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USING AI IN RISK ANALYSIS - CASE STUDY

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Dr inż. Marta Jagusiak-Kocik[1] – *orcid id: 0000-0001-6031-9169, e-mail: m.jagusiak-kocik@pcz.pl*
[1]Czestochowa University of Technology, Department of Production Engineering and Safety, Armii Krajowej 19B, 42-202 Czestochowa, **Poland**

Abstract: The aim of the work was to present the possibility of using a simple AI tool, i.e. a chatbot, to support risk analysis in a furniture industry enterprise and to assess its usefulness in identifying and monitoring types of risks (qualitative, operational and reputational). The chatbot functioned as an interactive communication channel available to customers on the website and in a popular messaging app. Reports regarding product, delivery, and customer service issues were collected through simple conversations with the bot and then automatically classified according to risk type and priority (high, medium, or low priority). The study was conducted over 3 months, analyzing a total of 487 reports. The results showed that the largest number of reports concerned quality risk. Using the chatbot helped reduce response times to reports, facilitated problem classification and generated reports and alerts for individual departments within the company. This tool enabled the rapid identification of recurring issues and supported the company's decision-making process. However, it was found that the chatbot required human supervision for more complex reports and data interpretation, which was a major limitation of the work.
Keywords: risk analysis, natural language processing, chatbots, furniture company

1. INTRODUCTION

The furniture industry, one of the most important sectors of Polish exports, has been facing a prolonged slowdown since the second half of 2022. The energy crisis, the war in Ukraine, and rising interest rates have led to a decline in demand in Europe, on which Polish companies are largely dependent. As a result, furniture production in Poland and the European Union has declined, and manufacturers' margins have been under pressure from rising labor costs and intensifying competition (Lost Spaces, 2025a; Lost Spaces, 2025b).

The furniture industry combines manufacturing, logistics, and retail processes, making risk management crucial to maintaining product quality and brand reputation. Risk in this sector can take many forms, from manufacturing defects and delivery delays to negative customer reviews in online stores and on social media. Monitoring and analyzing such risks allows companies not only to respond to problems but also to anticipate potential crises, resulting in improved customer service, increased sales, and reduced costs related to complaints.

In traditional methods, risk analysis requires, among other things, hazard identification, which can be time-consuming. Furthermore, humans can only analyze a certain number of threats and the connections between them, and traditional analysis often struggles to cope with large amounts of data.
Chatbots, one of the fundamental AI tools, take the form of conversations using natural language processing (NLP), allowing them to rapidly search, analyze, and detect connections across multiple databases, as well as continuously monitor them. In risk analysis, this allows them to quickly identify potential threats, propose action priorities, and answer questions about the risk of a specific activity.
The aim of this work was to demonstrate how a simple chatbot can support risk analysis in the furniture industry by identifying risk types and classifying them according to a specific priority.
The novelty of this work is the application of a practical, low-cost tool, a chatbot, in the furniture industry for SMEs. This tool supports risk analysis, shortens response times to problems, and supports decision-making.
The limitations of this work result primarily from the limited amount of data and the method of interpreting this data – the chatbot is only effective when opinions and reports are correctly formulated, which in some cases requires human supervision and periodic review of this data.

2. LITERATURE ANALYSIS

Risk is an ambiguous and multifaceted concept (Sołtysiak and Suraj-Sołtysiak, 2006, Thlon, 2013). It is an inherent attribute of every organization's functioning and accompanies all activities, both operational, investment, and financial (Młodzik, 2013). It is defined in many different ways. According to the Business Lexicon (Penc, 1997), risk is "the probability of incurring losses as a result of making a specific decision; an action in which not all variables can be estimated based on probability theory". Risk is "an uncertain event or group of such events that, if they occur, will have an impact on the achievement of goals, either negatively (a threat) or positively (an opportunity)" (Krawczyk and Wieczorek, 2020). Risk is "the possibility, probability that something may go wrong, an undertaking whose outcome is unknown, uncertain, problematic" (Sołtysiak and Suraj-Sołtysiak, 2006). Risk is a measure of the likelihood and severity of adverse effects (Aven, 2010, Holton, 2019, Karakanikas and Zerguine, 2025, Piskunov et al., 2024, Šotić and Rajić, 2015, Xu et al., 2024).
Risk assessment and risk management as a scientific field is young, no more than 30-40 years old (Aven, 2016). Risk analysis is a systematic process that involves identifying, assessing, and managing threats that may impact the achievement of enterprise objectives. It uses both qualitative and quantitative assessment methods to assess threats and opportunities related to a given project (Krawczyk and Wieczorek, 2020, Potter, 1996). Risk identification in risk analysis determines the risks to which the project is exposed, as well as the relationships between individual risks, and should be performed repeatedly during the planning and implementation of a given project (Piney, 2003, Soroka-Potrzebna, 2018). Risk assessment can be viewed as the process of determining the significance and acceptability of risks (Aven, 2023).
Classic risk analysis tools include: FMEA (Failure Mode and Effects Analysis) (Ennouri, 2015, Jagusiak-Kocik, 2023, Jagusiak-Kocik and Żywiołek, 2024, Lipeng et al., 2021), SWOT analysis (Benzaghta et al., 2021, Eid, 2025, Margaret, 2025), and risk matrices

(Duijm, 2015, Peace, 2017, Thomas et al., 2013). These are effective methods, but they are very time-consuming, require a large amount of input data, and the assessments are often subjective – what one client considers a nonconformity or threat, another may ignore.

Artificial intelligence (AI) is a field of computer science that focuses on creating computer systems capable of performing tasks that normally require human thought and decision-making (Kuzior, 2024, Zawada, 2024). The implementation of such intelligent solutions is currently identified as one of the key pillars of the Fourth Industrial Revolution, driving the digital transformation of manufacturing processes globally (Rosak-Szyrocka & Knop, 2024). AI is an umbrella term that encompasses many technologies, including deep learning, machine learning, and natural language processing.

Artificial intelligence is used in many fields, such as education (Rosak-Szyrocka, 2024), transportation (Bharadiya, 2023, Saki and Soori, 2025), healthcare (Poon et al., 2025, Sezgin, 2023), but also in customer needs research and behavior analysis (Edelman and Abraham, 2022, Nguyen et al., 2021, Sahut and Laroche, 2025).

Risk analysis is another field where AI is increasingly applied (Stødle et al., 2025, Yazdi et al, 2024). AI-powered risk management tools use machine learning to analyze massive amounts of data, predictive analytics to pinpoint risk factors, and real-time monitoring to prevent disasters before they occur.

The most commonly used tools for analyzing customer behavior using artificial intelligence are chatbots (Jagusiak-Kocik, 2025, Pizzi et al., 2021), CRM systems, and web analytics. Artificial intelligence (AI) plays a significant role in the development of natural language processing (NLP) technology. The primary goal of NLP is to enable communication between humans and machines in an efficient and natural way (Ramirez, 2024, Skaria et al., 2024). One of the main applications of NLP is improving customer service. NLP chatbots (Dhiman, 2025) understand customer messages and can respond appropriately. Using advanced NLP algorithms, automated response systems can interact with customers, identifying their needs and requirements, analyzing questions, and responding. This is done via text or speech.

Although risk analysis and AI technologies are widely described, their combination in the furniture SME sector remains a research gap. Previous studies indicate that furniture companies face significant barriers to implementing Industry 4.0 solutions, primarily due to limited financial resources and a lack of specialist support (Ingaldi et al., 2021). Therefore, this study proposes a low-cost chatbot as an accessible entry point for digital transformation in this sector.

3. METHODOLOGY

The study was conducted at a medium-sized furniture company based in the Opole Voivodeship. The company manufactures wooden and upholstered furniture, such as corner sofas, sofas, and armchairs. The company employs approximately 110 people, primarily in the production department, as well as in logistics, quality assurance, and customer service. The company operates primarily in the domestic market. It is active on social media (Facebook, Instagram) and has a well-developed website with an online store.

The study was conducted over three-month period, and the team included an IT coordinator responsible for technical matters and data collection; a quality specialist who verified that data was being collected and received correctly; customer service

representatives responsible for receiving reports, analyzing data, and preparing reports. The entire process was overseen by a project manager who was also responsible for communication with management.
The study was based on the premise that using a simple AI tool - a chatbot - can support risk analysis by increasing the efficiency of processes such as automating reports classification, reducing human error, and accelerating responses to risky events.
The chatbot collected data over a three-month period from three sources: customer quality reports and complaints, social media reviews, and comments from quality department employees regarding production issues. The chatbot automatically assigned each report to one of three risk categories:
• quality risk – product defects, damage in transit, assembly problems,
• reputation risk – negative customer reviews online,
• operational risk – delivery delays or production problems.
The chatbot assessed which reports required immediate attention and which could be monitored. A priority criterion was adopted, meaning that if, for example, five reports with the same issue arrived within a short period of time, it was considered a high-priority report. Reputation and quality risk were also prioritized over operational risk.
The chatbot was available to customers and employees both on the company's website (in the lower corner of the screen as an interactive chat window) and through the company's messaging service.
On the website, customers could initiate a conversation regarding a given issue, and the chatbot would lead the conversation, asking questions such as the product type or request, and then forward the request to the appropriate department and classify it according to the risk level.
In the company's messaging app, the chatbot operated in a similar manner, but the conversation was more natural, and customers could send photos, for example. The chatbot recognized the request category, assigned it to a risk category, and, similarly to the website, forwarded it to the appropriate department within the company.
Customer service employees had access to a dashboard where they could track new requests in real time, view their classification, and mark issues as "resolved" or "requiring attention."
Daily, the chatbot created a report summarizing all requests by risk category and sent real-time alerts to the quality or customer service department in the event of recurring product defects, a sharp increase in negative reviews, or logistical issues requiring immediate attention .
A total of 487 requests were collected.
Table 1 presents the process of handling a request by the chatbot.

Table 1.
The process of handling a request by the chatbot

Stage)	Action Description	Details / Example Messages
1.Start of Interaction (conversation)	Customer or employee launches the chatbot on the website or messenger	Chatbot displays a welcome message: "Hello! Please report a problem with a product or shipment. We will help you quickly forward the complaint to the appropriate department".
2.Collecting information	Chatbot conducts a conversation to collect data	Example questions: -"What type of product does the complaint concern?"

		-"Briefly describe the problem" -"Does the problem relate to quality, delivery, or another issue?"
3.Complaint classification	Chatbot analyzes the answers and assigns a risk category	Categories: - quality risk, -operational risk, - reputational risk
4.Prioritization	Chatbot assesses the urgency of the complaint	Example criteria: - number of similar cases, - impact on the customer
5.Complaint Forwarding	The system directs the complaint to the relevant department	Example redirections: - quality department, - customer service department
6.Confirmation to Customer	Chatbot informs about the acceptance of the complaint and the reaction time	Chatbot displays information: "Your complaint has been accepted. You will receive feedback within 48 hours".
7.Reports and Alerts	Chatbot generates reports and alerts about recurring problems.	Reports: - number of complaints, -categories. Alerts: -recurring defects, -increase in negative opinions.

Source: own study

Figure 1 presents a diagram of the process of handling a request by the chatbot.

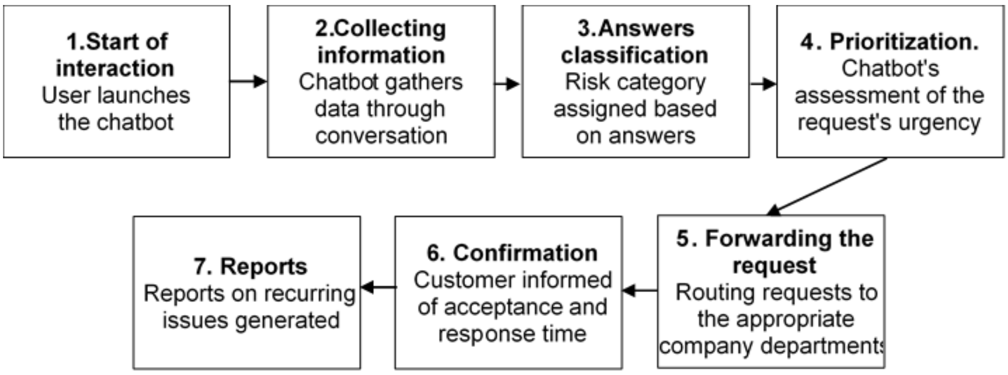

Fig. 1. Diagram of the chatbot's request handling process

Source: own study

After the study was completed, a survey was conducted among 34 employees who used the chatbot in their daily work to assess the usefulness of the chatbot.

4. RESULTS ANALYSIS

During the three-month period under review, the chatbot served as the primary communication channel between customers, employees, the quality department, and the customer service department. A total of 487 reports were recorded during the analyzed research period. The risk type structure (Table 2) indicates that the chatbot classified the majority of reports as quality risks (52.57%), suggesting the need to focus on quality control, both in the production process, packaging, and transportation.

Table 2.
The risk structure

Risk type	Number of reports	Percentage share
Quality Risk	256	52,57
Reputation risk	152	31,21
Operational risk	79	16,22
Total	487	100

Source:own study

Reputational risks are often linked to previous quality issues, which can be described as a "domino effect" - a product defect leads to customer dissatisfaction and, consequently, reputational damage. The chatbot classified 152 reports (31.21%) as these types of risks. In this case, online reviews should be regularly monitored, website readability should be improved, and communication between customer service and the customer should be improved. The final risk type, operational risk, is the risk associated with delivery delays or production issues. In this case, the chatbot classified 79 reports (16.22%) as these types of risks. It is recommended to implement a system for monitoring on-time delivery and use, for example, an Ishikawa diagram to analyze the causes of delays.
Table 3 presents examples of reports divided into quality, reputation, and operational risks, along with sample report content.

Table 3.
Examples of report types based on quality, reputation, and operational risks

Quality Risk	Reputation risk	Operational risk
– “The cabinet arrived with a cracked side panel". – The dresser had a scratched front and a detached handle". – "The components were not secured in the package - parts were loose". – "The assembly instructions do not match the actual components". – The table has an uneven surface; the top does not match the legs". – "The components do not fit properly - the doors do not close properly". – "Missing screws or fasteners". – "The holes in the furniture are not in the correct places".	– “The product is poorly described and does not meet customer expectations". – "The photos in the store differ from the actual color of the furniture". – "The quality is poor for the price". – "The complaints department responds too late, no response to emails". – "Unpleasant conversation with the helpline consultant". – "No information about the complaint status".	– "The furniture was supposed to be delivered within 3 days, but it arrived after a week". – "The courier did not contact me before delivery". – "The shipment tracking system did not function properly". – "The order was not completed due to a lack of material". – "A production line failure delayed order fulfillment". – "Incorrect order planning for component suppliers."

Source: own study

Table 3 presents real-world examples of reports identified by the chatbot, categorized into three risk categories. It shows that quality risks (e.g., broken components, incorrect assembly instructions, missing parts, incorrect mounting holes) primarily relate to physical product defects or errors in the manufacturing and packaging processes. Reputational risks (e.g., discrepancies between product images and actual appearance, rude service,

delayed responses) relate to customer perception and the quality of a company's communication with its external environment. Operational risks (e.g., delivery delays, production failures, errors in logistics planning) are related to the inefficiency of internal processes.
To assess the chatbot's effectiveness, we analyzed indicators related to response time, classification accuracy, and reduction in the number of recurring issues. These indicators are presented in Table 4.

Table 4.
Chatbot Effectiveness Evaluation

Indicator	Value before implementation	Value after chatbot implementation	Change (%)
Average submission time	20 min	2-3 min	–85%
Number of recurring quality issues (monthly)	48	41	–15%
Number of negative online reviews (monthly)	60	45	–25%
Number of manually entered submissions	100%	20%	–80%

Source: own study

Table 4 presents the measurable effects of implementing the chatbot in the risk analysis process. It shows that the average request submission time decreased from 20 minutes to 2-3 minutes (an 85% decrease), demonstrating a significant acceleration of communication between the customer and the relevant department. The number of recurring quality issues decreased by 15%, suggesting that the chatbot's rapid identification allowed for earlier corrective action. Negative online reviews decreased by 25%, indicating a positive impact on the company's reputation, and the number of manually entered requests decreased by 80%, demonstrating a significant level of automation and reduced employee workload.
After the study, a survey was also conducted among 34 employees who used the chatbot in their daily work (Quality, Customer Service, and IT departments). The results are presented in Table 5.

Table 5.
Employees' ratings of chatbot usefulness

Evaluation criterion	Positive responses (%)	Negative responses (%)	Comments
Chatbot speeds up ticket submissions	83	17	“Saves a lot of time”.
Chatbot helps identify recurring issues	80	20	“Easier to spot trends”.
Chatbot is intuitive to use	75	25	“Needs minor interface tweaks”.
Chatbot improves communication between departments	85	15	“Faster information delivery”.
Chatbot requires supervision for submitted tickets	100	—	“Cannot handle ambiguous cases”.

Source: own study

Based on the survey results, the chatbot was positively evaluated by the majority of users. The greatest benefits were noted in communication and response speed. However, employees noted the need for periodic updates to the system to improve its effectiveness in interpreting more complex requests.

5. CONCLUSION

The conducted research confirms that the chatbot is an effective and cost-effective tool supporting risk analysis in a furniture company in the SME sector. Report processing was significantly accelerated, recurring issues were better monitored, the number of errors and recurring complaints decreased, and communication between departments improved.

The chatbot proved particularly useful in identifying quality and reputational risks that dominate the report structure. This observation aligns with broader research, which indicates that while Industry 4.0 solutions offer significant potential for process optimization, SMEs face specific barriers such as skills gaps and high initial investments (Ingaldi & Ulewicz, 2025). Consequently, their implementation requires organizational adaptation and cost-effective strategies (Ślusarczyk & Wiśniewska, 2024). The effectiveness of the chatbot depends on the quality of the input data – imprecise or incomplete reports can lead to misclassification. Expert supervision is essential for ambiguous reports, indicating that the chatbot should act as a supporting tool, not a replacement for humans. The short study period (3 months) limits the ability to analyze long-term trends, and the small data sample (487 reports) may not reflect the full scale of the company's risk.

Implementing a chatbot at a furniture company in the SME sector confirmed that even a simple AI tool can truly support risk analysis and quality management in situations where the number of customer reports is high and staff resources are limited.

The system improved communication, shortened response times, and enabled ongoing monitoring of reports. At the same time, the development of NLP algorithms to improve the interpretation of more complex customer statements and integration with other systems are becoming necessary to obtain a more comprehensive picture of reputational risk. It is also worthwhile to regularly update the knowledge base with products and common quality issues, which will increase classification accuracy, as well as train employees in the analysis of data generated by the chatbot and the interpretation of risk reports.

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