accelerated AI-transformation methodology. It applies the full SPARK™ framework (see Appendix B for SPARK™ details) through an AI-assisted pipeline, delivering a complete engagement output in 24–48 hours. All financial estimates are Notional-level [Est.], for prioritization and board framing.

Discovery Summary

Here's what shaped this analysis. Take a moment to confirm it's right.

COMPANY

Company	Ford Motor Company	YOU TOLD US
Industry	Automotive — OEM (Vehicle Manufacturer)	YOU TOLD US
Company size	100,000+ employees	YOU TOLD US
Estimated annual revenue	$187.3B (FY2025) — SEC Form ARS FY2025; SEC Form 8-K Q3 2025; MacroTrends 2026	PUBLIC RESEARCH

STATED CHALLENGES

Primary challenge	Data is scattered and hard to use, competitors are moving faster on AI, and rising operational costs are creating pressure to find efficiency gains across the enterprise.	YOU TOLD US
Additional context	The core AI pain point is finding the right use cases — Ford has established AI capability but lacks disciplined use case selection tied to measurable business outcomes.	YOU TOLD US
Success looks like	A 5% improvement in employee productivity, alongside measurable reductions in warranty costs and accelerated EV launch execution.	YOU TOLD US
Industry validation	Automotive warranty costs can reach 5% of OEM revenue, yet only 18% of OEMs currently use AI in production to predict quality failures proactively — confirming that Ford's warranty cost reduction priority is both financially material and competitively underpenetrated.	PUBLIC RESEARCH

CURRENT AI POSTURE

AI maturity	Established — Ford has moved beyond early experimentation and has active AI capabilities, but maturity is uneven across functions and use case prioritization remains the primary gap.	YOU TOLD US
Data availability	Siloed, good quality — the raw data exists and is reliable, but cross-functional accessibility is the primary barrier to enterprise-wide AI use cases.	YOU TOLD US
Change readiness	Ready with support — adoption is achievable but requires active enablement; skills and training gaps are the primary organizational concern.	YOU TOLD US

Discovery Summary (continued)

CURRENT AI POSTURE (CONTINUED)

Peer comparison	75% of automotive OEMs have adopted AI in some form (ResearchAndMarkets Automotive AI Market 2025), meaning Ford's Established maturity is consistent with the industry median — but Tesla's vertically integrated AI and GM's $13–15B EBIT guidance powered by AI-driven fleet analytics signal that the competitive gap is widening at the top of the market.	PUBLIC RESEARCH

WHAT WE FOUND (CONTINUED)

Competitive signal	Tesla's vertically integrated AI — spanning Full Self-Driving, the Cortex training cluster, and AI robotics at scale — represents the most acute capability gap for Ford; Tesla's software-first model means it generates and acts on vehicle data at a speed and scale that legacy OEM architectures cannot currently match.	PUBLIC RESEARCH
Regulatory exposure	The EU AI Act's high-risk system rules take full effect in August 2026, with fines up to €35M or 7% of global turnover for non-compliance; Ford's cross-jurisdictional operations — including China's AI algorithm filing requirement for in-vehicle models — mean regulatory exposure is material and time-sensitive across multiple markets simultaneously.	PUBLIC RESEARCH

If anything above looks off, tell us. This summary is the foundation for everything that follows: the opportunities we've prioritized, the financial ranges we've estimated, and the roadmap we've built. A wrong number or an outdated fact here can throw off the analysis downstream, so it's worth a 30-second check before you read further.

Spot something that doesn't match your business? Reply to this email or contact us directly and we'll correct it and regenerate the affected sections at no charge.

SECTION 1 OF 6

Executive Summary

Confidence Qualification: This report was produced by the SPARKle AI engine. Financial projections are presented at three confidence tiers by deployment horizon: H1 (Foundation & Quick Wins, Months 1–4) at 80% confidence, H2 (Scale & Expansion, Months 5–8) at 55% confidence, and H3 (Transform, Months 9–12+) at 35% confidence. All figures are Notional-level estimates, directional for prioritization and board framing. We recommend that all use case financials, technical feasibility assessments, and implementation timelines be validated in a Day 2 Technical Deep Dive before any capital commitment is made.

AI Readiness Scorecard

Ford enters this engagement from a position of genuine AI strength. CEO-level sponsorship, high technical skills, and a confirmed Microsoft Azure partnership give you the organizational and infrastructure foundation that many OEM peers are still building. Your data is reliable — the challenge is not quality but connectivity, with siloed systems limiting the cross-functional AI use cases that would deliver the most value against your warranty cost and EV launch priorities. Governance is actively developing, which is the right posture for a company at this maturity stage, but it will need to accelerate ahead of the EU AI Act's August 2026 high-risk system rules. The single most important readiness gap is data integration: until warranty, telemetry, supplier, and dealer data can be accessed in a unified pipeline, the highest-value predictive use cases in this portfolio cannot be fully realized. The roadmap is sequenced to address this gap in H1 before the H2 scale-up begins.

Dimension	Readiness Signal	Score
Strategic Alignment	Three board-level priorities directly map to shortlisted AI use cases	**4.5/5**
Executive Sponsorship	CEO is primary contact and final approval authority for AI investment	**4.5/5**
Tech Infrastructure	High AI technical skills; Microsoft Azure partnership confirmed; prompt engineering at medium level	**4.0/5**
Organizational Readiness	Ready with support; skills and training gaps flagged as primary adoption risk	**3.5/5**
Data Readiness	Good quality data confirmed; siloing across functions is the primary integration barrier	**3.5/5**
Governance & Risk	AI governance actively developing; policies in progress but not yet consistently applied	**3.0/5**
Overall Readiness	*Established Scaling*	**3.8/5**

Scale: 1 = Early stage | 2 = Experimenting | 3 = In progress | 4 = Optimized | 5 = Industry-leading

Strategic Implication

The single highest-leverage action Ford Motor Company can take in the next 90 days is:

Unify warranty and dealer repair order data

Ford's H1 investment of $15.0M–$25.0M funds two immediate use cases — UC-005 and UC-009 — but the data normalization work that UC-005 requires also builds the pipeline that every H2 predictive model depends on. Without it, UC-001, UC-003, and UC-015 cannot begin model training, and $490M–$818M in H2 value remains locked. With it, Ford activates a connected warranty cost reduction stack and positions the EV battery early warning system for a Month 5 launch — turning a documentation automation pilot into the foundation of an AI-native vehicle quality operating model.

Three Key Findings

01 Your warranty data is an untapped competitive asset

Ford's warranty and repair order systems contain years of structured, high-quality claims data that most OEM peers cannot match in depth or volume. This asset directly enables three shortlisted use cases — UC-005 (Warranty Repair Documentation Automation), UC-001 (Predictive Warranty Claim Risk Scoring Engine), and UC-003 (Supplier Quality Failure Prediction Model) — which together address your Strategic Priority 2 of lowering warranty costs. McKinsey's Warranty Quality AI Survey 2026 benchmarks 5–10% warranty cost reduction via predictive analytics; applied to Ford's cost of sales base, that range represents hundreds of millions in recoverable value. The data exists today — the gap is integration and activation, not collection.

02 Data siloing is the constraint that limits every H2 use case

Your own team identified data siloing as the primary operational barrier, and this engagement confirms it as the binding constraint on the highest-value use cases in the portfolio. UC-001, UC-002, UC-003, and UC-014 — collectively representing $490M–$818M in 3-year H2 value — each require cross-system data integration across warranty, telemetry, supplier, and CRM sources before model training can begin. Discovery Hypothesis 4 (Data Silo Integration and AI-Ready Data Layer) maps directly to UC-011 (Enterprise Data Discovery and Silo-Breaking Assistant), which was evaluated but not shortlisted in this engagement due to its role as an enabling infrastructure play rather than a standalone value driver. UC-011 is flagged for prioritization in a follow-on engagement or as a concurrent H1 infrastructure workstream, not a deferred afterthought.

03 Tesla's software-first model is widening the gap faster than Ford's current AI pace can close it

Tesla's vertically integrated AI — spanning Full Self-Driving, the Cortex training cluster, and AI robotics at scale — gives it a data flywheel that compounds with every vehicle mile driven. GM is guiding $13–15B EBIT for 2026 with AI-driven fleet analytics embedded in its operating model. Ford's Strategic Priority 3 — AI-driven competitive parity — is addressed in this shortlist by UC-009 (Engineering Knowledge and Standards AI Copilot) in H1 and by the full H2 warranty and EV reliability stack. Your stated 5% employee productivity improvement target is directly advanced by UC-009, which embeds AI into engineering workflows within 90 days. Without accelerating the H1 foundation, the H2 scale-up that closes the competitive gap cannot begin on schedule.

SECTION 2 OF 6

Use Case Portfolio Summary

Ford's portfolio is dominated by Quick Wins — all seven shortlisted use cases score high on both impact and feasibility, reflecting established AI maturity and strong data assets across warranty, manufacturing, and EV systems. Strategic Priority 1 (EV Launch) is addressed by UC-002 and UC-014. Strategic Priority 2 (Lower Warranty Costs) is addressed by UC-005, UC-001, UC-003, and UC-015. Strategic Priority 3 (AI Competitive Parity and Cost Reduction) is addressed by UC-009. Discovery Hypothesis 4 — Data Silo Integration — maps to UC-011, which was evaluated but not shortlisted as a standalone use case; its data normalization dimension is embedded as a concurrent H1 infrastructure workstream supporting UC-005 and unlocking all H2 predictive models. Discovery Hypothesis 2 (EV Manufacturing Quality Intelligence) spans both UC-002 (battery degradation, shortlisted H2) and UC-006 (assembly line defect detection, not shortlisted); UC-006 was deferred due to higher sensor data pipeline integration complexity relative to the shortlisted use cases and is flagged for a follow-on engagement phase.

Prioritization Matrix

STRATEGIC INVESTMENTS *High Impact | Lower Feasibility*	**QUICK WINS** *High Impact | High Feasibility* **#1 Warranty Repair Documentation Automation (H1)** **#2 Predictive Warranty Claim Risk Scoring Engine (H2)** **#3 EV Battery Degradation Early Warning System (H2)** **#4 Engineering Knowledge and Standards AI Copilot (H1)** **#5 AI-Powered Proactive Recall and Service Notification (H2)** **#6 Supplier Quality Failure Prediction Model (H2)** **#7 Dealer Service Lane AI Diagnostic Assistant (H2)**
RECONSIDER *No use cases. A strong result.*	**EXPERIMENTAL** *0 use cases deferred pending H1/H2 validation.*

Axis: Impact (strategic value, 1–10) × Feasibility (implementation readiness, 1–10). Feasibility scores are estimated [Est.] and would be confirmed through further validation, such as a Day 2 Technical Deep Dive.

SECTION 2 OF 6 · CONTINUED

Shortlisted Use Case Portfolio

Use Case	Horizon	Value Low	Value High	Investment	ROI Range
Warranty Repair Documentation Automation	**H1**	**$87.19M**	**$145.32M**	**$9.36M – $15.60M**	**5.6x – 15.5x**
Engineering Knowledge and Standards AI Copilot	**H1**	**$44.77M**	**$74.61M**	**$5.62M – $9.37M**	**4.8x – 13.3x**
Predictive Warranty Claim Risk Scoring Engine	**H2**	$88.41M	$147.54M	$22.36M – $35.78M	**2.5x – 6.6x**
EV Battery Degradation Early Warning System	**H2**	$85.94M	$143.24M	$24.18M – $38.69M	**2.2x – 5.9x**
AI-Powered Proactive Recall and Service Notification	**H2**	$116.92M	$194.87M	$25.74M – $41.18M	**2.8x – 7.6x**
Supplier Quality Failure Prediction Model	**H2**	$83.84M	$139.73M	$20.14M – $32.23M	**2.6x – 6.9x**
Dealer Service Lane AI Diagnostic Assistant	**H2**	$115.47M	$192.45M	$22.88M – $36.61M	**3.2x – 8.4x**
PORTFOLIO TOTAL		**$622.54M**	**$1,037.76M**	**$130.28M – $209.46M**	**~5.3x – 14.7x (Mid: 8.8x) avg**

Sources: Industry-specific AI benchmark research (see Appendix A) | SAVA™ v2 Model — Ford Motor Company engagement

Section 3 of 6 — Top 3 Use Case Narratives

The following narratives detail the three highest-priority Quick Win use cases recommended for immediate H1 action. Each narrative follows the SPARK™ structure: Challenge / Future State / Implementation Path / Key Risks / Business Value / Pilot Scope.

SECTION 3 OF 6 · USE CASE 1 OF 3

1. Warranty Repair Documentation Automation

Horizon: H1 · Solution Area: Automate · Months 1–4

The Challenge Today

Ford's warranty repair technicians manually document repair orders, fault codes, and parts usage after every service event across a global authorized dealer network. Documentation practices vary by dealer, technician tenure, and vehicle line, producing inconsistent records that slow claim adjudication and make fleet-wide root cause analysis unreliable. The structured data that should power Ford's warranty analytics exists in unstructured form — locked inside repair narratives that no current system reads systematically.

Incomplete and inconsistent repair documentation inflates warranty write-offs, delays chargeback recovery from suppliers, and obscures systemic failure signals until they become costly recalls. With Ford targeting $1B+ in warranty cost savings in 2026 and absorbing $4.8B in Model e EBIT losses, every dollar of recoverable warranty cost matters. Tesla's software-first model means it detects fleet-wide failure patterns in near real time — Ford's manual documentation process creates a detection lag that compounds both cost and competitive exposure.

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SECTION 3 OF 6 · USE CASE 1 OF 3 · CONTINUED

The AI-Enabled Future State

"Imagine if every warranty repair event at Ford Motor Company generated a complete, structured, and audit-ready documentation record automatically — without the technician typing a single line. AI listens to or reads the repair interaction, extracts fault codes, parts used, labor performed, and technician observations, and populates the repair order in real time. Claims move faster, disputes drop, and fleet-wide failure patterns surface weeks earlier than they do today."

Ford gains a fully automated warranty documentation capability that converts unstructured repair data into structured, claim-ready records at the point of service. Claim adjudication accelerates, chargeback recovery improves, and the warranty analytics team gains a clean, consistent data foundation for systemic failure detection. Critically, the structured repair order data produced by this system becomes the training input for UC-001 (Predictive Warranty Claim Risk Scoring Engine) and UC-003 (Supplier Quality Failure Prediction Model) — making UC-005 not just a standalone efficiency gain but the data foundation for Ford's entire H2 warranty cost reduction stack.

IMPLEMENTATION PATH

A hosted NLP and document classification service is fine-tuned on Ford's historical repair order corpus and deployed as a service layer that intercepts repair order submission, auto-populates structured fields, and flags incomplete records before claim submission. No proprietary model training is required at pilot stage. The single most important integration consideration is connecting the NLP service to Ford's existing warranty management and dealer repair order systems across a heterogeneous dealer network.

KEY RISKS

Dealer network data standardization is the primary blocker — repair order formats, fault code conventions, and documentation practices vary across Ford's authorized service network, and normalizing input data sufficiently to train and validate the NLP model may extend pilot preparation beyond initial estimates. This risk resolves once a normalization schema is defined and the pilot cohort is limited to a single vehicle line and dealer region. Repair records containing vehicle identification and customer information require PII handling controls to be confirmed before data ingestion begins.

Business Value

5–10% warranty cost reduction achievable via predictive analytics applied to structured repair data McKinsey Warranty Quality AI Survey 2026	**Up to 30% total cost of quality reduction via AI-driven automation of quality documentation and process monitoring** McKinsey Advanced Analytics Quality Report	**5.6x – 15.5x** 3-Year ROI Range

Pilot Scope

Pilot the NLP documentation automation on warranty repair orders for a single high-volume vehicle line (F-Series trucks) across a cohort of 10–15 Midwest dealer locations. Automate structured field population for fault codes, parts used, and labor operations. Validate extraction accuracy against manually completed records and measure impact on claim submission completeness and adjudication cycle time.

Success metric: Achieve 85% or greater structured field auto-population accuracy on warranty repair orders within the pilot cohort, with a measurable reduction in claim submission incompleteness rate versus the pre-pilot baseline.

SECTION 3 OF 6 · USE CASE 2 OF 3

2. Engineering Knowledge and Standards AI Copilot

Horizon: H1 · Solution Area: Employees · Months 1–4

The Challenge Today

Ford's engineering teams spend significant unproductive time searching across fragmented standards repositories, internal technical documentation, and legacy design guidelines to answer routine questions. Knowledge is siloed by vehicle program, geography, and tenure — critical institutional expertise walks out the door when experienced engineers retire or transfer, and newer engineers repeat costly research cycles that their predecessors already completed. This is a direct expression of the data siloing challenge Ford identified as its primary AI barrier.

Unproductive knowledge search time compounds across Ford's global engineering workforce of tens of thousands, directly undermining the 5% employee productivity improvement target Ford named as its primary success metric. As Tesla and GM accelerate AI-assisted engineering and software development, Ford's manual knowledge retrieval process creates a design velocity gap that widens with every product cycle. The risk is not just inefficiency — it is slower time-to-market on EV programs where competitive windows are measured in months, not years.

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SECTION 3 OF 6 · USE CASE 2 OF 3 · CONTINUED

The AI-Enabled Future State

"Imagine if every Ford Motor Company engineer — from a first-year systems engineer in Dearborn to a senior powertrain specialist in Cologne — had an AI copilot that could instantly surface the right standard, the relevant design precedent, and the applicable regulatory requirement in plain language, without opening a single SharePoint folder or filing a knowledge request. The copilot learns from every query, continuously improving its understanding of Ford's own engineering vocabulary and program history."

Ford's engineering workforce gains a persistent, queryable AI layer over its entire standards and knowledge corpus. Engineers receive accurate, sourced answers in seconds rather than hours, reducing rework, accelerating design decisions, and preserving institutional knowledge that would otherwise be lost to attrition. This use case directly advances Ford's stated 5% employee productivity improvement target by eliminating one of the most pervasive sources of unproductive time in the engineering organization — and it does so within the H1 window, delivering measurable results before any H2 investment is committed.

IMPLEMENTATION PATH

A retrieval-augmented generation (RAG) architecture is deployed over Ford's engineering knowledge corpus on its existing enterprise AI infrastructure, with documents ingested, chunked, and stored in a vector index. Engineer queries are matched against the index and passed to a language model with retrieved context to generate sourced responses. The single most important build consideration is achieving consistent, clean ingestion of Ford's engineering standards corpus across multiple formats, version states, and access-controlled repositories before retrieval quality is reliable.

KEY RISKS

The single biggest blocker to a 90-day pilot is achieving consistent, clean ingestion of Ford's engineering standards corpus — documents may span multiple formats, version states, and access-controlled repositories, requiring a coordinated data preparation effort before retrieval quality is reliable. This risk resolves once the pilot corpus is scoped to a single engineering discipline and document set. Engineering documents may contain ITAR or EAR-controlled technical data, requiring access restrictions to be confirmed with Ford's export control compliance team before corpus ingestion begins.

Business Value

3-Year Value Range: $44.77M–$74.61M · **ROI Range:** 4.8x – 13.3x · **22–37% AI-driven uplift in product and service value when AI is embedded in knowledge worker workflows** (IBM Institute for Business Value Automotive AI Report 2025) · **5% employee productivity improvement — Ford's own stated success target for this AI program** (Ford Motor Company client intake 2026)

Pilot Scope

Deploy the AI knowledge copilot against a single, well-defined subset of Ford's engineering standards corpus — specifically powertrain engineering standards and design guidelines for one active vehicle program. Limit pilot to a single engineering discipline to control corpus scope, validate retrieval accuracy, and demonstrate time-to-answer improvement before broader rollout.

Success metric: Average time-to-answer for standards and design guideline queries reduced by 50% or more versus baseline, measured over an 8-week pilot period with at least 80% of pilot users actively querying the copilot.

SECTION 3 OF 6 · USE CASE 3 OF 3

3. AI-Powered Proactive Recall and Service Notification

Horizon: H2 · Solution Area: Customers · Months 5–8

The Challenge Today

Ford's current recall and service notification process is largely reactive and batch-driven — owners are notified by mail or generic broadcast after a recall is already issued, with limited personalization based on vehicle configuration, usage pattern, or owner communication preference. This process relies on CRM, vehicle registration, warranty, and dealer management data that currently sits in separate systems with inconsistent schemas, limiting Ford's ability to construct a unified owner-vehicle risk profile at scale.

The lag between issue identification and owner action increases the window of vehicle risk, drives unnecessary dealer traffic from owners who respond to generic outreach unnecessarily, and inflates warranty costs when issues escalate before owners act. Ford's Strategic Priority 1 — EV launch success — is directly exposed: EV owners have higher expectations for proactive digital communication than ICE vehicle owners, and a reactive notification posture on Ford's most strategically important product line creates a customer trust gap that Tesla's software-first ownership experience actively exploits. This use case addresses both Strategic Priority 1 and Strategic Priority 2 simultaneously.

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SECTION 3 OF 6 · USE CASE 3 OF 3 · CONTINUED

The AI-Enabled Future State

"Imagine if Ford Motor Company could identify, at the individual vehicle level, which owners are most at risk from an emerging service issue — before a formal recall is even issued — and reach them through their preferred channel with a personalized, plain-language message that explains exactly what to do and pre-schedules their dealer appointment. No more mass mailings. No more owners discovering a recall from the news. Just the right message, to the right owner, at the right moment, powered by AI that understands their vehicle's history and their communication preferences."

Ford gains a proactive, AI-driven recall and service notification capability that segments the owner population by risk profile, personalizes outreach by channel and vehicle configuration, and triggers notifications ahead of formal recall timelines — reducing the average time from issue identification to owner action and measurably lowering downstream warranty repair costs. For EV owners specifically, proactive battery and software service outreach becomes a brand differentiator rather than a reactive obligation, directly supporting the EV launch agenda.

IMPLEMENTATION PATH

A cloud-based machine learning platform with classification and segmentation capabilities is integrated with a multi-channel customer communication orchestration layer and a unified vehicle-owner data store. The single most important integration consideration is constructing a reliable owner-vehicle risk profile by normalizing and deduplicating vehicle registration, CRM, warranty claims, and dealer management data across Ford's global systems — this data pipeline is the critical path item and must be scoped before model development begins.

KEY RISKS

The single biggest blocker is constructing a unified, reliable owner-vehicle risk profile by integrating vehicle registration, CRM, warranty claims, and dealer management data across Ford's global systems — data normalization and deduplication across these sources is the critical path item for any 90-day pilot. This risk resolves once the H1 data normalization workstream initiated by UC-005 is operational and extended to CRM and registration sources. NHTSA and international recall communication regulatory requirements must be reviewed by Ford's Compliance team before proactive pre-recall outreach is deployed, to confirm alignment with formal recall notification obligations.

Business Value

3-Year Value Range: $116.92M–$194.87M · **ROI Range:** 2.8x – 7.6x · **5–10% warranty cost reduction achievable when proactive intervention reduces time from issue identification to owner action** (McKinsey Warranty Quality AI Survey 2026) · **22–37% AI-driven uplift in product and service value when AI personalizes customer engagement at scale** (IBM Institute for Business Value Automotive AI Report 2025) · **Only 18% of OEMs currently use AI in production to predict quality failures proactively — proactive notification is a genuine competitive differentiator** (ResearchAndMarkets Automotive AI Market 2025)

Pilot Scope

Deploy the AI-powered proactive notification capability for a single Ford recall or service campaign affecting one model line in the U.S. market. Scope the pilot to owners with complete CRM records and confirmed contact preferences. Measure owner response rate and time-to-dealer-visit versus the standard batch notification baseline for the same campaign.

Success metric: Owner response rate (scheduling or completing dealer service) increases by 20% or more versus the standard notification baseline, measured within 30 days of notification delivery for the pilot recall campaign.

SECTION 4 OF 6

Business Case — Financial Summary

The following table summarizes the SAVA™ v2 (Solution-Area Value Anchoring) financial model for Ford Motor Company's shortlisted use case portfolio. SAVA anchors each use case's value and investment range to its Solution Area, deployment horizon, and scoring, rather than relying on a single generic ROI assumption — full methodology details are in Appendix A. All values represent 3-year Notional-level estimates, built from published industry benchmark ranges and calibrated to Ford Motor Company's specific operational profile.

Financial ranges (Low/High) reflect conservative and aggressive adoption scenarios respectively. Investment ranges include discovery, development, integration, and change management costs.

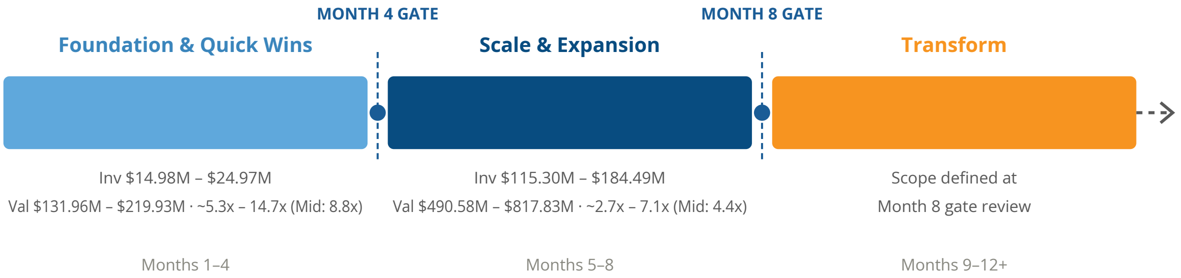
ID	Use Case	Horizon	Value Low	Value High	Investment Range	Payback	ROI Low	ROI High
UC-005	**Warranty Repair Documentation Automation**	H1	**$87.19M**	**$145.32M**	**$9.36M - $15.60M**	0.32 yr	5.6x	15.5x
UC-009	**Engineering Knowledge and Standards AI Copilot**	H1	**$44.77M**	**$74.61M**	**$5.62M - $9.37M**	0.38 yr	4.8x	13.3x
UC-001	Predictive Warranty Claim Risk Scoring Engine	H2	$88.41M	$147.54M	$22.36M - $35.78M	0.74 yr	2.5x	6.6x
UC-002	EV Battery Degradation Early Warning System	H2	$85.94M	$143.24M	$24.18M - $38.69M	0.82 yr	2.2x	5.9x
UC-014	AI-Powered Proactive Recall and Service Notification	H2	$116.92M	$194.87M	$25.74M - $41.18M	0.64 yr	2.8x	7.6x
UC-003	Supplier Quality Failure Prediction Model	H2	$83.84M	$139.73M	$20.14M - $32.23M	0.7 yr	2.6x	6.9x
UC-015	Dealer Service Lane AI Diagnostic Assistant	H2	$115.47M	$192.45M	$22.88M - $36.61M	0.58 yr	3.2x	8.4x
	PORTFOLIO TOTAL		**$622.54M**	**$1,037.76M**	**$130.28M – $209.46M**	—	**~5.3x – 14.7x (Mid: 8.8x) avg**	

Methodology: SAVA™ v2 (Solution-Area Value Anchoring with Horizon-Based Ceilings). ROI = 3-Year Value ÷ Total Investment. H1 use cases (blue) are recommended for immediate action. All values are Notional [Est.] — directional for board framing and prioritization.

SECTION 5 OF 6

12-Month AI Transformation Roadmap

Ford Motor Company's AI roadmap is organized across Three Horizons, each with a clear objective, a defined use case portfolio, an investment envelope, and a Gate decision that governs progression to the next phase. The Three Horizons structure is not a rigid schedule — it is a sequencing strategy that manages dependency risk and ensures each phase learns from the last.



H1 | Foundation & Quick Wins | Months 1–4

In the first four months, Ford's AI program delivers its first proof points against the warranty cost reduction mandate — without waiting for complex infrastructure to be built. UC-005 (Warranty Repair Documentation Automation) begins immediately, deploying NLP against existing repair order data to automate documentation and reduce manual processing costs. In parallel, UC-009 (Engineering Knowledge and Standards AI Copilot) embeds AI directly into engineering workflows using Ford's existing standards corpus. Both use cases were selected because they require no cross-system data integration and deliver measurable results within 90 days. By Month 4, Ford will have a working warranty documentation pilot and an AI-assisted engineering standards tool in active use — and the dealer data normalization infrastructure that every H2 model depends on. The Month 4 gate answers one question: have these pilots delivered measurable results sufficient to justify the larger H2 investment?

Investment Envelope: $14.98M – $24.97M **Value Range:** $131.96M – $219.93M **Avg ROI:** **~5.3x – 14.7x (Mid: 8.8x)**

▶ Month 4 Gate Decision

Have UC-005 and UC-009 delivered measurable results — documented cost reduction and confirmed retrieval quality — sufficient to validate the H2 investment in the full warranty cost reduction stack and EV battery reliability capability? Go releases $115M–$184M in H2 funding.

SECTION 5 OF 6 · CONTINUED

H2 | Scale & Expansion | Months 5–8

Months 5 through 8 are where Ford's AI program scales from proof to platform. With dealer data normalization operational and UC-005's structured repair data available as a training input, Ford activates the full warranty cost reduction stack: UC-001 (Predictive Warranty Claim Risk Scoring Engine) enables proactive intervention before claims escalate; UC-003 (Supplier Quality Failure Prediction Model) attacks defects at the source; and UC-015 (Dealer Service Lane AI Diagnostic Assistant) improves first-time fix rates across the dealer network. Simultaneously, UC-002 (EV Battery Degradation Early Warning System) protects Ford's highest-stakes product line, and UC-014 (AI-Powered Proactive Recall and Service Notification) drives proactive customer outreach at scale. These five use cases represent $490.58M–$817.83M in 3-year value. The H2 roi_low of 2.2x — driven by UC-002's telemetry data pipeline dependency — represents the downside risk scenario: if EV fleet telemetry completeness and pipeline reliability require more data engineering preparation than estimated, the low-end return reflects that extended timeline. The conservative scenario remains the planning anchor for board-level commitment at 55% confidence. The Month 8 gate evaluates whether model performance, data infrastructure, and organizational adoption are sufficient to sustain and expand the portfolio.

Investment Envelope: $115.30M – $184.49M **Value Range:** $490.58M – $817.83M **Avg ROI:** **~2.7x – 7.1x (Mid: 4.4x)**

▶️ Month 8 Gate Decision

Have the H2 warranty cost reduction stack — UC-001, UC-003, and UC-015 — delivered validated model performance and measurable claim reduction? Has UC-002 demonstrated reliable EV battery signal quality? Has UC-014 achieved proactive outreach at scale? Go confirms Ford's AI program is ready to define and fund the next transformation horizon.

SECTION 5 OF 6 · CONTINUED

H3 | Transform | Months 9–12+

No H3 use cases are scoped in this engagement. The five H2 use cases collectively represent the current transformation horizon for Ford's AI program — at full H2 deployment, Ford will operate a connected, AI-driven vehicle quality system: warranty claims scored and intercepted before they escalate, supplier defects predicted before they reach assembly, EV batteries monitored in real time, dealer technicians guided by AI diagnostics, and customers reached proactively before recalls become crises. This is not a collection of isolated pilots — it is Ford's AI-native vehicle quality operating model. The Month 8 gate is the moment Ford's leadership decides what the next transformation horizon looks like, informed by 8 months of live performance data across the most strategically critical use cases in the portfolio.

Investment Envelope: Not applicable — no H3 use cases in this shortlist **Value Range:** Not applicable

SECTION 5 OF 6 · CONTINUED

Program Risk Register

The following risks are program-level concerns that apply across the AI transformation portfolio. Each risk is drawn from discovery data, SAVA financial modeling, and use case implementation analysis. Mitigations are actionable and owner-attributed — not generic disclaimers.

Risk	Category	Horizons	Description	Mitigation
Dealer repair order data standardization failure	Data Governance	H1, H2	Ford's authorized dealer network operates heterogeneous repair order formats and fault code conventions. If input data cannot be normalized sufficiently before NLP model training, UC-005 pilot accuracy will fall below the 85% threshold and the H2 data pipeline will be delayed.	*Convene a cross-functional data normalization working group before Week 2 of the H1 kickoff; Ford's Warranty Operations lead should own schema definition and dealer cohort selection, with a normalization standard confirmed before NLP model training begins.*
Engineering document export control compliance gap	Regulatory	H1	Ford's engineering standards corpus may contain ITAR or EAR-controlled technical data. Ingesting controlled documents into a cloud-based RAG platform without confirmed access restrictions could create export control violations with material legal exposure.	*Complete an export control classification review of the pilot corpus before any document ingestion begins; confirm access restriction architecture with Ford's Export Control Compliance team as a gate condition for UC-009 pilot launch.*
Skills and training gaps slow H1 AI adoption	Change Management	H1, H2	Ford's own assessment identifies skills and training gaps as the primary organizational concern. If engineering and warranty operations teams are not actively enabled before pilot launch, adoption rates will fall below the 80% active user threshold required to validate UC-009's productivity improvement claim.	*Designate a Change Management sponsor at the VP level or above before H1 kickoff; establish a structured enablement program for pilot user cohorts in both UC-005 and UC-009 with adoption milestones tracked at the Month 4 gate.*

SECTION 5 OF 6 · CONTINUED

Program Risk Register (continued)

Risk	Category	Horizons	Description	Mitigation
EU AI Act high-risk system classification for in-vehicle AI	Regulatory	H2	The EU AI Act's high-risk system rules take full effect August 2026. Ford's EV battery degradation early warning system (UC-002) and proactive recall notification (UC-014) may qualify as high-risk AI systems under EU definitions, exposing Ford to fines up to €35M or 7% of global turnover for non-compliance.	*Initiate an EU AI Act classification assessment for UC-002 and UC-014 before H2 model development begins; Ford's Chief Legal Officer or designated AI Compliance lead should confirm high-risk classification status and required conformity assessment obligations before Month 5.*
Cross-system data integration delays H2 model training timelines	Technical	H2	UC-001, UC-002, UC-003, and UC-014 each require multi-source data integration across warranty, telemetry, supplier, and CRM systems. Ford's confirmed data siloing means pipeline build is the longest lead-time item in H2 — delays here compress the Month 8 gate evaluation window.	*Complete H2 data pipeline scoping and resource assignment by end of Month 3 (before the Month 4 gate); Ford's Chief Digital and Information Officer should assign dedicated data engineering resources to pipeline design as a gate condition for H2 funding release.*

Risk assessment performed in SPARKle simulation mode. All risks are directional — severity and ownership would be confirmed through further validation, such as a Day 2 Technical Deep Dive. Feasibility scores are estimated [Est.].

SECTION 6 OF 6

First 90 Days + Closing Recommendation

The following five actions are specific, sequenced, and attributable. Each has a named owner role and a week-level deadline. Executing these five actions in the order listed is the critical path to a successful H1 launch.

#	Action	Owner	Timeline
1	Convene warranty data normalization working group; select F-Series pilot dealer cohort of 10–15 locations and define repair order schema	Warranty Operations Lead	**Week 1–2**
2	Stand up NLP model training environment; initiate fine-tuning on historical F-Series repair order corpus	Chief Digital and Information Officer	**Week 3–4**
3	Designate pilot engineering team for UC-009; initiate powertrain standards corpus ingestion and format normalization across document repositories	Chief Engineer or VP of Product Development	**Week 3–6**
4	Establish AI program steering committee; define Month 4 gate evaluation criteria, decision authority, and H2 pipeline scoping resource assignments	Chief Digital and Information Officer	**Week 4–8**
5	Complete export control classification review of UC-009 pilot corpus and confirm PII handling controls for UC-005 repair order data before ingestion	Export Control Compliance Lead	**Week 2–6**

Closing Recommendation

Michael — based on this validated roadmap, The Holistyx Group recommends proceeding with the H1 Quick Win Package:

Warranty Repair Documentation Automation + Engineering Knowledge and Standards AI Copilot

— with Concurrent dealer repair order data normalization workstream to unlock all H2 predictive models

Investment: $14.98M – $24.97M **3-Year Value:** $131.96M – $219.93M **Avg ROI:** **8.81x average across these 2 Quick Win use cases**

To discuss next steps and receive your Statement of Work, contact The Holistyx Group at ***info@theholistyxgroup.com***

About The Holistyx Group

The Holistyx Group is a boutique AI transformation consultancy specializing in helping enterprise organizations move from AI enthusiasm to funded, implementation-ready execution. Our proprietary SPARK™ methodology combines structured discovery, financial modeling, and sequenced roadmapping to deliver board-ready AI investment strategies. We simplify the complexity of change so leadership can act with confidence.

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APPENDIX A

SAVA™ v2 Financial Model

Portfolio Financial Summary

All figures represent 3-year Notional-level estimates. ROI Conservative = Low Value ÷ High Investment. ROI Optimistic = High Value ÷ Low Investment.

ID	Use Case	Hz	Val Low	Val Mid	Val High	Inv Range	ROI Low	ROI High	Payback
H1 — Foundation & Quick Wins — Months 1–4									
UC-005	**Warranty Repair Documentation Automation**	H1	$87.19M	$116.26M	$145.32M	$9.36M - $15.60M	5.6x	15.5x	3.9 mo
UC-009	**Engineering Knowledge and Standards AI Copilot**	H1	$44.77M	$59.69M	$74.61M	$5.62M - $9.37M	4.8x	13.3x	4.5 mo
H2 — Scale & Expansion — Months 5–8									
UC-001	**Predictive Warranty Claim Risk Scoring Engine**	H2	$88.41M	$117.98M	$147.54M	$22.36M - $35.78M	2.5x	6.6x	8.9 mo
UC-002	**EV Battery Degradation Early Warning System**	H2	$85.94M	$114.59M	$143.24M	$24.18M - $38.69M	2.2x	5.9x	9.9 mo
UC-014	**AI-Powered Proactive Recall and Service Notification**	H2	$116.92M	$155.89M	$194.87M	$25.74M - $41.18M	2.8x	7.6x	7.7 mo
UC-003	**Supplier Quality Failure Prediction Model**	H2	$83.84M	$111.79M	$139.73M	$20.14M - $32.23M	2.6x	6.9x	8.4 mo
UC-015	**Dealer Service Lane AI Diagnostic Assistant**	H2	$115.47M	$153.96M	$192.45M	$22.88M - $36.61M	3.2x	8.4x	7 mo
PORTFOLIO TOTAL | All Horizons			**$622.54M**	**$830.16M**	**$1,037.76M**	$130.28M – $209.46M	**3.0x**	**8.0x**	—

SAVA™ v2 (Solution-Area Value Anchoring). All values are Notional-level [Est.] — directional for prioritization and board framing. Investment-grade projections require further validation beyond this report's scope.

APPENDIX A · CONTINUED

Payback Period Analysis

Payback = Investment Mid ÷ Annual Value · Annual Value = 3-Year Value Mid ÷ 3 · Investment Mid = (Low + High) ÷ 2

ID	Use Case	Hz	Conf.	Val Mid	Annual Val	Inv Range	Payback (mo)	Payback (yr)
H1 — Foundation & Quick Wins — Months 1–4								
UC-005	**Warranty Repair Documentation Automation**	H1	80%	$116.26M	$38.75M	$9.36M - $15.60M	3.9 mo	0.32 yr
UC-009	**Engineering Knowledge and Standards AI Copilot**	H1	80%	$59.69M	$19.90M	$5.62M - $9.37M	4.5 mo	0.38 yr
H2 — Scale & Expansion — Months 5–8								
UC-001	**Predictive Warranty Claim Risk Scoring Engine**	H2	55%	$117.98M	$39.33M	$22.36M - $35.78M	8.9 mo	0.74 yr
UC-002	**EV Battery Degradation Early Warning System**	H2	55%	$114.59M	$38.20M	$24.18M - $38.69M	9.9 mo	0.82 yr
UC-014	**AI-Powered Proactive Recall and Service Notification**	H2	55%	$155.89M	$51.96M	$25.74M - $41.18M	7.7 mo	0.64 yr
UC-003	**Supplier Quality Failure Prediction Model**	H2	55%	$111.79M	$37.26M	$20.14M - $32.23M	8.4 mo	0.7 yr
UC-015	**Dealer Service Lane AI Diagnostic Assistant**	H2	55%	$153.96M	$51.32M	$22.88M - $36.61M	7 mo	0.58 yr

APPENDIX A · CONTINUED

A. Horizon Confidence Ceilings

Horizon	Confidence	Description
H1 — Foundation & Quick Wins	**80%**	Conservative — near-term, mature data
H2 — Scale & Expansion	**55%**	Moderate — requires H1 data infrastructure
H3 — Transform	**35%**	Directional — dependent on H1 and H2 outcomes

C. ROI Calculation Methodology

Metric	Formula	Description
ROI Conservative	Low Value ÷ High Investment	Worst-case value against worst-case cost
ROI Mid	Mid Value ÷ Mid Investment	Expected value against expected cost
ROI Optimistic	High Value ÷ Low Investment	Best-case value against best-case cost
Payback Period	Investment Mid ÷ (Value Mid ÷ 3)	Months to recover investment at mid-scenario annual value
Value Basis	3-Year Undiscounted Cumulative	No discount rate applied — Notional level

SAVA™ v2 is a proprietary methodology of The Holistyx Group. All values are Notional-level estimates — directional for board framing, not capital commitment. Investment-grade projections require further validation beyond this report's scope.

B. Industry Benchmark Ranges

Solution Area	Low %	High %	Source
Predict	**5%**	**10%**	McKinsey Warranty Quality AI Survey 2026 — OEMs expect 5–10% warranty cost reduction via predictive quality analytics
Automate	**15%**	**30%**	McKinsey Transforming Quality and Warranty via Advanced Analytics — automotive AI/ML reduces total cost of quality up to 30%
Employees	**5%**	**15%**	Deloitte 2025 AI Survey; IBM IBV Automotive AI Report 2025 — generative AI delivers measurable productivity gains in automotive OEM workforces
Customers	**22%**	**37%**	IBM Institute for Business Value Automotive AI Report 2025 — auto execs expect AI to boost product value 22% and digital service value 37%
Magic Wand	**10%**	**25%**	McKinsey Automotive Software and Electronics Market 2026 — gen AI lowers costs and shortens R&D cycles significantly for OEM software development

Solution Area definitions appear on page 26 (Input 1 — Solution Area Anchor).

APPENDIX A · CONTINUED

Horizon Investment & Value Plan

Three Horizons Summary — Investment envelopes and value ranges from SAVA™ v2 model

Hz	Horizon	Timeframe	Conf.	Value Range	Investment Envelope	Avg ROI
H1	**Foundation & Quick Wins**	Months 1–4	80%	**$131.96M – $219.93M**	**$14.98M – $24.97M**	~5.3x – 14.7x (Mid: 8.8x)
H2	**Scale & Expansion**	Months 5–8	55%	**$490.58M – $817.83M**	**$115.30M – $184.49M**	~2.7x – 7.1x (Mid: 4.4x)
H3	**Transform**	Months 9–12+	35%	**Not applicable — no H3 use cases in this shortlist**	**Not applicable — no H3 use cases in this shortlist**	~N/A
PORTFOLIO TOTAL				**$622.54M – $1,037.76M**	**$130.28M – $209.46M**	**3.0x – 8.0x**

APPENDIX A · CONTINUED

About the SAVA™ Model

All financial projections in this report were produced using THG's proprietary SAVA™ v2 (Solution-Area Value Anchoring) financial modeling methodology. SAVA is purpose-built for AI transformation engagements where traditional ROI models fail — specifically, where the value of AI is diffuse across multiple operational functions and cannot be reduced to a single cost-line calculation.

SAVA produces defensible, board-ready financial ranges by anchoring estimates to three independent inputs that combine to determine the final value projection for each use case.

The Three Inputs

Input 1 — Solution Area Anchor

Every AI use case in this portfolio is assigned to one of five Solution Areas: Predict, Automate, Employees, Customers, or Magic Wand. Each Solution Area has a published benchmark range derived from current industry-specific AI adoption research calibrated to Ford Motor Company's actual sector — see the Industry Benchmark Ranges table in this appendix for the specific source cited per Solution Area.

Solution Area	What It Covers
Predict	Forecasting, anomaly detection, and predictive analytics — anticipating outcomes before they happen (demand, risk, churn, failure).
Automate	Workflow and process automation — removing manual, repetitive work from existing operational processes.
Employees	Internal productivity tools — AI that helps staff work faster or better (search, drafting, internal knowledge, decision support).
Customers	Customer-facing AI — service, personalization, and next-best-experience applications aimed at external users.
Magic Wand	Transformative or novel use cases that don't fit the other four categories — new capabilities or business models AI makes possible for the first time.

APPENDIX A · CONTINUED

Input 2 — Horizon Ceiling

Each use case is assigned to a deployment horizon — H1, H2, or H3 — based on data readiness, technical complexity, and organizational readiness. The horizon assignment applies a confidence ceiling to the value projection, preventing the model from projecting full benchmark value for use cases that carry meaningful execution risk or data dependency.

Input 3 — Workshop Scores

Each use case is scored on two axes during the SPARK engagement: Strategic Impact (1–10) and Implementation Feasibility (1–10). In SPARKle mode, these scores are estimated by THG from the client intake profile and sector benchmarks rather than generated in a live workshop — all estimated scores are tagged [Est.] and would be confirmed through further validation, such as a Day 2 Technical Deep Dive.

Composite Score = (Impact × 0.40) + (Feasibility × 0.25) + (Strategic Alignment × 0.20) + (Time to Value × 0.15). This is SPARK's default weighting, applied unless Ford Motor Company specified custom priorities during discovery. This score determines each use case's ranking in the Full Scored Portfolio (Appendix D); raw Impact and Feasibility scores alone determine placement in the Prioritization Matrix.

Strategic Alignment (1–10) reflects how well a use case fits executive visibility, regulatory deadlines, existing technology investment, or priorities Ford Motor Company stated during discovery — it is scored independently of Impact and Feasibility. **Time to Value** (1–10) is one of the four weighted sub-dimensions inside the Feasibility Score itself, then carried into the Composite Score a second time as its own factor, since speed to a working pilot weighs heavily in how Ford Motor Company would realistically prioritize this work.

The composite formula is weighted rather than a simple product of Impact and Feasibility because a straight multiplication can let one axis dominate — for example, a high-Impact idea with modest Feasibility can outrank a well-rounded, executive-sponsored use case purely on scale. Weighting Impact most heavily while still crediting Strategic Alignment and Time to Value keeps the ranking anchored to what a client can realistically fund and deliver in the near term, not just what scores highest on paper.

APPENDIX A · CONTINUED

How the Value Range Is Calculated

Low scenario — Conservative adoption rate × Solution Area benchmark low end × Horizon ceiling applied.

Mid scenario — Midpoint adoption rate × Solution Area benchmark midpoint × Horizon ceiling applied.

High scenario — Full adoption rate × Solution Area benchmark high end × Horizon ceiling applied.

All values represent undiscounted 3-year cumulative value. No discount rate is applied at this stage, consistent with Notional-level estimation practice.

How ROI Is Calculated

- **Conservative ROI** = 3-Year Value Low ÷ Total Investment High
- **Optimistic ROI** = 3-Year Value High ÷ Total Investment Low
- **Mid ROI** = 3-Year Value Mid ÷ Total Investment Mid

Payback period is calculated at the Mid scenario: Total Investment Mid ÷ Annual Value Mid (3-Year Value Mid ÷ 3).

Confidence and Limitations

These projections are Notional-level estimates — directional for prioritization and board framing, not capital commitment figures.

Benchmark Sources

Source	Application in This Model
Industry-specific AI benchmark research	Solution Area value benchmark ranges — see the Industry Benchmark Ranges table earlier in this appendix for the specific study cited per Solution Area
THG SAVA™ v2 Rate Card	Investment range calculations
THG Engagement History	Adoption curve and payback period assumptions

APPENDIX B

About SPARK™: The AI Transformation Methodology

What Is SPARK™?

SPARK™ is The Holistyx Group's proprietary AI transformation methodology — a structured, repeatable process for helping enterprise organizations move from AI enthusiasm to funded, implementation-ready execution. SPARK was designed to solve the boardroom funding problem: most AI initiatives fail not in production, but because they lack a structured process for translating ambition into a defensible, sequenced investment portfolio that leadership will actually fund. SPARK was developed and refined over hundreds of live client consulting engagements, and SPARKle applies that same proven methodology through an AI-assisted delivery mode built for rapid turnaround.

The Five Phases

Phase 1 — Discovery

Structured discovery builds a complete picture of the client's strategic context, AI maturity, data readiness, and opportunity landscape. Discovery produces a Pre-Flight Briefing — an internal intelligence document that synthesizes market research, competitive positioning, and client-specific context into workshop facilitation intelligence.

Phase 2 — Use Case Generation

Using the Imagine If™ framework, SPARK generates a comprehensive portfolio of AI use case candidates across five Solution Areas: Predict, Automate, Employees, Customers, and Magic Wand. A well-run SPARK use case generation session produces 15–25 candidates.

Phase 3 — Prioritization

SPARK applies a dual-axis Impact/Feasibility scoring model to rank every use case candidate, producing a four-quadrant Prioritization Matrix that separates Quick Wins from Strategic Investments and Experimental ideas.

Phase 4 — Financial Modeling

SPARK applies the SAVA™ v2 financial model to quantify 3-year value potential, investment range, and ROI for every shortlisted use case, producing figures that can withstand CFO scrutiny.

Phase 5 — Roadmap and Executive Readout

SPARK synthesizes the prioritized portfolio and financial model into a Three Horizons AI Roadmap with defined investment envelopes, Go/No-Go gates, and a First 90 Days action plan.

SPARK Engagements at a Glance

Format	Delivery	Output	Best For
SPARKle Free	24 hours	Industry AI Snapshot — sector benchmarks and top use case hypotheses	First exposure to AI opportunity landscape
SPARKle Express	24 hours	Full portfolio, financial model, and 12-month roadmap	Leadership alignment and board framing
SPARKle Pro	48 hours	Everything in Express plus use case cards, QA review, and implementation guidance	SOW scoping and H1 investment authorization
SPARK Live	2 workshop days	Confirmed portfolio with live-scored feasibility, validated financial model, and facilitated stakeholder alignment	Investment-grade capital commitment decisions

Ready to Go Deeper?

If you would like to progress from this SPARKle report to a confirmed investment plan, the next step is a **Day 2 Technical Deep Dive** — a structured working session with your engineering, data, and operations leads that validates feasibility assumptions, confirms data readiness, and produces an Investment-grade financial model suitable for capital budget approval.

Upon confirmation, The Holistyx Group will deliver a Statement of Work covering the Day 2 scope within 48 hours.

To discuss next steps, contact The Holistyx Group at info@theholistyxgroup.com

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SPARK™ is a proprietary methodology of The Holistyx Group. Simplifying the complexity of change.

APPENDIX C

Use Case Dossiers — Shortlisted Portfolio

Compact reference dossiers for all 7 shortlisted use cases. Financial figures from SAVA™ v2. All financial fields are estimated (Est.) and would be confirmed through further validation, such as a Day 2 Technical Deep Dive.

UC-005 · AUTOMATE · H1

Warranty Repair Documentation Automation

Quick Win

Score: 8.075/10

CHALLENGE

Ford's warranty repair technicians manually document repair orders, fault codes, and parts usage after every service event, producing inconsistent records that slow claim adjudication, inflate warranty write-offs, and make fleet-wide root cause analysis unreliable.

PILOT: WARRANTY DOCUMENTATION AUTOMATION — F-SERIES TRUCK LINE, MIDWEST DEALER COHORT

Pilot NLP documentation automation on F-Series warranty repair orders across 10–15 Midwest dealer locations, automating structured field population for fault codes, parts used, and labor operations.

Success: Achieve 85% or greater structured field auto-population accuracy on warranty repair orders, with a measurable reduction in claim submission incompleteness rate versus pre-pilot baseline.

Timeline: 60 to 90 days

FINANCIAL SUMMARY

3-Yr Value Low	**$87.19M**
3-Yr Value Mid	**$116.26M**
3-Yr Value High	**$145.32M**
Investment Range	**$9.36M – $15.60M**
ROI Range	**5.6x - 15.5x**
Payback Period	**3.9 months**

APPENDIX C · CONTINUED

UC-001 · PREDICT · H2

Predictive Warranty Claim Risk Scoring Engine

Quick Win

Score: 7.8/10

CHALLENGE

Ford's warranty organization adjudicates claims reactively with no systematic mechanism to identify high-risk claims early — those likely to escalate in cost, involve repeat failures, or indicate systemic component issues — before they consume disproportionate warranty reserves.

PILOT: PREDICTIVE WARRANTY CLAIM RISK SCORING — POWERTRAIN CLAIMS, NORTH AMERICA

Pilot risk scoring engine on North American powertrain warranty claims, training on three or more years of adjudicated claim history, routing high-risk claims to a priority review queue for 60–90 day live validation.

Success: Achieve 80% or greater accuracy identifying claims that exceed a defined high-cost threshold, with a reduction in average time-to-escalation for flagged claims over the pilot window.

Timeline: 90 days

FINANCIAL SUMMARY

3-Yr Value Low	**$88.41M**
3-Yr Value Mid	**$117.98M**
3-Yr Value High	**$147.54M**
Investment Range	**$22.36M – $35.78M**
ROI Range	**2.5x - 6.6x**
Payback Period	**8.9 months**

APPENDIX C · CONTINUED

UC-002 · PREDICT · H2

EV Battery Degradation Early Warning System

Quick Win

Score: 7.625/10

CHALLENGE

Ford's EV fleet generates continuous battery telemetry data, but no systematic capability exists to detect early-stage degradation before it results in a warranty claim or roadside event, leaving Ford exposed to high-cost battery warranty events on its most strategic product line.

PILOT: EV BATTERY DEGRADATION EARLY WARNING — MUSTANG MACH-E FLEET, NORTH AMERICA

Pilot anomaly detection model on the North American Mustang Mach-E fleet, training on two or more years of battery telemetry labeled against known degradation events, generating risk alerts for vehicles exceeding anomaly thresholds.

Success: Achieve 75% or greater precision on degradation risk alerts, with a false positive rate below 15%, measured against subsequent warranty claims or confirmed diagnoses within 90 days.

Timeline: 90 days plus data engineering preparation

FINANCIAL SUMMARY

3-Yr Value Low	**$85.94M**
3-Yr Value Mid	**$114.59M**
3-Yr Value High	**$143.24M**
Investment Range	**$24.18M – $38.69M**
ROI Range	**2.2x - 5.9x**
Payback Period	**9.9 months**

APPENDIX C · CONTINUED

UC-009 · EMPLOYEES · H1

Engineering Knowledge and Standards AI Copilot

Quick Win

Score: 7.55/10

CHALLENGE

Ford's engineering teams spend significant unproductive time searching fragmented standards repositories and legacy design guidelines. Knowledge is siloed by vehicle program and geography, and critical institutional expertise is lost when experienced engineers retire or transfer.

PILOT: ENGINEERING KNOWLEDGE COPILOT — POWERTRAIN STANDARDS PILOT

Deploy AI knowledge copilot against powertrain engineering standards and design guidelines for one active vehicle program, limiting scope to a single engineering discipline to validate retrieval accuracy and time-to-answer improvement.

Success: Average time-to-answer for standards and design guideline queries reduced by 50% or more, measured over an 8-week pilot period with at least 80% of pilot users actively querying the copilot.

Timeline: 60–90 days

FINANCIAL SUMMARY

3-Yr Value Low	**$44.77M**
3-Yr Value Mid	**$59.69M**
3-Yr Value High	**$74.61M**
Investment Range	**$5.62M – $9.37M**
ROI Range	**4.8x - 13.3x**
Payback Period	**4.5 months**

APPENDIX C · CONTINUED

UC-014 · CUSTOMERS · H2

AI-Powered Proactive Recall and Service Notification

Quick Win

Score: 7.525/10

CHALLENGE

Ford's recall and service notification process is reactive and batch-driven, with limited personalization based on vehicle configuration, usage pattern, or owner preference. This lag increases vehicle risk windows, drives unnecessary dealer traffic, and inflates warranty costs when issues escalate before owners act.

PILOT: PROACTIVE RECALL NOTIFICATION PILOT — SINGLE MODEL LINE, U.S. MARKET

Deploy AI-powered proactive notification for a single recall or service campaign on one U.S. model line, scoped to owners with complete CRM records and confirmed contact preferences, measuring response rate versus standard batch notification baseline.

Success: Owner response rate increases by 20% or more versus the standard notification baseline, measured within 30 days of notification delivery for the pilot recall campaign.

Timeline: 90 days

FINANCIAL SUMMARY

3-Yr Value Low	**$116.92M**
3-Yr Value Mid	**$155.89M**
3-Yr Value High	**$194.87M**
Investment Range	**$25.74M – $41.18M**
ROI Range	**2.8x - 7.6x**
Payback Period	**7.7 months**

APPENDIX C · CONTINUED

UC-003 · PREDICT · H2

Supplier Quality Failure Prediction Model

Quick Win

Score: 7.325/10

CHALLENGE

Ford's supplier quality management relies on lagging indicators — incoming inspection results and warranty field data — that reflect problems after defective parts have already entered the supply chain or reached customers, making remediation far more costly than prevention.

PILOT: SUPPLIER QUALITY FAILURE PREDICTION PILOT — SINGLE COMMODITY, NORTH AMERICA

Deploy predictive quality model for a single high-risk commodity category across Ford's North American supplier base, using historical inspection and warranty data to train the model and surface risk scores to a defined cohort of supplier quality engineers.

Success: Model correctly identifies at least 70% of suppliers who subsequently experience a quality event within 30 days of a high-risk score, validated against holdout set and live pilot outcomes over 90 days.

Timeline: 90 days

FINANCIAL SUMMARY

3-Yr Value Low	**$83.84M**
3-Yr Value Mid	**$111.79M**
3-Yr Value High	**$139.73M**
Investment Range	**$20.14M – $32.23M**
ROI Range	**2.6x - 6.9x**
Payback Period	**8.4 months**

APPENDIX C · CONTINUED

UC-015 · CUSTOMERS · H2

Dealer Service Lane AI Diagnostic Assistant

Quick Win

Score: 7.4/10

CHALLENGE

Ford's dealer service lanes face a persistent first-time fix challenge: technicians frequently misdiagnose vehicle faults or apply incorrect repair procedures, driving repeat warranty claims, higher dealer labor costs, extended vehicle downtime, and eroding satisfaction scores during intense EV service scrutiny.

PILOT: DEALER SERVICE LANE DIAGNOSTIC ASSISTANT PILOT — SELECT NORTH AMERICAN DEALERS

Deploy AI diagnostic assistant at 10–15 Ford authorized dealers in North America on the same dealer management system, scoped to high-frequency fault code categories where TSB coverage and historical repair outcome data are sufficient for model training.

Success: First-time fix rate for targeted fault code categories improves by 10 percentage points or more versus the pre-pilot baseline, measured across the pilot dealer cohort over a 90-day period.

Timeline: 90 days

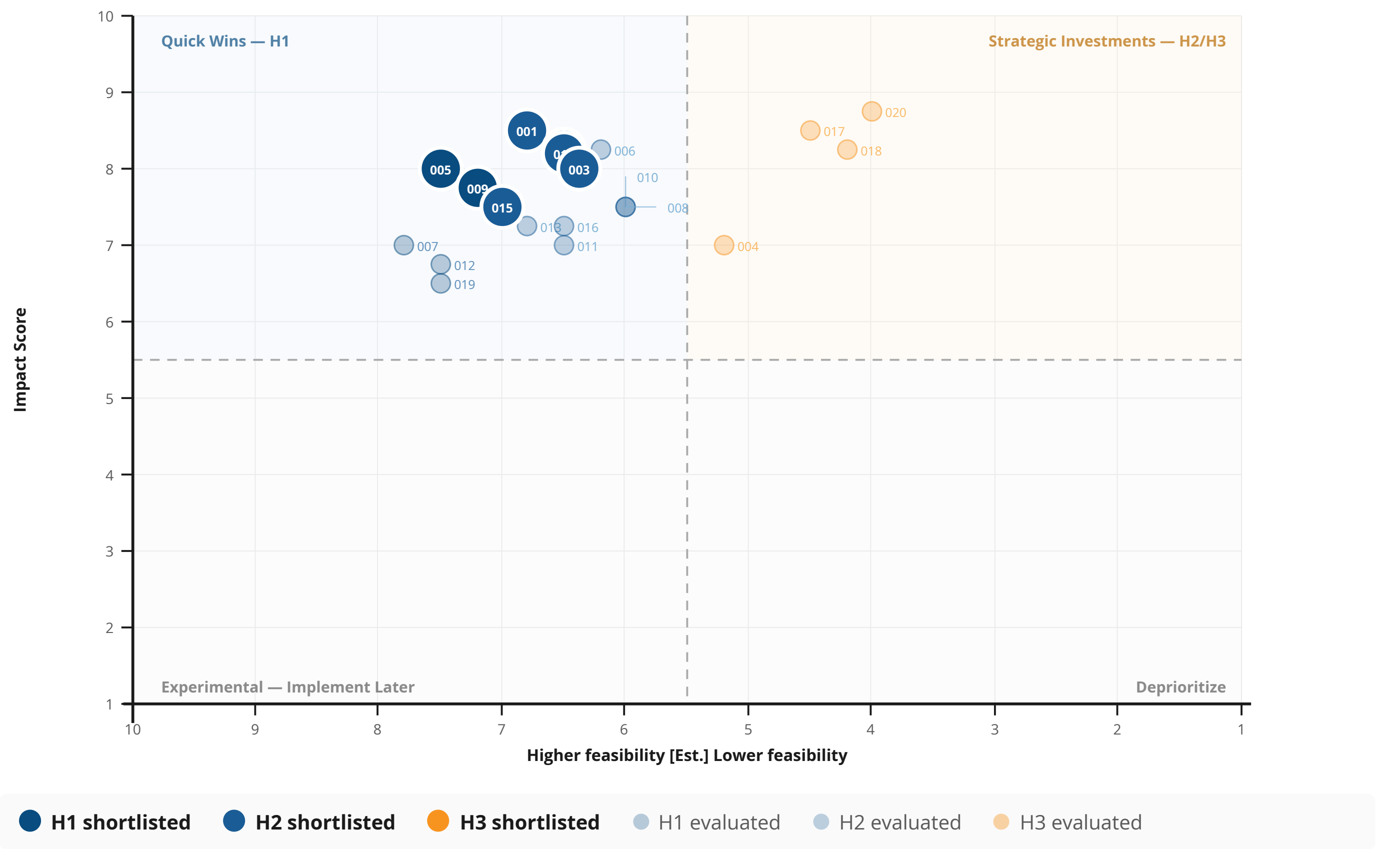
FINANCIAL SUMMARY

3-Yr Value Low	**$115.47M**
3-Yr Value Mid	**$153.96M**
3-Yr Value High	**$192.45M**
Investment Range	**$22.88M – $36.61M**
ROI Range	**3.2x - 8.4x**
Payback Period	**7 months**

APPENDIX D · PRIORITIZATION MAP

Impact vs. Feasibility — Full Portfolio

All 20 use cases plotted by Impact score (Y axis) and Feasibility score (X axis). Horizon zones divide the portfolio into sequencing bands. Shortlisted use cases are shown in solid color; evaluated-only use cases appear lighter. Feasibility scores are estimated [Est.] in SPARKle simulation mode.



Shortlisted use cases (solid circles, 7 total) labeled by ID. Evaluated-only use cases (faded dots) shown for portfolio context — full scored portfolio in Appendix D. X axis reversed: feasibility reads high (left) to low (right). Use cases sharing identical scores are offset for legibility. Feasibility scores are estimated [Est.] in SPARKle simulation mode.

SPARK™ Three Horizons — Delivery Sequencing

H1 — FOUNDATION & QUICK WINS

Months 1–4

High feasibility, mature data, deployable now with minimal dependencies. Builds AI credibility and data infrastructure for later horizons.

H2 — SCALE & EXPANSION

Months 5–8

Moderate feasibility. Builds on H1 data infrastructure and process changes. Broader integration and change management required.

H3 — TRANSFORM

Months 9–12+

Highest impact, lowest near-term feasibility. Platform-level bets that require H1 and H2 foundations to be fully operational first.

APPENDIX D

Full Scored AI Use Case Portfolio

All 20 use cases evaluated during the SPARK™ Imagine If™ brainstorm session, ranked by composite score. Shortlisted use cases are highlighted.

Abbreviations: Hz = Horizon | Feasib. = Feasibility | Align = Strategic Alignment | TTV = Time to Value

ID	Use Case	Area	Hz	Quadrant	Impact	Feasib.	Align	TTV	Score	Status
UC-005	**Warranty Repair Documentation Automation**	Automate	**H1**	Quick Win	**8.0**	**7.5**	**9**	**8**	**8.075**	Shortlisted
UC-001	**Predictive Warranty Claim Risk Scoring Engine**	Predict	**H2**	Quick Win	**8.5**	**6.8**	**9**	**6**	**7.8**	Shortlisted
UC-002	**EV Battery Degradation Early Warning System**	Predict	**H2**	Quick Win	**8.25**	**6.5**	**9**	**6**	**7.625**	Shortlisted
UC-009	**Engineering Knowledge and Standards AI Copilot**	Employees	**H1**	Quick Win	**7.75**	**7.2**	**8**	**7**	**7.55**	Shortlisted
UC-014	**AI-Powered Proactive Recall and Service Notification**	Customers	**H2**	Quick Win	**8.0**	**6.5**	**9**	**6**	**7.525**	Shortlisted
UC-003	**Supplier Quality Failure Prediction Model**	Predict	**H2**	Quick Win	**8.0**	**6.5**	**8**	**6**	**7.325**	Shortlisted
UC-015	**Dealer Service Lane AI Diagnostic Assistant**	Customers	**H2**	Quick Win	**7.5**	**7.0**	**8**	**7**	**7.4**	Shortlisted
UC-006	EV Assembly Line Defect Detection Automation	Automate	H2	Quick Win	8.25	6.2	8	5	7.2	Evaluated
	Strong H2 candidate; computer vision integration on active assembly lines lowered feasibility. Recommended after UC-005 and UC-001 establish data foundations.									
UC-007	Procurement Contract Review and Extraction Automation	Automate	H1	Quick Win	7.0	7.8	6	8	7.15	Evaluated
	Highest feasibility in portfolio but excluded due to lower strategic alignment with Ford's three stated priorities. Strong standalone procurement efficiency play.									
UC-013	EV Owner Personalized Charging and Range Advisor	Customers	H2	Quick Win	7.25	6.8	8	6	7.1	Evaluated
	Narrowly missed shortlist; UC-014 and UC-015 prioritized as they address warranty cost reduction simultaneously. Recommended H2 addition once EV telemetry pipelines are established.									

APPENDIX D · CONTINUED

Abbreviations: Hz = Horizon | Feasib. = Feasibility | Align = Strategic Alignment | TTV = Time to Value

ID	Use Case	Area	Hz	Quadrant	Impact	Feasib.	Align	TTV	Score	Status
UC-016	Personalized EV Configurator and Purchase Journey AI	Customers	H2	Quick Win	7.25	6.5	8	6	7.025	Evaluated
	Lower composite score than top 7; benefits from UC-013 and telemetry infrastructure being in place first. Strong H2 candidate for Ford's EV commercial team.									
UC-019	AI Competitive Intelligence and Strategy Signal Tracker	Magic Wand	H1	Experimental	6.5	7.5	7	8	7.075	Evaluated
	Fast to deploy but strategic alignment is moderate; competitive intelligence is not a board-level forcing function. Scored Experimental; useful for building AI literacy in strategy teams.									
UC-012	Finance and FP&A Generative AI Reporting Copilot	Employees	H1	Experimental	6.75	7.5	6	8	6.975	Evaluated
	High feasibility and fast time to value, but strategic alignment is lower; FP&A automation does not directly advance EV launch, warranty cost reduction, or competitive parity priorities.									
UC-010	Manufacturing Operations AI Decision Support Tool	Employees	H2	Quick Win	7.5	6.0	8	6	7.0	Evaluated
	Meaningful operational impact but overlaps significantly with UC-006 and UC-003 in scope. Excluded to avoid redundancy and preserve portfolio diversity across value driver types.									
UC-008	Vehicle Software Release Validation Automation	Automate	H2	Quick Win	7.5	6.0	8	5	6.85	Evaluated
	Lower time-to-value due to CI/CD pipeline integration complexity. Recommended as H2 follow-on once engineering AI literacy is established via UC-009.									
UC-011	Enterprise Data Discovery and Silo-Breaking Assistant	Employees	H2	Quick Win	7.0	6.5	7	6	6.725	Evaluated
	Important enabler but an infrastructure play rather than a direct value driver, resulting in lower impact scores. Best positioned as an H2 dependency for UC-017 and UC-020.									
UC-020	End-to-End AI Quality Closed-Loop System	Magic Wand	H3	Strategic Investment	8.75	4.0	9	3	6.75	Evaluated
	Highest impact in portfolio but assigned H3; requires quality data loops, supplier prediction models, and assembly detection from H1/H2 to be in place first. Capstone, not starting point.									
UC-017	AI-Unified Vehicle Telemetry Intelligence Platform	Magic Wand	H3	Strategic Investment	8.5	4.5	9	3	6.775	Evaluated
	Transformational but assigned H3 due to significant data integration complexity across vehicle lines and regions. Requires H1/H2 data infrastructure from UC-011 and UC-001 first.									
UC-018	Autonomous EV Program Cost Optimization Engine	Magic Wand	H3	Strategic Investment	8.25	4.2	9	3	6.6	Evaluated
	High impact but very low feasibility; requires integrated cost, engineering, and supply chain data not yet unified. Assigned H3 with dependency on H1/H2 data foundations.									
UC-004	Cross-Jurisdictional Regulatory Compliance Risk Monitor	Predict	H3	Strategic Investment	7.0	5.2	7	4	6.1	Evaluated
	Penalized on feasibility due to genuine multi-jurisdictional complexity across 6 or more countries. Assigned H3 pending data infrastructure and cross-border governance framework readiness.									

Scoring methodology: Composite Score = (Impact × 0.40) + (Feasibility × 0.25) + (Strategic Alignment [Align] × 0.20) + (Time to Value [TTV] × 0.15) — SPARK's default weighting, applied unless the client specified custom priorities during discovery. See Appendix A, Input 3, for the full rationale. Feasibility scores are estimated (Est.) in SPARKle mode and would be confirmed through further validation, such as a Day 2 Technical Deep Dive. Use cases sorted by composite score descending.