Enhancing Customer Complaint Management through AI-Based Business Process Improvement

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ABSTRACT

The rapid advancement of digital technology has transformed business process management, particularly in the telecommunications sector, where manual customer complaint handling often causes inefficiencies such as delays, ticket backlog, and human error. The purpose of this study is to investigate how artificial intelligence can enhance the efficiency and effectiveness of customer complaint handling by redesigning workflows through process automation. This study employs a qualitative descriptive approach combined with business process analysis, with data collected through observations, in-depth interviews with 32 participants, and document reviews. NVivo software was used to code interview data, while Bizagi Modeler was used to visualize both the existing and proposed business processes. The results indicate several bottlenecks in the existing complaint handling process, including manual first call resolution activities, inefficient complaint classification, redundant coordination between units, and low customer confirmation rates. To address these issues, the proposed improved process introduces artificial intelligence–based solutions, such as automated first-call resolution, ticket classification using natural language processing, intelligent ticket routing, and automated customer confirmation systems. These improvements are projected to reduce complaint-handling time by 25–40 percent, minimize service-level agreement violations, and optimize resource allocation. This study concludes that integrating artificial intelligence into customer complaint handling processes significantly improves efficiency, accuracy, and service quality, while also supporting organizational digital transformation. Furthermore, the findings make theoretical contributions to the business process management literature and provide practical insights for implementing artificial intelligence–driven automation in large-scale telecommunications environments.

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1. INTRODUCTION

The rapid advancement of digital technology has brought significant changes to how organizations manage business processes, particularly in terms of automation and integration [1]. Traditional business processes often rely on manual tasks, fragmented systems, and siloed data, leading to inefficiency, delays, and high operational cost [2]. These issues have emerged as major challenges for organizations seeking to remain competitive in the digital age. Business Process Management (BPM), combined with automation technologies, offers an effective solution to enhance the efficiency, accuracy, and flexibility of handling complex workflows [1, 3, 4].

From the studies conducted by Ahmadi et al., we found that manual data processing remains a major obstacle within organizations, increasing the likelihood of workflow duplication and errors [2]. Furthermore, recent research indicates that artificial intelligence (AI) plays a pivotal role in automating repetitive tasks, enabling predictive decision-making, and facilitating real-time process monitoring [4]. Unfortunately, the organization met several obstacles in implementing AI in their organization, such as technical limitations, functional requirements mismatch, implementation issues, the quality of data provided, model gaps, scalability, bias, integration complexity, and security vulnerability [3, 4].

Despite these advancements, a research gap remains in understanding how AI-driven process automation can be effectively designed and implemented in the context of business process improvement for organizations with legacy manual systems. Many studies have focused on technical implementation or single use cases, yet comprehensive studies that map the as-is and to-be business processes, supported by AI integration, are still limited [1, 5, 6]. This highlights the importance of conducting a structured analysis to identify inefficiencies in the current process and propose a redesigned model that integrates automation technologies.

The objective of this study is twofold: (1) to analyze the existing business process in its current condition and identify key inefficiencies that hinder organizational performance, and (2) to design an improved future-state business process supported by automation and artificial intelligence technologies to optimize efficiency, reduce errors, and improve decision-making. By mapping the transformation from manual processes to workflows assisted by artificial intelligence, this study aims to contribute both theoretically and practically to the growing body of knowledge in Business Process Management and digital transformation.

To achieve these objectives, this study employs a Business Process Analysis (BPA) approach, which is widely used to systematically examine and redesign organizational workflows. BPA enables researchers to map existing "as-is" processes, identify bottlenecks, and propose a redesigned "to-be" model supported by automation and AI. This method is particularly suitable for analyzing complex service operations such as customer complaint handling, as it provides both a qualitative and quantitative foundation for process improvement and ensures alignment with organizational goals [5].

2. RESEARCH METHOD

The methodology is structured to answer the main research question: "How can Artificial Intelligence improve the efficiency and effectiveness of a Telco company's complaint handling process?" To achieve this, the study employs a qualitative descriptive approach combined with Business Process Analysis (BPA). This approach allows the researcher to explore the existing workflow (As-Is process), identify pain points through interviews and observations, and design a proposed improved workflow [1, 7, 8].

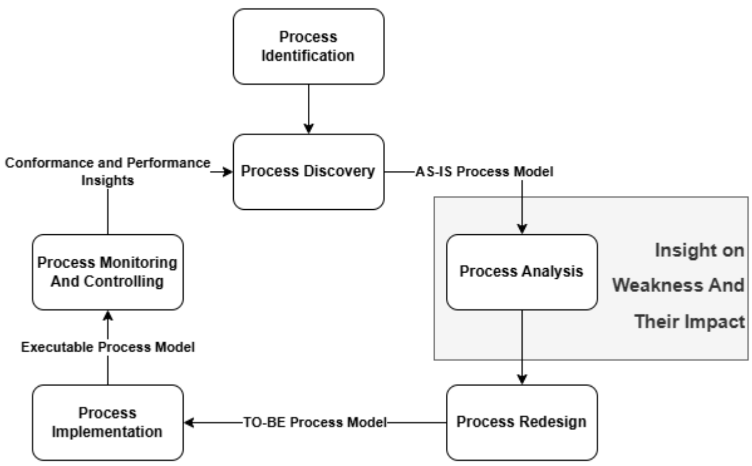

Figure 1. Business process analysis method [1]

As illustrated in Figure 1, the Business Process Analyst Method [1], BPA provides a structured and iterative framework that guides the systematic analysis and redesign of business processes. The method consists of a series of interconnected stages: process identification, process discovery, process analysis, process redesign, and validation and evaluation. The iterative nature of these stages ensures that the findings of earlier steps inform the development of more refined solutions in subsequent steps, thereby strengthening both the accuracy and the applicability of the proposed improvements.

This study employed a qualitative descriptive research design with a BPA approach to examine and improve the complaint handling process of the telco company, aligning with the emphasis that evaluating and improving business processes requires integration between BPM methods and organizational performance objectives [1]. The research was conducted by mapping the As-Is process, identifying pain points, and developing a To-Be process that integrates Artificial Intelligence (AI). The qualitative approach was considered appropriate because it allows for an in-depth exploration of workflows, employee experiences, and organizational bottlenecks, which are often overlooked by purely quantitative methods [1, 5].

The BPA method was implemented in several stages. The first stage, process identification, focused on determining the scope of analysis, with the complaint handling workflow identified as the primary object of study. The activities in this phase involved mapping process boundaries and identifying relevant stakeholders. Tools such as stakeholder mapping and process scoping matrices were applied, resulting in the establishment of the complaint handling process as the research object.

The second stage, process discovery (As-Is analysis), involved collecting data through observations, semi-structured interviews, and documentation review. Using Bizagi Modeler, the workflow was modeled into BPMN diagrams to capture activities, interactions, and task dependencies across customer service units. The result was a comprehensive visualization of the As-Is process, providing an overview of workload distribution and workflow characteristics.

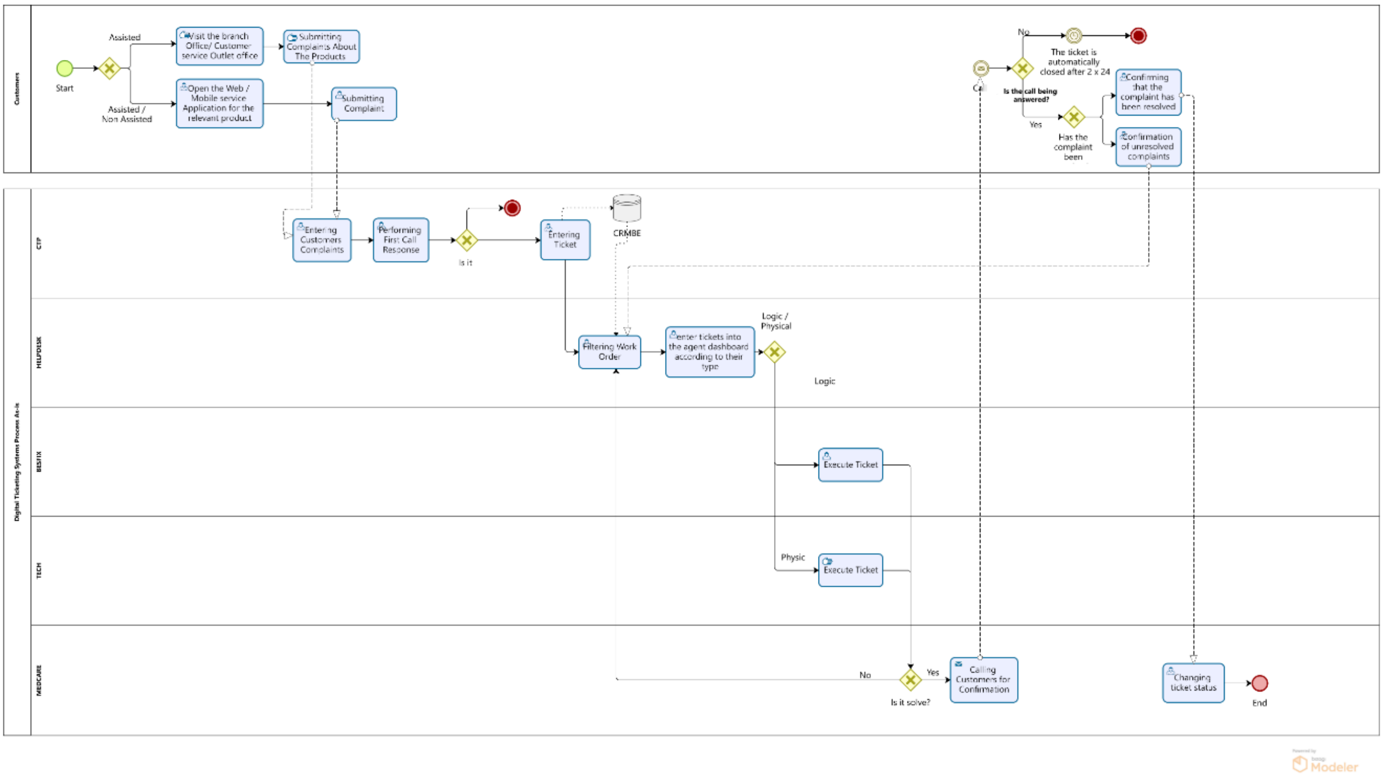

Figure 2. As-is business process digital ticketing system

The As-Is process for the customer complaint handling workflow was modeled in Bizagi Modeler based on observations and interviews. This visualization aimed to provide a clear representation of the existing workflow, task dependencies, and information flow across units. The resulting As-Is process model is presented in Figure 2.

The third stage, process analysis, aimed to identify inefficiencies and bottlenecks within the As-Is process. This stage utilized thematic coding of interview transcripts with NVivo and cross-referencing of SOPs and SLAs. The analysis highlighted key problems such as excessive manual workload, delayed responses, miscommunication between units, and redundant activities [9, 10]. The main outcome of this stage was a systematic identification and categorization of pain points requiring intervention.

The fourth stage, process redesign (To-Be process), proposed integrating AI technologies to address the identified issues. The design process incorporated automated ticket classification, chatbot-based customer interaction, and predictive analytics to anticipate service issues. Workshops and iterative discussions were conducted to align the redesigned process with organizational objectives. Bizagi Modeler was again used to produce BPMN diagrams of the To-Be process. The outcome of this stage was an optimized process model designed to enhance efficiency and effectiveness.

The final stage, validation and evaluation, ensured the practical feasibility of the redesigned process. Feedback sessions were conducted with selected participants, using validation checklists and structured group discussions. The result was a refined To-Be model that addressed existing pain points and aligned with organizational goals to improve service quality and customer satisfaction [11].

The study involved 32 participants across the company's different Customer Service (CS) units, selected purposively to ensure adequate representation. The participants comprised Customer Touch Point (CTP) agents (n = 10) responsible for First Contact Resolution, helpdesk agents (n = 8) who filter and route tickets, unit solvers or field technicians (n = 7) who resolve non-logic tickets requiring on-site visits, and members of the Medcare team (n = 7) who conduct post-resolution follow-ups. Demographic data, including age, years of service, and job role, were collected to contextualize their responses.

The research employed several materials and tools to support data collection and analysis. These included an interview guide developed based on prior studies in business process improvement, observation checklists to document workflow activities, voice recording devices and transcription software to capture interview data, and Bizagi Modeler for BPMN visualization [12]. Data collection methods included direct observations at Grapari outlets and CS divisions, semi-structured interviews with participants lasting 30-60 minutes (with participant consent), and documentation review of Standard Operating Procedures (SOPs), Service Level Agreements (SLAs), and internal company guidelines to triangulate the findings.

The collected data were analyzed through a combination of thematic analysis and process mapping. Interview transcripts were imported into NVivo and analyzed using a structured coding procedure. Initially, open coding was performed to identify meaningful segments of text related to participants' experiences in handling customer complaints. These initial codes were then grouped through axial coding to form broader categories such as process inefficiencies, system limitations, and user challenges. Finally, selective coding was conducted to identify key themes and recurring pain points across participants. NVivo features such as node classification, coding queries, and word frequency analysis were utilized to ensure consistency and to highlight dominant patterns in the data.

In parallel, BPMN diagrams were used to model the As-Is process based on observation and interview findings. The identified pain points were systematically mapped to specific process stages and subsequently addressed in the To-Be process design through AI-based solutions. To quantitatively evaluate the effectiveness of the proposed improvements, a comparative analysis between the As-Is and To-Be processes was conducted. This approach is supported by prior studies indicating that business process simulation combined with BPMN modeling can effectively identify inefficiencies and enable process redesign, leading to improved performance and reduced processing time [12, 13]. The evaluation focused on reducing complaint-handling time across key process stages. The percentage of improvement was calculated using the following formula 1.

$$Reduction(\%) = \frac{\text{As is time - To be time}}{\text{As is time}} \times 100 \tag{1}$$

The time estimates for both As-Is and To-Be processes were derived from process observation, interview insights, and validation with domain experts. The comparison was further supported by process modeling using BPMN in Bizagi Modeler to simulate workflow efficiency and identify time reductions resulting from automation and improved task allocation. The results of this comparison provided a quantitative basis for evaluating the impact of AI integration, particularly in reducing manual activities, improving ticket routing accuracy, and accelerating resolution time. Finally, validation was conducted with participants to ensure that the proposed model was both relevant and feasible.

3. RESULT AND ANALYSIS

The first step of this research is conducting stakeholder mapping. This process used interviews, observation, and document analysis. The stakeholder identified in this process will be used as the entity in the business process. After all stakeholders have been identified in the first process, the next step is to identify the as-is process. The as-is process is shown in Figure 2. The next step is conducting process analysis. The results of process analysis of the customer complaint handling process at the case company showed several pain points. The results show that several major pain points exist in the current customer complaint handling process (As-Is), as summarized in Table 1.

Table 1. Identified Pain Points in Customer Complaint Handling Process

Process Stage	Pain Point Identified	Impact
Customer Touch Point (CTP)	FCR is not optimal; network reset/manual check takes a long time	Handling time increases, and customers wait longer
Ticketing & Filtering	Complaint topic classification is still manual	Potential for human error and ticket backlog
C4 Helpdesk	Ticket distribution to logic/non-logic teams is not yet automated	Inefficiencies in ticket routing
Unit Solver (Technicians)	Technician coordination in the field is still done manually	SLA exceeded in some cases
Medcare Follow-up	Low customer confirmation (no response to phone calls/text messages)	Low ticket closing rate, recurring tickets

These problems were identified across multiple stages of the workflow, from ticket creation to final resolution by the technical unit and Medcare team. At the Customer Touch Point (CTP) stage, the First Call Resolution (FCR) process was found to be suboptimal, as manual network resets and checks required a significant amount of time, thereby prolonging customer waiting time. In the Ticketing and Filtering stage, complaint classification remained manual, which opened the possibility of human error and created risks of ticket backlog. At the C4 Helpdesk, ticket distribution between logic and non-logic teams was not automated, resulting in inefficiencies in routing. For the Unit Solver (Technicians), coordination in the field was still conducted manually, leading to several cases where the Service Level Agreement (SLA) was exceeded. Finally, in the Medcare Follow-up process, low customer responsiveness to calls and messages hindered confirmation rates, thereby reducing the efficiency of ticket closing and contributing to recurring complaints.

Quantitative data obtained from in-depth interviews further confirmed these findings. Out of ten CTP agents, seven respondents (70%) agreed that the FCR process was excessively time-consuming. Similarly, out of seven technicians, four respondents (57.1%) reported difficulty in achieving SLA compliance due to improper ticket distribution. In addition, out of seven Medcare team members, three respondents (42.9%) acknowledged challenges in follow-up activities caused by low customer response rates.

Furthermore, additional findings from the aggregated questionnaire results indicated that a majority of respondents also experienced inefficiencies related to manual ticket classification and distribution processes, which contributed to delays and increased workload. These findings emphasize the urgent need for process redesign to minimize inefficiencies, reduce dependency on manual work, and ensure faster and more accurate complaint resolution. To address these challenges, a redesigned To-Be Business Process model in Figure 3 was proposed, with Artificial Intelligence (AI) positioned as the central enabler of automation, as summarized in Table 2.

Table 2. Questionnaire Results on Customer Complaint Management Process

Questionare	Results
Do you experience difficulties in understanding customer complaint tickets?	A total of 66.7% of respondents (16 out of 24) reported difficulties in understanding complaint tickets, mainly due to unstructured and incomplete information.
Does the current ticket classification process require a relatively long time?	Approximately 79.2% of respondents (19 out of 24) indicated that the classification process is still performed manually and requires considerable time before further handling.
Do you frequently receive tickets with incorrect categories?	Around 62.5% of respondents (15 out of 24) stated that they often receive misclassified tickets, requiring re-classification.
Does the current system assist you in determining ticket handling priorities?	About 50.0% of respondents (12 out of 24) reported that the system does not optimally support prioritization, leading to reliance on subjective judgment.
Do you encounter difficulties in accessing customer history or previous data?	Approximately 70.8% of respondents (17 out of 24) experienced difficulties in accessing customer history due to limited system integration.
Do you believe that AI technologies (e.g., auto-classification or recommendation systems) would support your work?	A significant 87.5% of respondents (21 out of 24) agreed that AI technologies could substantially improve work efficiency through automated classification and solution recommendations.
Can ticket resolution time be improved through AI-based automation?	Around 79.2% of respondents (19 out of 24) believed that AI-based automation could significantly reduce ticket resolution time.
Do you frequently encounter duplicate tickets in the system?	About 58.3% of respondents (14 out of 24) reported frequent occurrences of duplicate tickets, leading to inefficiencies in handling processes.
Are the current ticket notifications and status updates sufficiently informative?	Around 54.2% of respondents (13 out of 24) indicated that the current notifications are not sufficiently informative and do not fully support monitoring needs.
Do you require an automated solution recommendation feature based on similar past cases?	A total of 87.5% of respondents (21 out of 24) expressed a strong need for automated solution recommendation features to improve both speed and accuracy in handling complaints.

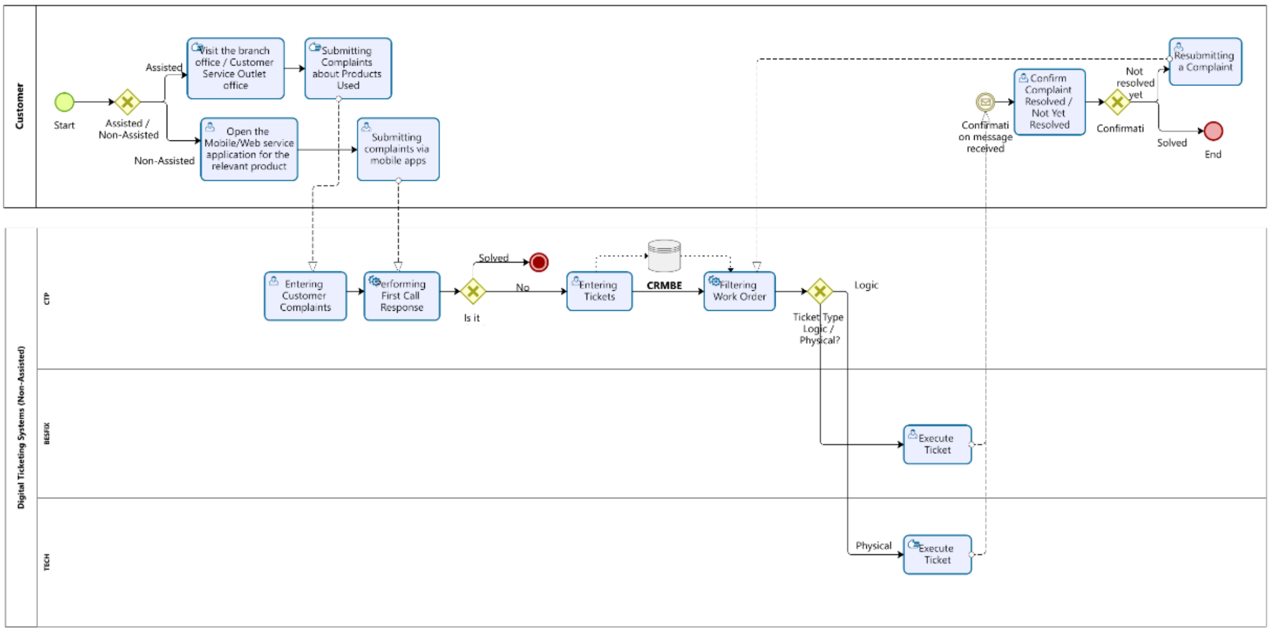

Figure 3. To-be business process digital ticketing system

Based on the identified pain points in the As-Is process, the redesigned To-Be Business Process was developed, with AI as the core enabler of automation. The proposed improvements aim to eliminate manual dependencies, reduce bottlenecks, and ensure faster resolution of customer complaints while maintaining accuracy and efficiency. AI is positioned not only to support decision-making but also to execute operational tasks, ranging from automated classification to customer follow-up. By embedding AI across all stages of the complaint-handling workflow, the To-Be model introduces a more streamlined, scalable, and customer-centric approach that directly addresses the limitations of the current process.

As illustrated in Figure 3, the proposed To-Be process introduces several AI-driven innovations. AI-based Ticket Classification leverages Natural Language Processing (NLP) to automatically categorize customer complaints, thereby reducing the manual filtering workload of CTP and C4 agents. Automated FCR Tools integrate AI-based diagnostic applications that detect network disruptions, perform automatic resets, and deliver immediate solutions without manual intervention. Additionally, the AI-powered Chatbot for Follow-up replaces a significant portion of Medcare's initial interactions, ensuring faster confirmation of complaint resolution status and accelerating ticket closure rates.

These improvements are expected to reduce the average complaint-handling time by approximately 25–40 percent. To further validate this estimation, a comparative analysis between the As-Is and To-Be processes was conducted, focusing on time efficiency across each process stage. The results of the comparison are presented in Table 3.

Table 3. Comparison of As-Is and To-Be Complaint Handling Time

Process Stage	As-Is Time (minutes)	To-Be Time (minutes)	Improvement (%)
Ticket Classification	15	5	66.7%
Ticket Routing	20	10	50.0%
Complaint Analysis	40	30	25.0%
Resolution Handling	30	25	16.7%
Follow-up & Closing	15	10	33.3%
Total	120	80	33.3%

Based on the comparison between the As-Is and To-Be processes, the total complaint-handling time is reduced from 120 minutes to 80 minutes, resulting in an efficiency improvement of approximately 33.3%. This reduction is primarily achieved through automation in ticket classification, improved routing mechanisms, and reduced process redundancies. The result quantitatively supports the estimated improvement range of 25–40% presented in this study.

Similar to the empirical results of the Journal of Business Research [14], AI-enabled complaint handling can perform as effectively as human agents when responsiveness and personalization are well designed, improving overall recovery outcomes and customer loyalty. Furthermore, Zheng et al. [15] demonstrated that poorly managed AI interactions can intensify negative emotional responses during service failures, underscoring the need for reliable and empathetic automation in complaint management. Consequently, the integration of AI in PT. XYZ not only enhances operational efficiency but also mitigates emotional dissatisfaction, strengthens compliance with Service Level Agreements (SLAs), and increases customer trust.

Despite these promising outcomes, the study has certain limitations. First, the data collection was limited to a single telecommunications company, which may limit the generalizability of the findings to other industry contexts. Second, the analysis was conducted primarily from the perspective of internal stakeholders such as CTP agents, technicians, and Medcare teams, without directly incorporating customer perspectives.

For future research, it is recommended to integrate customer experience data from digital service channels to capture the "voice of the customer" as part of the evaluation process. Moreover, a comparative quantitative analysis of SLA metrics before and after AI implementation is suggested to objectively assess the effectiveness of the proposed improvements. This would provide a more comprehensive understanding of the impact of AI-driven automation on both operational performance and customer experience.

4. CONCLUSION

This study confirms that the integration of Artificial Intelligence in handling customer complaints at PT. XYZ has high potential to improve the efficiency and effectiveness of the process. Based on As-Is mapping, pain point identification, and To-Be design, it can be concluded that FCR automation for logical complaints, automatic ticket classification, automatic routing to logical or physical units, and an automatic follow-up system (WhatsApp/robotic call) are capable of reducing ticket resolution time, lowering manual workload, and minimizing errors in ticket distribution. This directly addresses the research objective of analyzing and formulating better business processes with AI integration. The implications in the field of industrial engineering include efficient utilization of human resources, workflow optimization, and reduced operational costs in customer service units.

The recommendation arising from this study is for PT. XYZ to conduct a pilot implementation of the proposed To-Be process, particularly focusing on the FCR automation and ticket classification modules, while measuring performance metrics such as average handling time, FCR rate, ticket classification accuracy, and customer satisfaction before and after implementation. A technical evaluation is also necessary to ensure that the AI/diagnostic tools operate effectively under real operational conditions. For further research, it is recommended to expand the sample to include direct customer perspectives and data from various products of the telco company, and to consider combining process mining techniques with quantitative analysis to strengthen the empirical evidence.

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6. DECLARATIONS

AI USAGE STATEMENT

During the preparation of this work, the authors used ChatGPT (OpenAI) to improve the language and clarity of the manuscript. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

AUTHOR CONTIBUTION

Zain Ammar Falih and Deki Satria contributed equally to the conceptualization, methodology, analysis, and manuscript preparation. Zain Ammar Falih led the data collection, process mapping, and visualization using Bizagi Modeler, while Deki Satria focused on validation, supervision, and refinement of the research framework. Both authors reviewed and approved the final version of the manuscript.

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COMPETING INTEREST
The authors declare that there are no conflicts of interest.

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