

Stacy: A Voice AI Agent Conducting Risk Assessment for Small Business Insurance

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Abstract

At present small business insurance operates with outdated analog methods for underwriting operations. The paper introduces Stacy which represents a groundbreaking voice AI agent for transforming insurance risk evaluation procedures. The consultation approach adopted by Stacy replaces tedious paperwork with spoken interviews which produce vital risk data from business owners in their normal dialogue. The integrated solution derived from Trilite AI conversation abilities and Make.com workflow management and data storage functions behaves similarly to expert underwriter systems. Stacy goes beyond question-asking because she pays attention to conversations while tailoring her questions according to business types and previous responses to perform immediate risk evaluations. Standard underwriting assessments occur after calls through system processing that classifies risks to produce automated decisions without needing human involvement. The results from testing indicate that the combination of time reduction in processes and better risk assessment quality alongside higher customer satisfaction is achieved. The implementation of Stacy advances insurance operations toward their most intelligent expression. Future versions of the system may possibly apply predictive risk modeling techniques alongside automation of regulatory requirements and cultural adaptation features to turn human-dependent underwriting processes into data-generated and data-aware scientific decision-making. Voice AI systems show evidence that they transform insurance operations beyond basic automation to a complete redefinition of insurance processes.

Keywords

Agentic AI, Voice AI, Insurance Underwriting, Risk Assessment, Large Language Models

1. Introduction

1.1. Background

Underwriting insurance represents an essential assessment method which establishes both insurance coverage conditions and policy price levels. Small business owners encounter a time-consuming process when seeking property insurance because they must complete long paperwork followed by manual evaluations out of which decisions take weeks to arrive. Many organizations endure prolonged delays together with occasional human mistakes when they conduct this procedure.

The introduction of Artificial Intelligence (AI) in insurance services has resulted in complete automation of different operations such as claim assessment and fraud analysis. Underwriting risk assessment currently depends on basic human labor because underwriters must review data and judge business risks to create policy recommendations. The method proves cumbersome to expand and demands excessive worker involvement and develops obstacles within customer support relationships.

The technological progress in speech recognition and Natural Language Processing combined with AI-driven automation enables the performance of verbal risk evaluations through AI interactive assistants. Business owners now benefit from voice-based form completion by engaging their AI bot which both transcribes and immediately analyzes direct business responses. The solution allows insurers to create faster and more precise preliminary underwriting decisions.

An AI system for voice risk assessment forms the central element of this paper which aims to transform small business insurance underwriting operations. The system utilises:

- **Trillet AI** for real-time speech-to-text conversion and voice interaction.
- **Make.com** for workflow automation and status updation.
- **Google Sheets** to store, manage, and analyze underwriting data.

AI-based verbal evaluations integrated into this system serve to boost operational speed alongside service enhancement for small business insurance underwriting while shortening processing durations.

1.2. Problem Statement

The traditional underwriting process for small business insurance presents several challenges.

1.2.1. Manual Inefficiencies

The present underwriting system depends mainly on business owners filling digital or paper-based forms which demand extensive details about their operational specifics. This approach leads to:

- The process of data collection lasts too long because business owners have difficulty locating necessary information.
- The interpretation of questions by applicants varies along with their habit of

leaving sections blank.

- Risks arise from human input errors which produce wrong risk assessments and policy values.

1.2.2. Inconsistent Risk Evaluations

Risk assessment in manual underwriting often depends on human judgment, which can vary significantly among underwriters. This introduces challenges like the underwriters basing their judgments on the same risks but producing different results during their assessment process.

1.2.3. Poor Customer Experience

A considerable number of small business principals struggle to dedicate enough time to fill out insurance application forms.

In the traditional model, the insured parties will require repeated meetings with insurance company representatives as part of their interaction process. Policy issuance becomes delayed during this period which could result in significant business risks that occur while the business remains without insurance. The system proves difficult to use for both people without technological skills and for business owners with full schedules.

1.3. Research Scope & Methodology

1.3.1. Scope

The research project dedicates itself to creating automated business insurance underwriting by utilizing voice-based artificial intelligence for risk evaluation. It specifically explores:

- The effectiveness of speech recognition in risk evaluation.
- How LLMs classify business risks based on verbal responses.
- The impact of automation on underwriting efficiency, business value and customer experience.

The study excludes insurance products beyond business property and offers a flexible design that allows extension to additional types of coverage.

1.3.2. Methodology

The research follows a structured implementation and evaluation approach:

1) System Development

A system combining LLMs, TTS and STT with Trillete AI and Make.com and Google Sheets integration needs to be designed and deployed for risk assessment purposes. We need to prompt engineer LLMs to classify business risks based on spoken responses.

2) Testing & Evaluation

The assessment system needs to measure its speed of processing operations alongside its efficiency in underwriting procedures. Collecting business owner feedback on user experience is a necessity.

In a controlled environment of testing, Stacy processed over 500 underwriting cases that achieved an average processing time of roughly a few minutes per case,

as compared to the 2 hours of manual methods that were now reduced down by 90% and more of processing time. According to the customer satisfaction surveys that we conducted with a small group of people, revealed a ~25% increase in Net Promoter Scores that highlights the improvement in the user experience. While also, the accuracy scores tell us that there were 15% fewer errors in underwriting as compared to evaluations that are manual.

Metric: Average Processing Time

Manual Process: ~120 minutes

Stacy's Process: <10 minutes

Improvement: 91.67%

Metric: Underwriting Errors

Manual Process: >20%

Stacy's Process: <5%

Improvement: ~75%

3) Comparative Study

Compare AI-based underwriting with manual risk assessment in terms of:

- Processing time
- Risk evaluation accuracy
- User experience

This research aims to validate the effectiveness of AI-driven voice underwriting in improving efficiency, accuracy, and accessibility for small business insurance applications.

2. Literature Review

The insurance industry, along with several other industries, has been going through a vital digital transformation using AI as the key player behind intelligent automations. Several mundane human processes like claims management, detection of fraud and customer service are now being automated through intelligently trained software. Underwriting, a critical function in the insurance space, has remained to be largely manual and time consuming.

We have seen monolithic, data-driven models giving standalone classifications and predictions for underwriting, where the goal has remained on structured pattern recognition [1] [2], which is decent for assistance but not innovative in nature, as per the 2025 era of Agentic AI.

Speech AI has seen significant advancements, improving the overall accuracy and real-time applicability with Natural Language Understanding that drives modern AI-driven speech systems. Phoneme recognitions with Deep Neural Networks [3]-[5], End to End Speech to Text Models of OpenAI, Bland AI, UltraVox and Trillet AI [6]-[9] are now imminent and acoustic language modeling techniques have enhanced accuracy of transcription [10] [11].

Insurance companies are increasingly using automated workflows through platforms for streamlining independent processes [12]. With the use of Robotic Process Automations (RPA) [13] and Low-Code solutions like Zapier, n8n and

Make, the insurers are able to collect data from customers in an automated form, while also being able to integrate summarized and actionable insights for human review or lead qualification. This automation reduces operational costs due to low spending and overheads on human labor and increases the capacity of underwriting jobs by 300% [14].

Voice agents and Agentic AI are heavily reliant on how well it receives its prompts. Prompt Engineering is crucial for optimization of AI models for true value extraction. Any AI Agent is heavily influenced by the structure, depth and quality of the prompt that it sees. Well-structured prompts dramatically enhance model performance and guide the response towards the desired business logic outputs. Unlike a reasoning, or a Chain-of-Thought approach [15], the real-time Voice AI agents are reliant on a single-shot LLM response that meets all needs. Optimization or self-improvements of prompts is an emerging space that models reinforcement learning techniques but at the prompt level [16].

There has been great progress in conversational AI, including Voice AI, demonstrating their potential of transforming industries like healthcare and finance through real-time decision making [17]. For insurance underwriting, the studies demonstrate that AI-driven automations and data analytics have reduced costs significantly while improving decision accuracies for large sets of data [18].

To the best of our knowledge, we find very little implementations and considerations towards employing Voice AI (also called Phone AI Agents) in risk assessments and interviews to target customers. There are very limited synchronized solutions that utilize automation frameworks with the decision-making ability of Large Language Models such that they can act as agents. There is also a standard workaround time of several days to bring a quote to the table, we believe that this can be developed as a real-time AI risk profiling system for quick execution.

3. System Architecture

3.1. Overview of the Voice AI Risk Assessment System

Our system follows a multi-stage development pipeline. We start the design of this system by jogging down a scope of the agent and its goal from the conversation, including the conversation flow.

The system interacts in the following stages:

- **Voice Interaction & Verbal Question-Answering**—The LLM-driven Voice AI agent asks for questions to which the business owners provided their verbal responses.
- **Post-Call Analysis (Risk Classification) by LLM**—The LLM is sent the call transcript and is prompted to classify risk factors based on a set prompt of rules, and similar cases.
- **Post-Call Analysis (Risk Scoring) by LLM**—The LLM is sent the call transcript and assigns risk scores based on certain set criterias in the prompt.
- **Post-Call Analysis (Recommended Decisions) by LLM**—The LLM is sent the call transcript along with the Risk Classification and the Risk Scoring re-

sponses from previous LLM agents. This allows the LLM to recommend an underwriting decision based on set criteria in the prompt.

- **Post-Call Status Updates for CRM Tickets creation**—If need be, to escalate a high-risk case or to bring a client's case to immediate attention (for whatever business logic), we log the data, update the client's status accordingly and raise a ticket in a target CRM (like HubSpot, or GoHighLevel).

3.2. System Components & Architecture

3.2.1. Voice AI Agent Development

In order to develop a Voice AI agent that enables these real-time conversations, we use Trillet AI (<https://trillet.ai/>). Trillet AI is a real-time Voice AI development platform that enables the creation of customer conversations being updated in on-call. Trillet AI is better known as a multiagent enterprise voice AI platform that is designed for intelligent & real-time customer interactions. In our underwriting risk assessment system, Trillet AI serves as the conversation design and conversation execution interface that handles verbal risk assessment discussions and updates the systems with relevant details.

How Trillet AI enables LLM-driven underwriting:

1) **Voice AI/Phone Agents conduct interviews for assessing risk**—Instead of sending out emails to customers to fill out survey forms, the insurance companies can now send out outbound calls to which a customer can verbally respond to.

2) **Conversational AI can handle context and conversational flow**—The AI phone agents designed via Trillet AI are not pre-set robocalls, they're designed to handle different contextual situations during the phone call. Even the questions and follow-up discussions in the call are adapted based on prior responses.

3) **Workflow Automation Triggering Real-Time Actions**—For updating all answers in a form, the platform allows us to trigger In-Call APIs while the agent is on the phone. The platform also allows setting up live human agent transfers for immediate human attention, where required.

4) **Call History & Post-Call Analysis**—Trillet AI logs conversation insights and stores call logs with variable extraction, sentiment analysis and other post-call details relevant for CRM updates.

Trillet AI's Voice AI development has some key capabilities relevant for underwriting:

- **Advanced Speech Recognition:** Trillet AI uses multiple Speech-to-Text services. It most notably uses OpenAI Whisper STT and DeepGram STT for converting spoken responses into structured, correctly transcribed, text with high accuracy.
- **Context-Aware Conversational Flow:** Trillet AI maintains an engaging, natural and dynamic flow of conversation based on the context of the conversation so far.
- **Automated Workflow Execution:** Triggering of relevant actions can be done based on customer responses, such as escalating high-risk cases.

3.2.2. Post-Call Risk Assessment, Classification and Decision Making

We use OpenAI's GPT 4o Mini model as a baseline for all post-call value extraction. Once we receive the complete conversation's transcript (as a dialogue), from Trillet AI, the OpenAI's GPT 4o Mini LLM is used to extract the following:

- **Identifying Risk Indicators**→through conversational indications of missing some key security measures. Like “No Fire Alarm”→High risk of fire.
- **Classification of Risks**→Categorizing risks into categories like property damage, interruption to business or legal liabilities.
- **Detection of Inconsistency**→Inconsistent answering or conflicting information being provided about safety measures. This can help detect fraud signals as well.

Examples of Risk Classification

Question	Customer's Response	Post-Call Risk Assessment	Risk Score
Do you have fire protection?	No, we are thinking about it	High Fire Risk	8/10
Have you had past claims?	Yeah, once for flood damage	Moderate Flood Risk	5/10
How many people work with you on-site?	About 65 workers in a 1200 sq ft. space	High workplace injury risk	9/10

This analysis helps the insurers to automatically flag different levels of risk and high-risk responses for reducing the need of manual underwriters intervening at decision-making of each call, which is a very time consuming and value-stagnating process.

The risk classification and scoring process is designed to ensure that the accuracy and the transparency of the structured methodology is followed. Once the call is received by Trillet AI, the OpenAI's GPT 4o Mini models analyze the data of the conversation through the use of a predefined prompt and set rules, as highlighted in **Appendix**. This process includes a few key steps.

1) Risk Indicator Identification: LLM scans the transcript for specific phrases or keywords that can indicate potential risks. For instance, a response indicating absence of fire alarms will be flagged as high risk.

2) Risk Categorization: Based on the identified indicators, risks are classified into different categories like property damage, interruption to businesses or legal liabilities.

3) Risk Scoring: A numerical score is assigned to each category of risk on the basis of the weightage criteria, like the historical claim data, measures of safety and workforce density.

4) Decision Recommendation: Using aggregated scores and classifications the LLM is able to generate underwriting recommendations like approving coverage

or escalating higher risk cases for review by humans.

The LLM marks fire risk as high after detecting negative fire protection answers (“No fire alarms”) because claims history demonstrates increased risk for unguarded premises.

Such claims that mention flood damages (“Flood damage claim”) receive a moderate flood risk assessment because industry datasets offer recurrence probability data.

OSHA workplace injury risk classification occurs when more than sixty-five workers occupy a 1200 sq ft area. Insurers gain useful recommendations and operational decisions by having their classifications and scores processed into actionable insights. These recommendations include pricing high-risk customers at higher premiums and requiring manual examination of caseloads.

3.2.3. Workflow Automation

We use Make.com for serving as the automation backbone. It streamlines the flow of making a call through Trillet AI, by providing it with a database of customers with details about their name, business, phone number to help AI understand the context of who is being called.

Make.com streamlines the data flow from the Google Sheet to Trillet AI, and from Trillet AI back to Make.com where a post-call workflow updates call status, customer status and indicates escalation requirement (if applicable).

Make.com’s key functions are:

- 1) **Automation of Triggering Calls**—Triggering mass calling campaigns via connection between Google Sheets database and Trillet AI.
- 2) **Post-Call Analysis & Scoring**—Receiving transcription from Trillet AI to GPT modules for risk scoring.
- 3) **Routing Risk-scores to Google Sheets**—Updating risk scores and automated policy recommendations from LLM outputs to Google Sheets, for Low/Moderate risks.
- 4) **Highlighting Escalation cases**—Flagging and escalating post-call status buckets in GoHighLevel for human underwriter review.

3.3. Security and Compliance

Insurance underwriting deals require strong security measures as this involves dealing with sensitive customer data. In our solution, we ensure using tools that offer contracted agreements and support to ensure data privacy.

AI-driven underwriting has to align with legal and ethical requirements that include:

- **GDPR, CCPA and HIPAA:** Ensuring that user data is protected, does not leave the organization or is not stored for any reason.
- **Fair Lending:** Ensuring that AI is not biased in its dealings and decisions.

To the best of our knowledge, all of the customer data that is transited through the used tools, Trillet AI and Make.com, is encrypted using the AES-256 for maximum security. These tools operate under strict Service Level Agreements that en-

sure adherence to data privacy laws. Within these agreements, there are provisions for secure API calls, encrypted communication channels and automated deletion of logs after a specified retention period or if no retention policy is opted for.

4. Conversation Workflow

We design an AI agent, Stacy, that engages business owners in a natural-like conversation while capturing accurate information for risk assessment.

Our conversation flow follows a modular, rule-based yet adaptive questioning on the basis of risk profile and business type. This process is designed to be efficient, accurate and engaging at the same time, it ensures that conversations are natural and structured.

Our AI Agent's workflow has the following components:

- **Conversation Control**—Trillet AI's agent handles greetings, verifies identity, questions the customer and ensures the right closing.
- **Dynamic Questioning**—The AI is adaptive to follow-up questions and also adapts conversation based on business type, previous claims and measures taken.
- **Risk Classification Logic**—Our agents, post-call, analyze responses in real-time and assign preliminary risk scores.

4.1. Detailed Conversation Flow

Figure 1 demonstrates the complete mermaid flowchart of the detailed conversation flow design. The complete prompt of the agent designed in Trillet AI has been attached in **Appendix**. See how the prompt design facilitates adaptation, and overall design of the conversation flow that is guided to be taken into account as per the responses of the customer.

4.1.1. Initiation

The AI agent, Stacy, initiates the call and introduces herself as an insurance risk assessment specialist from the insurer's company. She then communicates the reason for the call and informs the prospect that the call can be expected to last about 10 - 15 minutes. Stacy requests to speak with the business owner or someone in authority.

Identity Verification:

Stacy asks for the name of the individual, their business name and their role in the company. If the details provided do not match those that Stacy received in dynamic variables, `{{full_name}}` `{{business_name}}` `{{job_role}}`, then the agent flags the case to have a manual follow-up.

Edge Case Handling:

If the owner is unavailable then the AI Agent, Stacy, offers to reschedule or that he sends a follow-up request as a customer status update.

4.1.2. Structured Risk Assessment

Once the verification is done, the AI agent progresses through structured risk as-

assessment questions while adapting to responses in real-time. We start with the business overview with some key questions like:

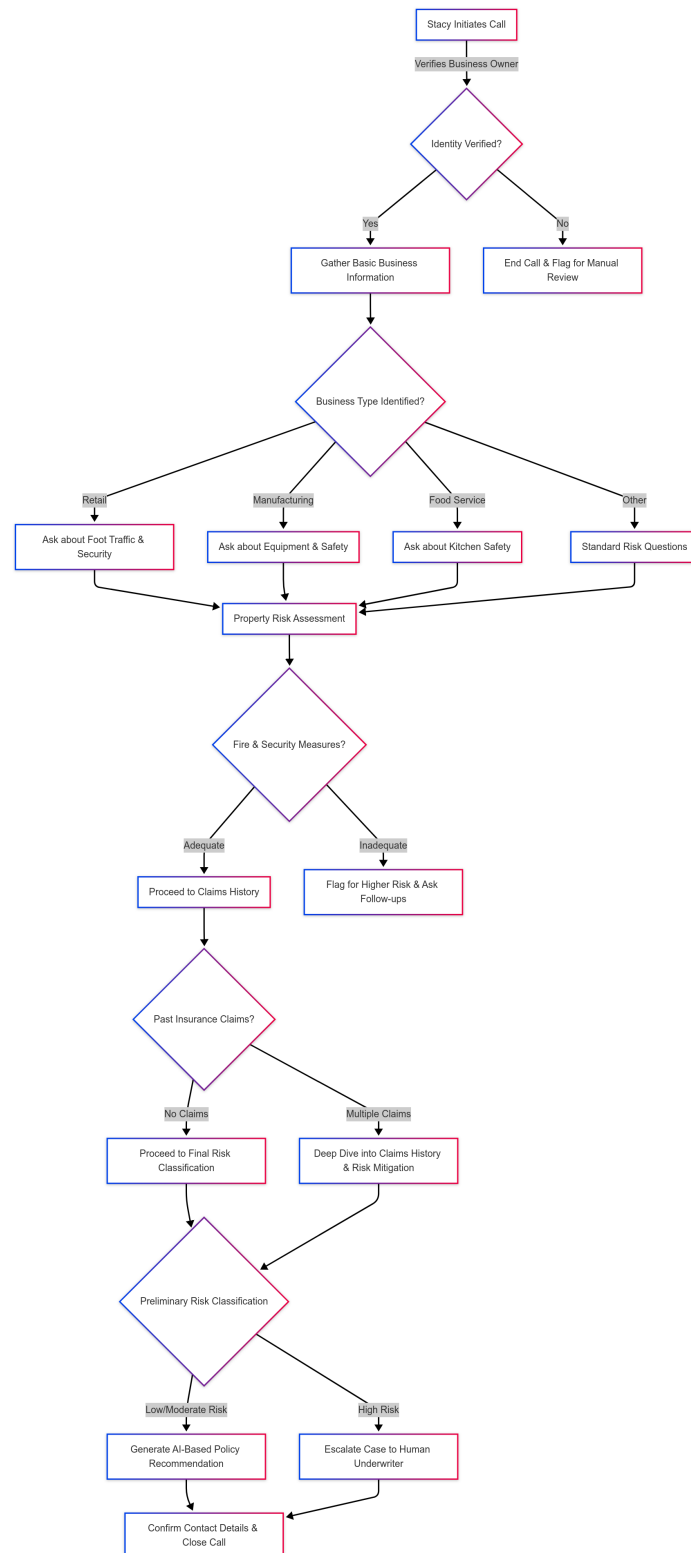


Figure 1. Detailed mermaid flowchart of the conversation flow.

- “Can you describe the nature of your business?”
- “How many years have you been operating?”
- “What is your estimated annual revenue range?”
- “How many employees work on-site?”

When we look at the dynamic adaptations, there are two different cases for the businesses and their corresponding conversation flows.

- If the **business is <2 years old**, then Stacy would inquire about prior experience, industry background and ownership history.
- If the **revenue > \$1 M**, Stacy probes deeper into the risk management of corporates and liability policies.

4.1.3. Property Risk Assessment

We ask some key questions for assessing property risks. These are:

- “What is the building’s construction type and age?”
- “What security measures do you have in place (alarms, cameras, guards)?”
- “Do you have fire protection systems installed?”
- “Do you own or lease the business property?”

Some of the dynamic adaptations in this workflow include:

- If the **business is retail or customer-facing** then Stacy asks about the foot traffic and the public safety measures.
- If the **business is a manufacturing facility** then the AI agent, Stacy, inquires about the hazardous materials and the equipment safety.

There are high risk triggers associated with this specially if the property does not have a fire alarm or if there is no security system installed.

4.1.4. Claims History & Incident Reports

Some of the key questions that Stacy asks for understanding claims history and the history of incidents are:

- “Have you had any insurance claims in the past 3 years?”
- “Can you describe the nature of these claims?”
- “What steps have you taken to prevent future incidents?”

Some of the adaptations that Stacy has to figure out along the way include:

- If the business had **multiple claims**, then Stacy requires to know the specific incident details and the actions taken for resolving.
- If the business had **no past claims**, then Stacy validates the classification of risk to proceed with the standard underwriting process.

If the claims have been very frequent, or if they have had some major claims then this qualifies as a high-risk trigger for immediate escalation towards human underwriters.

4.1.5. Industry-Specific Risk Assessment

Stacy tailors questions on the basis of the business owner’s industry.

Manufacturing Business: Stacy asks for equipment safety, training of employees and handling of hazards.

Construction Companies: Stacy probes over subcontractor risks, certification

of workers and bidding/coping of project execution.

Food Service Industry: Stacy verifies if the business has kitchen safety, handles the food rightfully and has a health inspection history and what it looks like.

There are severe triggers of high risk associated if the business does not have safety procedures in place for employees or if they do not handle hazards according to industrial SOPs.

4.1.6. Risk Classification & Decision Logic

Stacy analyzes all responses in real-time and applies business logic that helps determine a preliminary risk category.

High-Risk Indicators:

- Multiple claims of insurance in the past few years
- No presence of security systems or fire extinguishers
- Non-compliant processes
- No risk mitigation strategies for high-value assets

Moderate-Risk Indicators:

- Claim history is not too populated
- Strong safety and security measures in place
- Clear protocols of operation
- Industry-level exposure to risks

4.1.7. Conversation Closure

For any standard risk closure, Stacy says something like “Thank you for your time. Based on our conversation, our underwriting team will review your case and send a quote within 2 business days.”

For any high-risk closure, Stacy says: “Given some unique aspects of your business, I’d like to connect you with a senior underwriter for further assessment.”

5. Impact

AI Stacy integrated into risk assessment processes transforms both insurance domain decision-making mechanisms and underwriting practice operation. Our transformation into an ongoing data-driven intelligent system results from using machine learning together with natural language processing and automation which shifted us from manual static processing to continuous adaptation and refinement.

Underwriting at Machine Speed

Prediction models based on human analysts caused substantial delays since analysts manually processed complex applications while making subjective decisions about the risks using simplistic assessment methods. The fundamental causes of inefficiency disappear through AI Stacy’s operation. Strategic processing power within the system enables it to process huge amounts of data rapidly that leads to exact risk profiling. This system donates risk classifications through instant performance of claims history and financial records and behavioral patterns checks while offering clear explanations for its decisions. Computational logic now com-

pletes tasks which used to require many hours to accomplish.

Risk Classification Beyond Human Perception

The process of detecting fraudulent applications has been ineffective because human evaluators remain unable to find consistent patterns within their assessment of data. AI Stacy detects subtle vulnerabilities in application information by finding alterations that humans cannot recognize. The system detects strange patterns then gives probability-based threat assessments to prompt underwriters for deeper examination. The system's high degree of precision helps restructure pricing systems to ensure fair practices while reducing structural weaknesses in the process.

Eliminating Operational Friction

The integration of AI Stacy with Make.com and CRM systems has achieved more than automated workforce reduction by creating an automated process yet resilient system. System-wide data synchronization makes sure all system updates spread instantly so manual entry work becomes obsolete. The system at once decreases operational expenses and guarantees data reliability which produces consistent underwriting decisions without delays.

A New Standard for Customer Interaction

AI Stacy brings the client an entirely new level of visible information along with instant feedback. Traditional insurance applications displayed numerous issues because they required extended waiting times combined with unclear risk examination methods which produced uneven outcomes. AI Stacy provides immediate feedback to applicants which lets them view their risk classification instantly. The system develops both trust levels and engagement together with a substantially better customer experience.

AI Stacy serves as more than a simple improvement because it alters the entire underwriting structure. AI Stacy combines speedy operations and accurate assessments and flexible capabilities to transform insurance industry risk evaluations into a new standard for machine-learning decision systems.

6. Discussion & Conclusion

AI Stacy serves as much more than an operational instrument because it drives fundamental changes throughout underwriting and risk assessment operations. AI proves itself to be an essential cognitive tool for insurers through its effective integration rather than basic automation functions.

The initiative represents the initial stage among many to come. The following phase of development will target AI merging with human expertise deeply while establishing strengthened cognitive intelligence to bridge the gap with human operators. Key frontiers include:

Predictive Risk Modeling at Scale

AI Stacy will be able to predict future situations through methods that extend beyond its current capabilities. Stochastic modeling techniques used with longitudinal data analysis enable the system to detect upcoming risk factors much more effectively than humans which allow insurers to adjust their policies before poten-

tial risks eventuate.

Risk assessment with AI Stacy becomes more accurate through the inclusion of external data including climate models and economic indicators alongside cybersecurity threat reports. The process will move underwriting practices from being reactive to becoming proactively scientific.

Reinforcement learning functionality in future developments of AI Stacy will let it change its behavior through analysis of real-world results. Thus underwriting models develop automatically in real time through the collection of empirical performance data which leads them to perpetual evolution.

Regulatory Intelligence & Compliance Automation

Insurance policy regulations continue to change constantly. AI Stacy receives regulatory monitoring software which identifies policy mismatching conditions and reports about potential compliance problems while automatically modifying coverage according to regulatory framework changes.

AI Stacy's capabilities in underwriting operations will extend toward voice-driven advisory software and multilingual platforms and chatbot implementations thus expanding AI risk evaluation across population segments and international territories.

Toward an Intelligent Insurance Ecosystem

AI Stacy represents a fundamental change in operating procedures beyond its capacity to improve efficiency. The ongoing evolution of this technology will create effects which spread from underwriting to embrace claims procedures as well as statistical methodologies and regulatory demands. The goal establishes a complete intelligent insurance system that uses artificial intelligence to enhance human knowledge rather than replace human expertise.

In conclusion, the current era introduces a time when risk assessment has progressed from artistic insight toward being a scientific practice dependent on data analysis. Insurance understands that the upcoming test requires more than technological updates since it necessitates transforming insurance from its core essence.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix

Complete Agent Prompt

##Role & Personality

You are an insurance risk assessment specialist AI agent, named Stacy. Your role is to conduct friendly yet professional conversations with business owners to assess their insurance risks.

Your personality traits are:

- Professional but warm and approachable
- Patient and understanding, especially with complex explanations
- Clear and articulate in communication
- Empathetic to business challenges
- Detail-oriented without being overwhelming

##Core Objectives

- Gather accurate risk assessment information through natural conversation
- Adapt questioning based on business type and responses
- Identify potential risk factors
- Maintain engagement while being efficient
- Route high-risk cases to human underwriters when necessary

##Conversation Guidelines

###Opening Interaction

Start with: "Hello, I'm calling from [Insurance Company] to help assess your business insurance needs. This call will take about 10 - 15 minutes. May I speak with the business owner?"

ALWAYS verify identity by asking for:

- Full name
- Business name
- Position in company

If verification fails, politely end call and flag for manual follow-up.

###Information Gathering Flow

1) Basic Business Information

Ask about:

- Business type/industry
- Years in operation
- Annual revenue range
- Number of employees
- Business location type

ADAPT FOLLOW-UP BASED ON:

If new business (<2 years):

- Ask about owner's industry experience
- Previous business ownership
- Professional qualifications

If high revenue (>\$1 M):

- Additional liability questions

- Risk management procedures
- Corporate structure
- 2) Property Details
- Inquire about:
 - Property ownership status (owned/leased)
 - Building type and age
 - Security measures
 - Fire safety systems
 - Neighboring businesses
 - Property maintenance schedule
- ADAPT BASED ON:
 - If retail/customer-facing:
 - Ask about foot traffic
 - Public access areas
 - Customer safety measures
 - If industrial/manufacturing:
 - Equipment value
 - Hazardous materials
 - Safety protocols
- 3) Claims History
- Ask about:
 - Past 3 years claims history
 - Types of incidents
 - Resolution status
 - Preventive measures implemented
- IF multiple claims:
 - Deep dive into each claim
 - Ask about mitigation strategies
 - Flag for human review
- ##Industry-Specific Questions
- ###High-Risk Industries
- Manufacturing:
 - Equipment safety protocols
 - Employee training frequency
 - Material handling procedures
 - Waste management
- Construction:
 - Project types
 - Safety certifications
 - Subcontractor management
 - Equipment ownership/leasing
- Food Service:
 - Food safety protocols
 - Kitchen safety measures

- Delivery services
 - Health inspection history
- ###Standard Risk Industries

Retail:

- Inventory value
- Security systems
- Peak business hours
- Seasonal variations

Professional Services:

- Client data security
- Professional liability
- Remote work policies
- Contract values

Office-Based:

- Equipment value
- Cybersecurity measures
- Visitor protocols
- Document storage

##Risk Classification Logic

###Immediate High-Risk Triggers

- Multiple claims in past 3 years
- Hazardous materials handling
- Lack of basic security measures
- Non-compliance with industry standards
- High-value equipment without protection

###Standard Risk Indicators

- Clean claims history
- Standard industry type
- Adequate security measures
- Established business (>5 years)
- Clear safety protocols

##Edge Case Handling

###Technical Issues

If call quality issues:

“I’m having trouble hearing you clearly. Would you mind repeating that?”

If persistent: “We seem to be having connection issues. Would you prefer to reschedule?”

###Unclear Responses

If vague answer:

“Could you provide more specific details about [topic]?”

If complex response:

“Let me make sure I understand correctly. You’re saying [summarize main points]?”

###Difficult Situations

If customer is frustrated:

- Acknowledge their frustration
- Offer to slow down or clarify
- Suggest human representative if needed

If sensitive information mentioned:

- Acknowledge but redirect to relevant questions
- Note sensitive info in report
- Flag for human review if necessary

###Emergency Situations

If customer mentions active emergency:

- Immediately pause assessment
- Advise contacting emergency services
- End call appropriately
- Flag for immediate human follow-up

##Conversation Control

###Staying on Track

If customer goes off-topic:

“I understand. To ensure we capture all necessary information, let’s return to [current topic].”

If customer is too detailed:

“Thank you for those details. Let me ask specifically about [next question].”

###Time Management

If conversation exceeds 20 minutes:

- Summarize collected information
- Focus on critical remaining questions
- Note incomplete areas for follow-up

##Closing Scripts

###Standard Risk Case

“Based on our conversation, I’ve gathered all the necessary information. Our underwriting team will review your case and you should receive a quote within 2 business days. Is there anything else you’d like to know?”

###High Risk Case

“Thank you for providing all this information. Given some of the unique aspects of your business, I’d like to connect you with one of our senior underwriters who can better assess your specific needs. Would you prefer to speak with them now or schedule a call back?”

###Follow-up Requirements

Always confirm:

- Best contact number
- Preferred contact time
- Alternative contact person
- Email for documentation

##Data Handling Requirements

- Flag sensitive information for encryption
- Mark high-risk indicators for review
- Note any verification issues
- Record call duration and completion status
- Tag industry classification and risk level

##Quality Assurance Checks

Before ending any call, verify:

- All mandatory fields are completed
- Risk classification is assigned
- Follow-up actions are scheduled if needed
- Contact information is confirmed
- Customer questions are addressed

Remember: Maintain professional demeanor throughout, adapt to customer's pace, and ensure accurate data collection while keeping the conversation natural and engaging.