2024-H1 Project Progress report

OMD

OPTIMAL MANAGEMENT OF DEMAND

Edited by: Hatice Betül HERSEK, PMP

Date: 30.09.2024

Project key data

ACRONYM and full-length title

20003	OMD
Program Call	ITEA 3 Call 7
Full-length Title	Optimal Management of Demand
Roadmap Challenge	Smart Industry

Project duration and size

Size	Effort: 66.03 PY	Costs: 2.2 M€
Time frame	Start: 2022-01-01	End: 2024-12-31 (36 months)

Coordinator

Türkiye	Experteam
Type	Small and Medium sized Enterprise
Contact Person	Dr. Demet Seyhan
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Project Status

Latest FPP	Change Request (27-01-2024)
Latest PPR	2023 Semester 2
Latest Review	OMD #2 (a.m.) (29-02-2024)
Upcoming Review	OMD #3 final (a.m.) (19-11-2024)
PCA status	PCA Signed.pdf (Signed: 30-03-2023)

Consortium

Country	Funding Status	National Coordinator (Company)	Total Effort (PY)	List of Partners
Austria	Self funded (SF)	George Suciu (BEIA Austria)	3 PY	BEIA GmbH
Hungary	Funded (Y)	Tibor Bakota (FrontEndART Software Ltd.)	5 PY	FrontEndART Software Ltd., University of Szeged
Portugal	Funded (Y)	Goreti Marreiros (Instituto Superior de Engenharia do Porto (ISEP))	15 PY	FTP - Com. Equip. Inf. Lda, Instituto Superior de Engenharia do Porto (ISEP)
Slovenia	Funded (Y)	Simona Brezar (Caretronic d.o.o.)	11 PY	Caretronic d.o.o.
Spain	Funded (Y)	Alberto Oliva (Strategy Big Data)	13 PY	Strategy Big Data
Türkiye	Funded (Y)	Demet Seyhan (Experteam)	20 PY	ARD GROUP, DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ, Experteam, Hiperlink Eğitim İletişim Yayıncılık Gıda San. Paz. ve TIC. LTD. STI.

Project Acronyms

AI	Artificial Intelligence
ARR	Automated Request Routing
DL	Deep Learning
GDPR	General Data Protection Regulation
HLA	High Level Architecture
ITSM	Information Technology Service Management
KPI	Key Performance Index
Min.s	Minutes
ML	Machine Learning
NLP	Neuro-Linguistic Programming
OMD	Optimal Management of Demand
PCA	Project Cooperation Agreement
PPR	Project Progress Report
PT	Portuguese
SDM	Service Demand Management
SoTA	State of The Art
STG	ITEA Steering Group

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1. Project one-page description

OMD is a product that helps businesses to assign the correct agent to a specific service demand effectively, and remotely. In our speedy internet era, it meets the need of a fast processing of each call on the demand side, and the effective management of resources on the supply side of businesses. Increasing demands and time pressures accelerated by the pandemics make organizations ask for new automations to proactively manage their environments. SDM tools are important to do so, and existing products focus mainly on IT support: ITSM. The ITSM tool market can be considered mature as in the number of products, yet in AI capabilities they are in their infancy. Meanwhile, we need advanced approaches for optimizing demand management and a better utilization of resources in many domains. However, there is no general framework providing SDM in multiple sectors such as judicial, health, sales, marketing or manufacture. The OMD will address the high demand for online service support for numerous different sectors due to the pandemics and thus will create a significant business impact.
OMD embodies a number of technological innovations aimed at providing cross-domain enhanced tools, components and services for efficient service demand management and remote customer support. By applying novel approaches mainly from AI, ML/DL, and NLP, OMD will significantly impact the market, providing cross-domain breakthroughs that will be validated in nine domains: software support, justice, healthcare, consumer electronics, e-commerce, telemarketing, manufactury, logistics and software development.

Our innovation applies novel AI solutions to support a general SDM framework, considering many parameters related to request, service experts (agents), customer, and company from various domains. Bringing together technology providers and use case owners from different sectors, OMD goes far beyond the state of the art. OMD strengthens the concept of Cross-Domain Cognitive Service Management for enhanced customer satisfaction, user experience, and cost savings. OMD will analyse different approaches to create efficient workflows for dynamic priority management in customer support teams. The profiling of customers and agents based on data-driven social mood analysis, will help to process new dimensions of customers, designing a methodology that captures emotions that will increase the quality of the customer experience. OMD will perform research and development in key topics: category classification, emotion classification, semantic capabilities to easily extract information from unstructured data, topic detection, demand and service level classification, intent classification, entity recognition and linking, request summarization and standardization, agent classification, solution classification and dynamic “time to finish” prediction using state-of-the-art AI and ML/DL models. Furthermore, we plan to open source some core components of the project to facilitate its cross-domain sustainability.

The OMD framework produced in this project will rapidly contribute to many sectors effectively using AI models to improve service as a CSM approach. With the remote working model now more intensely in our lives, companies providing remote support will dramatically increase in number and so our product will be high in demand.

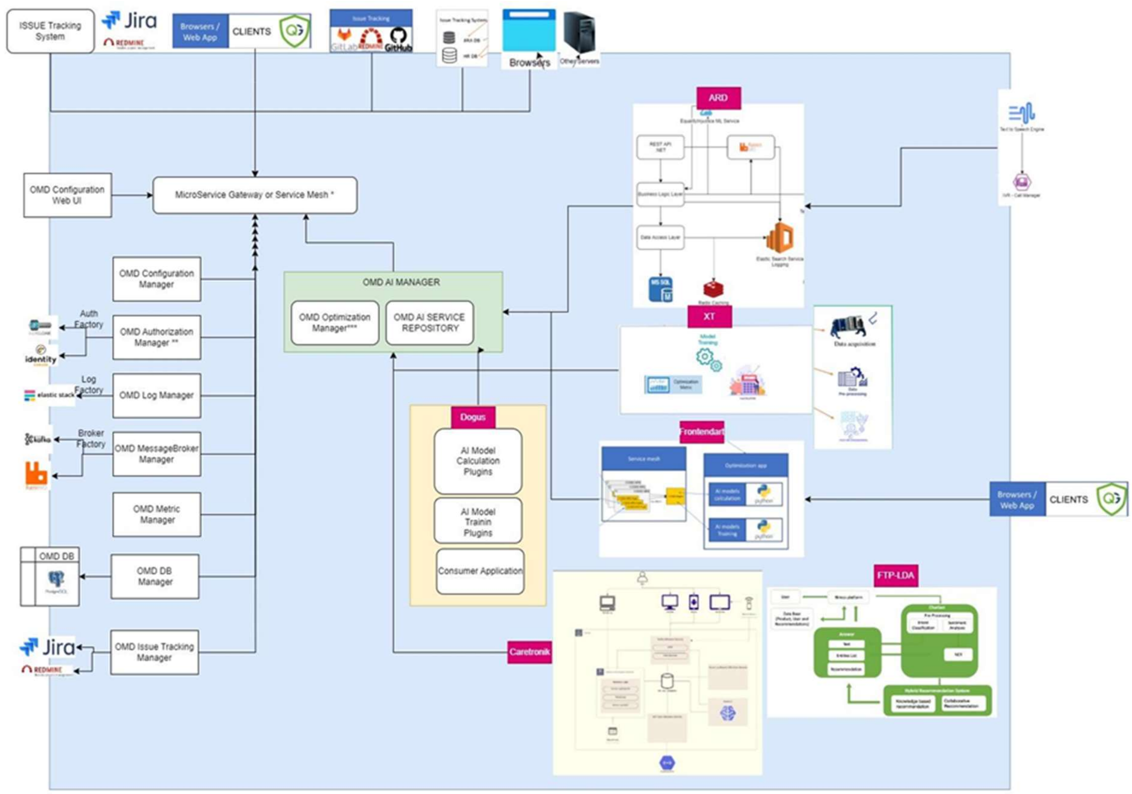
2. Project overall status

2.1. Top 4 overall targeted innovations

1. Framework for a multi-domain service management software

Main contributors: Doğuş, Hiperlink, Experteam and All

Short description of innovation and the State-of-the-Art:



Our innovation focuses on reference architecture for multi-domain service management software that integrates advanced AI technologies with existing service management infrastructures. Unlike existing frameworks, our solution introduces a unique reference architecture that allows seamless integration and communication between different use cases through an API gateway. This approach overcomes the limitations of current technologies, which often require domain-specific adjustments and lack flexibility for cross-domain interoperability. The framework's capability to integrate various AI-driven projects with legacy systems represents a significant leap beyond the state of the art, setting a new standard for flexibility and scalability in multi-partner environments.

Moreover, our framework addresses the challenges of integrating AI solutions in a multi-partner setup by establishing a standard interface for collaboration, which facilitates the embedding of AI technologies across different domains. This not only enhances interoperability but also enables the effective sharing and transfer of AI models, advancing beyond the current ITSM applications that are still in the early stages of AI adoption. The innovation thus provides a robust foundation for future technological expansions, ensuring that AI can be seamlessly incorporated into existing service management infrastructures, thereby enhancing both operational efficiency and technological advancement across sectors.

This revision provides a clearer response to the action item by directly comparing our innovation to the state of the art and emphasizing its unique technological contributions.

2. Optimization via AI-supported assignment tools

Main contributors: Hiperlink and all

Short description of innovation and the State-of-the-Art:

Optimization via AI-supported assignment tools is pivotal in streamlining operations and enhancing efficiency in call centers or help desks. The core objective is to optimize the assignment of requests or tickets to agents leveraging AI technologies. This innovation begins with a thorough analysis of the distribution and characteristics of incoming requests, utilizing data analytics to grasp the nature and variability of these requests over time.

By employing advanced AI methodologies, including natural language processing (NLP), machine learning (ML), and deep learning (DL), OMD aims to improve the prediction and assignment processes significantly. These technologies enable a more nuanced understanding of both demand patterns and agent capabilities, including their specialized skills and availability. This approach moves beyond traditional demand-supply models, integrating multifaceted constraints and parameters such as agent profiles and external factors like weather, to refine service level agreement (SLA) predictions and optimize resource allocation.

The solution adopts a mixed integer programming approach, tailored for scheduling challenges involving multi-skilled agents. This method not only considers the current tickets but also incorporates predictive insights about future requests, facilitating a more dynamic and responsive task assignment system. By analyzing task duration metrics and agent performance data, along with employing predictive models like Long Short-Term Memory (LSTM) networks for demand forecasting, the system can assign tasks more efficiently. This strategy aims to reduce overall task completion time and balance agent workloads, thereby minimizing service costs while maintaining or enhancing customer satisfaction levels. Through this innovation, OMD not only streamlines operations but also sets a new standard for intelligent resource management in service-oriented sectors.

3. Use of NLP for topic classification

Main contributors: DT, XT, USZ, SBD

Short description of innovation and the State-of-the-Art:

The current state-of-the-art in probably most NLP applications is to utilise a large pre-trained language model and either fine-tune it in a domain-specific downstream task with a number of labelled examples, or use a meta-training strategy, e.g., few-shot learning without actual model weight updates. The latter requires much less labelled data than the proper fine-tuning, however, works only with relatively large and carefully pre-trained language models.

The global OMD project involves mainly classification tasks in various domains. In the Software Development use case, USZ together with the use case owner, FEA develops an NLP-based AI solution to assign source code bugs to developers. This task can be considered as a classification over the available developers considering a complex set of features describing, among others, the code, the bug, and the developers themselves. The main idea in this, and also in other classification tasks is to develop AI-based solutions relying on pre-trained language models, namely one of the many variants of the BERT or the GPT families of language models. The particular choice of model and fine tuning strategy depend on the specific task at hand.

Dogus has successfully developed an AI model that outperforms baseline models in terms of efficiency and effectiveness. Technically this is a multilabel classification model for issues using pre-trained models and finetuning.

FastText text classification model used as a benchmark. FastText, developed by Facebook, is noted for its efficiency and ease of implementation, making it capable of fast performance and low memory consumption even with large datasets.

For evaluating text classification models, various score metrics like accuracy, precision, recall, and F-1 score are used. However, the macro F-1 score, which averages the F-1 scores of each class without considering the importance of each class, is preferred for imbalanced datasets. This makes it a more reliable metric in situations where all classes are equally important.

The trained FastText model achieved a macro F-1 score of 0.90 on a test dataset. Following FastText, more complex and advanced pre-trained natural language models have been employed, specifically the “dbmdz/bert-base-turkish-uncased” and “dbmdz/distilbert-base-turkish-cased” models from the Huggingface platform, which have been pre-trained for classification with Turkish data. In both model trials, the best scores are listed in the table below.

Model	**Makro F-1 Score**
bert-base-turkish-uncased	0.94
distilbert-base-turkish-cased	0.93

To gauge the model's performance in real-life scenarios, specifically with customer complaint sentences, it is believed that data from sikayetvar.com, which contains such customer complaints, will serve as a significant resource. Consequently, a project has commenced to scan the site for comments related to consumer electronics. After the data collection, it is planned to have the customers label the data, which will then be used to assess the model's effectiveness.

Efforts have been made to ensure the model can identify device models within sentences. Research into literature and keywords recommended by our advisor for Named Entity Recognition (NER) includes:

- Entity Linking

- Fuzzy Word Matching

- NER + Disambiguation

- NER using gazetteer lists

- Trie structures

Following these investigations, an application combining the advantages of these methods has been developed for entity extraction:

- An API has been developed using Autocorrect with Trie structures for word correction and BM25 for information retrieval from documents. Trie structures enhance fast search and automatic correction capabilities, while BM25 is utilised for extracting information from documents.

- This API has been developed using training data from various fields and is planned to be retrained and tested with OMD entity data.

Research into reinforced learning and human feedback has been conducted to improve the model based on end-user feedback. These studies demonstrate how human feedback can enhance model performance and how these techniques could be employed in future projects. Specifically, works such as "Deep Reinforcement Learning from Human Preferences" and "Training a Helpful and Harmless Assistant with Reinforcement Learning from Human Feedback" indicate that it is possible to refine models using human feedback. These approaches could contribute to making future artificial intelligence systems more effective and user-friendly.

4. Recommendation system for issue assignment

Main contributors: All

Short description of innovation and the State-of-the-Art:

OMD introduces innovations across various use cases through the use of Artificial Intelligence (AI) and optimization techniques. Particularly, the fourth innovation titled "Recommendation System for Issue Assignment" aims to innovate the process of assigning issues within OMD. By integrating the most advanced ticket classification methods with the latest solutions for category and intent classification, this innovation seeks to achieve a new level of efficiency and precision in demand management processes. The AI-based recommendation system is designed to analyze incoming requests and intelligently route each issue to the appropriate person or team. Utilizing state-of-the-art approaches in natural language processing (NLP), machine learning (ML), and deep learning (DL), the system can deeply understand the content and context of requests. Thus, it ensures that issues are smartly assigned to the most suitable resolution partners, accelerating business processes and enhancing customer satisfaction. This innovation by OMD, especially targeted at ITSM and OSMTA use cases also aims to support the automation and optimization of demand management in more traditional processes like health and judicial services.

1. Recommendation System / Health Use-case: The healthcare recommendation system is designed to enhance service delivery in nursing homes by predicting and recommending actions. Running alongside a Speech-to-Service (S2S) module, the system is trained on existing nursing home databases and combines expert knowledge, clustering techniques, and machine learning to make accurate predictions. Its main function is to assist healthcare providers in nursing homes by automating decision-making processes, thereby improving the quality and efficiency of care provided to residents.

2. Automated Customer Support / Electronics Use-case: AI-powered chatbots and virtual assistants are increasingly used in service management to handle routine customer queries and provide 24/7 support. These systems can understand natural language, learn from interactions, and escalate complex issues to human agents when necessary.

3. Service Ticketing and Routing / ITSM Use-case / OSMTA Use-case: AI algorithms can analyze incoming service requests, categorize them, and route them to the most appropriate team or individual for resolution. This helps streamline the service process and ensures that requests are handled efficiently.

4. Optimized Scheduling and Dispatching / Telemarketing Use-case: AI algorithms can optimize scheduling and dispatching of service technicians based on factors such as technician availability, location, skills, and priority of tasks. This helps maximize resource utilization and minimize response times.

5. Demand Forecasting / Telemarketing Use-case: In service management industries such as hospitality and transportation, AI can analyze historical data and external factors to forecast demand accurately. This enables better capacity planning and resource allocation.

6. Workflow Automation / Justice Use-case: Recommendation systems for lawyer-case assignments take into account a number of important parameters such as location, practice areas of lawyers and characteristics of cases. In this way, it is aimed to make the legal system healthier by optimising the time and resources in assignments made by human or rule-based systems.

a. Top 4 overall targeted business impacts

1. Equality in Justice Business Impact

Short description: The EqualityInJustice solution facilitates enterprise licensing for governmental bodies, including the Ministry of Justice, General Directorate of Police, and Union of Turkish Bar Associations. It is planned that the EqualityInJustice Cloud Application will be licensed to the 82 Bars and the Union of Turkish Bar Associations, with an end-user licensing model provided for attorneys participating in counselling assignments. This solution targets end users such as attorneys, law enforcement personnel, and Ministry of Justice personnel, while also aiming for international markets. Currently, there is no competition in AI/NLP integrated demand management systems within the justice domain.

Main contributors: ARD

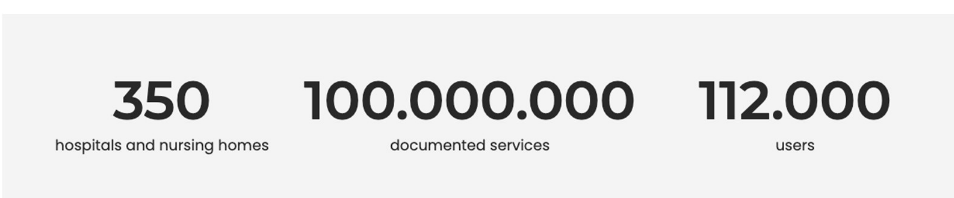
Market / competitors:

There are 185.586 attorneys registered to the union as of December 2023 (6.3% more than one year earlier). End users (attorneys, law enforcement personnel and Ministry of Justice personnel) will be connecting the EqualityInJustice Cloud Application via the web application and mobile application, which will provide flexibility of usage. Furthermore, this business model will be targeted for other countries. There is no competition in the AI / NLP integrated demand management systems in the justice domain. Compared to the previous year, there has been an increase in our market potential. The number of current bar associations using our solution has increased by 2, resulting in a 5.1% rise, and the current number of attorneys has increased by 11,053, leading to a 6.3% growth.

*Please note that while the statistical data in this report typically undergoes updates, the most recent figures available are from December 2023. This is because the statistical reports from the Union of Turkish Bar Associations are only released at the end of each year. As such, the data presented here reflects the latest available information, and any updates will be incorporated as new reports are published.

2. Health Care Business Impact

Short description: Caretronic has a strong international network of distributors mostly in EUROPE and all around the world. Based on the Caretronic has developed the business model and road to market that includes market introduction to hospitals, nursing homes, care organisations, telecom companies, our international distributors' network.



In the highly competitive healthcare industry, establishing a unique differentiator can significantly impact business success.

Caretronic's extensive network of distributors, combined with its advanced technology solutions, can offer the following business impacts that set it apart from competitors:

- Wider Market Reach: Caretronic's global distributor network provides unparalleled access to healthcare institutions, including hospitals, nursing homes, and care organisations. This wide reach allows the company to penetrate diverse healthcare markets more effectively than competitors.
- Streamlined Market Introduction: Caretronic's established network simplifies market introductions. New healthcare products and services can be efficiently introduced to a broad customer base, reducing time-to-market and enhancing revenue generation.
- Enhanced Product Adoption: The distributor network facilitates quicker adoption of Caretronic's innovative healthcare solutions. With distributors familiar with local healthcare needs and regulations, the company can tailor its products to meet specific market requirements, increasing adoption rates.
- Global Expertise: Caretronic's international distributors bring valuable local knowledge and expertise. This knowledge helps the company navigate complex healthcare landscapes, adapt to cultural nuances, and stay compliant with regional regulations.
- Competitive Advantage: Competitors may find it challenging to replicate Caretronic's vast and well-established distribution network. This network provides a competitive advantage, making it harder for rivals to enter or gain traction in certain healthcare markets.

- Improved Customer Service: With local distributor support, Caretronic can offer prompt and effective customer service. This enhances customer satisfaction and loyalty, critical factors in the healthcare sector.

- Market Expansion Opportunities: The distributor network not only serves as a sales channel but also as a valuable source of market intelligence. Caretronic can identify emerging healthcare trends and expansion opportunities more readily through its network.

- Risk Mitigation: Distributors can help Caretronic manage risk in various markets. They understand local regulations, manage logistics, and navigate potential challenges, reducing the company's exposure to risks.

- Scalability: The existing distributor network provides a scalable infrastructure for growth. As Caretronic expands its product offerings or enters new healthcare segments, it can leverage its network's established infrastructure.

- Brand Credibility: Collaborating with respected international distributors enhances Caretronic's brand credibility. This trust in the distribution channel can positively influence healthcare organizations' purchasing decisions.

In summary, Caretronic's extensive distributor network serves as a potent differentiator in the healthcare business. It not only expands market reach but also streamlines market entry, enhances product adoption, and provides a competitive edge. This unique business impact can be leveraged to achieve sustainable growth and success in the healthcare industry.

Main contributors: Caretronic

Market / competitors:

Rauland, Ackerman, Tunstall

3. Contact Services, Telemarketing, and Big Data Business Impact

Short description: Both the initial business model proposal and the estimates will have to be updated during the execution of the project. SBD proposes a sales model for contact process optimization services. OMD's services are also applicable to corporate clients and users of contact and telemarketing solutions in general. The following table shows the estimated sales of corporate and individual licences for OMD services.

	2025	2026	2027	2028	2029
Corporate licences	45	75	125	180	340
Individual licences	400	580	720	890	970

SBD will integrate OMD's results as part of its strategy to automate and optimize sales agent selection and sales agent prediction. sales agent selection and resource forecasting for Telemarketing and Contact centers based on customer characteristics (Speech-to-text, NLP, Entity Extraction, sentiment analysis) and product characteristics (Target, audience and trends).

SBD will improve with OMD the customer experience, by analyzing external sources to better identify the mood, culture and socio-economic profile of a new customer in order to better match the customer with the most suitable agent and product campaign. This new strategy will have a positive impact that will scale beyond the customer interaction processes of contact services, enhancing security, providing feedback based on cognitive parameters (what is expressed, how it is expressed, what is perceived and how it feels...) and on artificial intelligence, natural language processing and Deep Learning / Machine Learning.

The Konecta Group has:

- An R&D&I strategy based on the optimization of all aspects that accompany contact processes.
- Data, based on the daily relationship of more than 71,000 agents internationally with more than 2 million daily contacts.
- A specific BIG DATA and Modelling company with experts in Data Science as STRATEGY BIG DATA.
- A proprietary S2T model, developed according to the problems of a Contact Center and telematic models.
- A distribution of operation centers in Spain based in Castilla y León where the human capital is distributed.
- A distribution of operation centers in Spain where human capital is distributed.
- A process of attracting resources and a local and international training model.
- The need to systematize learning with new real KPIS.

Additionally, the current situation has allowed:

- Large corporate clients assume teleworking as a reality.
- Homeshoring model is a necessity.

- The user experience in the contact is a variable with as much weight as the efficiency of the process.
- SBD, bases OMD's marketing strategy on:
  - The sale of new Language optimization services based on artificial intelligence, natural language processing, Deep Learning / Machine Learning and all the aspects that accompany the contact processes.
  - A huge database, based on more than 55 million conversations per year, in Spanish with different accents and dialects.
  - Modelling with Data Science experts in voice processing.

Based on the business strategy described above, and taking into account the discussions held with the members of the consortium, a preliminary analysis of the exploitation of results has been carried out. Both the initial business model proposal and the estimates will have to be updated during project execution. SBD proposes a sales model for contact process optimization services. OMD's services are also applicable to corporate clients and users of contact and telemarketing solutions in general.

Main contributors: SBD

Market / competitors:

Strategy Big Data S.L. frames OMD's results in the field of contact services, Telemarketing and Big Data. It is increasingly difficult for companies to differentiate themselves. Therefore, they must offer remarkable experiences to customers, leaving a positive memory. In this sense, the Call Center can be a support for business success.

The key factor is to have the necessary technology to offer a unique customer experience, meet their needs and expectations to create a bond. Many companies invest in the Call Centers to maintain the relationship with the customer, launch campaigns, sell products, answer questions and conduct opinion surveys.

Technology companies

In general, the service used by the sector is based on the helpdesk style. It has, in general, the function of providing solutions to technical problems that the customer may have. It has different levels of service.

Financial Institutions

Banks, insurance companies and credit card companies also use call center services to maintain customer relationships. The call center also becomes an alternative, new sales channel for offering investment and financing products. It also ends up facilitating the fulfillment of the objectives of professionals, who do not need to move from their work environment to conduct a negotiation.

Product sales and convergence

In addition to traditional product sales (telemarketing), providers (i.e. cable TV, Internet and telephone channels...) use the Call Center to offer products to customers and increase their chances of sales. It is based on customer prospecting, satisfaction surveys and product sales.

The contact center sector is undergoing a major change in the way it operates.

Until now, the massive incorporation of resources, manual call validation processes and/or the implementation of automation (IVRS) that flattened the demand curve sought to bring quality and profitability to the service.

The increase in process capabilities and the emergence of Machine Learning techniques has enabled a change in this model where Big Data and Inference processes allow a proactive exploitation of the customer relationship.

4. Consumer Electronics Targeted Business Impact

Short description: The demand for consumer gadgets has remained high as people continue to adjust to working and learning remotely. With a forecasted consumer electronics market size of $15.3 billion in 2024 and growth of 5.32% CAGR from 2024 to 2029, Turkey continues to lead the European market. The country's status as a major producer of TVs and white goods is highlighted by the fact that the export value has increased to $25 billion.

It's imperative to concentrate on learnings from customer feedback, particularly after-sales, in order to spur additional growth. Because customer care platforms and call centres are sophisticated, there is currently a disconnect between sales and after-sales support. In 2023, the call centre sector in Turkey generated TRY 9.4 billion in revenue and employed 125,000 people. By 2025, the industry is expected to employ 350,000 people.

To improve decision-making, the OMD project's Smartfix solution places a strong emphasis on improved data governance. It seeks to decrease the amount of tickets and enquiries by using AI to expedite problem identification and provide answers. 60% of customer enquiries at this time deal with straightforward problems that can be automated, saving a significant amount of money and effort.

The OMD API offers a special chance to transform support services since it may interface with many platforms, such as contact centres and websites dedicated to customer service. Major consumer electronics businesses' customer care platforms still don't often feature these AI-driven solutions, which gives those who do a competitive advantage.

Sources:

Here are the references with their URLs:

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Main contributors: DOGUS

Market / competitors:

In 2024, there will be more competitors in the market for customer interaction and service efficiency solutions. Leading the way will be companies like Qudini, ServiceHub by HubSpot, Qless, Zendesk, Freshdesk, and Zoho Desk. These businesses set themselves apart by providing a broad range of capabilities, such as automated customer assistance and appointment scheduling, that use AI and automation to enhance customer experience management.

With smooth integration across sectors including retail and healthcare, Qudini focusses on optimising appointment scheduling and queue management, boosting the in-store and online customer experience.

HubSpot's ServiceHub is well-known for its customer care suite, which includes AI-powered chatbots to expedite customer interactions, knowledge base capabilities, and ticketing.

Qless is a leading provider of customer flow and queue management systems, enabling companies in industries including retail, healthcare, and government to maximise wait times and service effectiveness.

With its AI-powered messaging and automation technologies, Zendesk continues to be a pioneer in customer care software, giving businesses omnichannel support capabilities.

With its all-inclusive helpdesk and AI-powered solutions, Freshdesk by Freshworks distinguishes itself from the competition and gives businesses better tools for managing client enquiries and streamlining tedious chores.

Zoho Desk is well-known for its AI-powered customer care and support ticketing solutions, which let businesses handle client contacts more effectively across a variety of channels.

Major consumer electronics companies like Samsung, Sony, and LG are substantially investing in research and development to expand their customer service capabilities, in addition to these platforms. To meet changing customer expectations and stay competitive in an increasingly automated service world, these industry titans are incorporating automation, AI, and machine learning into their support systems.

Utilising AI-driven technologies like machine learning, natural language processing (NLP), and predictive analytics to deliver more effective and personalised consumer interactions is the common goal across these rivals. This pattern emphasises how crucial technology is becoming to satisfying customer expectations, especially in sectors where prompt, precise service is critical.

2.2. Top 4 overall project KPIs

	Initial value	Targeted value	Current value
1 Decreasing the overall time of appointment/assignments, lawyer confirmation and notifications to stakeholders.	Minimum 30 minutes (depending on number of lawyers called)	Minimum 3-4 minutes (depending on number of lawyers called)	Hours to minutes

The KPI for the OMD project focuses on reducing the time for appointment/assignments, lawyer confirmation, and stakeholder notifications. To measure this, data on the duration of these processes is collected before and after implementing the product.

The metric is the average time to complete the lawyer assignment process, calculated by dividing the total time by the number of assignments. The goal is to decrease the average time for each process, with the percentage reduction indicating the system's efficiency improvement. A significant reduction signifies success in enhancing service demand management and customer satisfaction.

2. Sales Per Hour (SPH)	0,700	0,740	0,725

SPH is calculated by dividing the total sales by the total labour hours worked per a worker. A higher sales per labour hour number indicates that the business is more efficient in using its labour resources, which can lead to higher profits. At the end of the project, we expect a 0,04 SPH increase. That means 1 sale more per week per agent. Konecta Group (SBD belongs to Koneta Group) has over 130.000 sale agents around the world. This increase will made 600.000 sales more per month in the group.

3. SLA Compliance	%85	%95	%91,5

This KPI measures the ticket routing success of our general model, which is formed by combining three sub-models with our user experiences. We aim to measure this target with the number of tickets resolved within SLA time constraints.

4. Average time-to-fix reduction of software maintenance tasks (by 20%)	38,2 days	30,5 days	N/A

We have chosen one of our long running internal projects as the subject of our OSMTA use case. In this project, the average time between opening and closing a task (e.g. fixing a bug or adjusting a feature) was 38.2 days. As model experiments and refinement reached the state that is worth experimenting with by the end of 2023, and we integrated the model in our systems and processes in 2024H1, we do not yet have statistical data with using the models. By the nature of the KPI and the SW maintenance tasks we handle, it is not possible to use old tasks and recreate KPI values using the models - we simply cannot re-create the same circumstances for each task (load of developers, other tasks in the queue, dependencies, etc.), thus cannot re-measure the time-to-fix values reliably and comparably. KPI measurement with the platform will be run from August 2024.

b. Top 4 overall risks

	Severity	Probability	Stage
1. Efforting the search for the markets for an integrated product	High	Possible	Monitoring & Controlling

Avoidance action:

We have a company dedicated to WP6, to do only the exploitation work. They still do not have funding and keep searching for it.

Back-up / Mitigation plan:

If the WP leader fails to do the exploitation work, we may still look for online markets for software products.

A period in which the risk is relevant

Throughout the project, but more relevant towards the end of the project.

2. Marketing or selling to customers outside of the company / abroad	High	Possible	Monitoring & Controlling

Avoidance action:

Project market search can be started and to seek for selling opportunity and possibility.

Back-up / Mitigation plan:

Partners may search for the possibilities of making structural data templates for use case implementation and if it possible they may be implemented.

A period in which the risk is relevant

Relevant also after project lifetime.

3. API related risks	Critical	Possible	Monitoring & Controlling

Avoidance action:

1. APIs may not be standard, use-case models or the gateway may lack standardization:

Microservices will make it easy for multi-domain OMD teams to work in parallel. We focus on use-cases for feature engineering, and they use a standardised way to share data (MQTT, etc.).

2. API integration in the OMD project introduces significant risks, such as data leaks, unauthorized access, and security vulnerabilities. Here is a brief overview of how to manage these risks:

- Monitor Access and Set Limits: Keep track of how much a user or API key accesses to prevent overuse and potential misuse.
- Implement Comprehensive Logging: Have a system to log API requests and link them to users, aiding in the detection of suspicious activities.

Back-up / Mitigation plan:

The consortium aims to generate a set of flexible APIs - reference patterns - that allow easy connection and disconnection of services.

To mitigate security risks:

- Enforce API Key Usage: Require a valid API key for all web application accesses, rejecting any request without one.
- Regularly Test Security: Use tools to check SSL implementations and improve security measures.

A period in which the risk is relevant

Until the end of the project.

4. Product related risks of integration	High	Possible	Monitoring & Controlling

Avoidance action:

Creating API Gateway between use case applications may not work for all use-cases, such as those exiting the project, having GDPR issues or servicing public institutions and they may keep their product as an in-house application.

For avoidance, various technical workshops will be organised with the consortium members, and we shall choose a course of action.

Back-up / Mitigation plan:

Exclusive use-cases partake in the common platform through exploitation activities. Connecting only those models which have standardisation and API provided.

A period in which the risk is relevant

Until the end of the project.

2.3. Change in the technology and market during the reporting period

There have not been any relevant changes in SOA or market since the last review period.

3. Market access & Exploitation

3.1. Partners' market access

Strategy Big Data	ind	ESP	13 PY
Big Strategy data is currently part of ROCKETHALL Group. ROCKETHALL Group has a vast network of customers in Spain and LATAM, with presence in several countries such Colombia, Mexico and Peru. Strategy Big data will integrate the project results to advance its portfolio of highly innovative, added-value niche services on AI, ML and NLP techniques. Strategy Big Data estimates that the new emerging opportunities will impact in the company with an expected employment growth, as a result of the project, of 8%, and an impact on annual turnover of 9%. A positive ROI is estimated to be achieved within 18 months of commercial exploitation.			
Caretronic d.o.o.	sme	SVN	11 PY
Caretronic is communicating the results of the OMD project across several levels: - Internal Dissemination Activities: Within the company, Caretronic regularly shares updates on the project through internal emails and monthly presentations at general company meetings. Caretronic also holds task-specific meetings with the OMD project team on a weekly basis or as needed. - Domestic Market (Slovenia): Caretronic engages with a strong customer base in Slovenia, including nursing homes, healthcare facilities, and care organizations, involving both primary and secondary end-users, as well as other market players. Caretronic promotes the OMD system through direct outreach via personal visits and e-mail newsletters. Additionally, Caretronic organizes business events where new developments are presented to both existing and potential customers, with the OMD solution being showcased. The OMD solution is also featured on the company's website. - International Markets (EU and beyond): Caretronic promotes the OMD solution across international markets, including the EU, Turkey, Israel, the Middle East, New Zealand, Brazil, Latin America, and more.			
Instituto Superior de Engenharia do Porto (ISEP)	uni	PRT	9 PY
As a research center that works closely to a diversity of companies and associations, ISEP-GECAD will develop, promote, install, and undertake the maintenance of the results of this project. More in detail, ISEP-GECAD expects to develop new recommendation and search services and applications to help customers search products in web stores. Also, we will contribute to the project dissemination actions such as marketing leaflets, press releases and results presentation in conferences, journals, seminars or other events as a writer or a co-writer, as organizer or a participant.			
ARD GROUP	ind	TUR	6 PY
EqualityInJustice use case will enable enterprise licencing for Government Authorities including Ministry of Justice, General Directorate of Police and Union of Turkish Bar Associations. The EqualityInJustice Cloud Application is planned to be licenced for the Unuion of Turkish Bar Associations and end user licencing model will be provided for the attorneys who will participate in assignments to counsel. There are 160.651 attorneys registered to the union as of December 2021. End users (attorneys, law enforcement personnel and Ministry of Jusitce personnel) will be connecting the EqualityInJustice Cloud Application via the web application and mobile application which will provide flexibility of usage. Furthermore this business model will be targeted for other countries.			
Experteam	sme	TUR	6 PY
Competitors and Alternatives to Tickota: Some important competitors of Tickota are Freshservice, Ivanti Neurons for ITSM, ServiceNow ITSM, SolarWinds Service Desk. All competitors are prioritizing tickets based on knowledge. Help desk management is supported with incident reporting interfaces, process workflow and dashboards. Technical comparisons cannot be made because competitors do not disclose the technologies they use in their products. However, Tickota predicts completion times (ticket resolution times) of ITSM task and			

classifies the priority / urgency of an incoming ticket to ensure quality, minimizing response times and reducing SLA penalties. The goal is to route the ticket to the most appropriate expert.			
FTP - Com. Equip. Inf. Lda	sme	PRT	6 PY
Over the past few years, e-commerce has become a key part of selling physical, digital, and service products. Thanks to the constant evolution of the Internet, its growth has been constant from year to year and the projections also point to the continuation of this increase. In 2021 it reached 5 billion dollars in sales and the estimate for 2026 is 8 billion dollars. From the technological point of view, several tools and technologies have also evolved to make e-commerce more accessible. This accessibility applies not only to the consumer who makes his purchases but also to those who sell since several platforms and services facilitate operationalizing the entire process. However, many custom-developed systems still allow for complete customization, but at the cost of greater complexity during development. E-commerce will be the target of constant investment and technological evolution, because of its growing adoption and practical use. We focus on developing a recommended system t			
DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ	ind	TUR	4 PY
Leading the way in the creation of digital assistants that are AI and NLP-based and designed to address client issues and maximize service effectiveness is Dogus Technology. These AI solutions are available to Dogus Group companies as well as external clients in areas such as customer service, sales, and after-sales support. Initially, they were aimed at important partners such as Samsung. Dogus Group's early adopters are anticipated to reap benefits, paving the way for wider adoption in sectors like technology, retail, and food. Furthermore, a variety of industries stand to benefit greatly from these AI-powered solutions: Customer service and support goals include raising post-purchase satisfaction levels, optimizing online chat support, and streamlining contact center operations to provide seamless client experiences. Retail & E-Commerce: Taking care of common customer complaints and streamlining order fulfillment, especially for industries like clothing, electronics, and food. Banking and financial services: Streamlining regular operations, answering client questions, and improving client satisfaction all around. Healthcare: Assisting with medication reminders, scheduling appointments, and patient observation to enhance patient care. Automobile Industry: Providing digital assistants for upkeep, fixing, and warranty assistance, enhancing the clientele's experience in situations after the sale. Services related to tourism, hospitality, and government: expediting bookings, enquiries, and public service operations through prompt, AI-powered support. Dogus Technology intends to progressively expand globally, providing multilingual solutions customized to meet the specific requirements of global clients, while concentrating on serving local clients in the Turkish market. AI-driven growth of this magnitude lays a solid basis for major advancements in customer satisfaction, operational efficiency, and service automation in a variety of sectors.			
Hiperlink Eğitim İletişim Yayıncılık Gıda San. Paz. ve TIC. LTD. STI.	sme	TUR	4 PY
We will use the product that will come out as a result of the project as a priority in the products we have developed, to direct the errors we caught from the trace logs to the correct team and to show the correct error messages to the user. In addition, we will work effectively in projects such as licensing this product in departments such as universities, university libraries, and municipalities in terms of marketing and sales. We have studies on universities that provide American Turcology education abroad. Currently, 4 universities in America are using our products. We are planning marketing activities for our own products in the next year as the European Union countries and the UK.			
BEIA GmbH	sme	AUT	3 PY
BEIA already supplies big data and speech processing solutions to various customers in Romania (automotive, academia, car insurance, tourism, etc.) and will be able to sell the platform in a basic scenario as a nationwide SaaS service platform to public & private stakeholders in the profiling and analysis call-center business domain. In an extended scenario, the commercialization of the services of the platform will be enlarged in the			

Balkan/Danube region through BEIA's sales and partners network. BEIA had several presentations of the solutions advanced within the project objectives, focusing on RPA for tenders. We proposed to expand the targeted companies from other fields that have support operations and logistics, not only from the field of industrial production.			
FrontEndART Software Ltd.	sme	HUN	3 PY
By integrating the results of the project into FrontEndART's source code quality management system, all the users will benefit from the project's outcome. First, the internal development of FrontEndART's services will be enhanced, improving the reputation of the company and its services. Second, the developed functionality will be offered to FrontEndART's customers as a separate service or as an extension of the existing services. The increased service quality and the savings realized at our customers will probably convince them to accept the slightly increased license prices. We primarily focus on the Hungarian market, aiming our current customers and planning to contract with new companies. We made a market analysis of the German and UK market too, which are our next targets. Furthermore, provided that we'll continuously analyze a large number of open source software systems, the tool will be able to generate maintenance tasks for the community members automatically in an optimal way			
University of Szeged	uni	HUN	2 PY
USZ collaborates with many prominent industrial partners and research organizations worldwide, ensuring its leading position on the list of higher education institutions in Hungary according to the QS World University Rankings of 2022. As Healthcare and Health Sciences are essential parts of USZ, it will be possible to directly evaluate and use the relevant project output in a real working healthcare environment. The innovative solutions and knowledge output, on one hand, are great opportunities for USZ to strengthen its R&D activities, encouraging new collaborations and future projects. On the other hand, being a higher educational institute, USZ can also take part in various teaching activities, and help its students or the project output's end users gain high quality, state-of-the art knowledge of a modern and innovative new technology. Furthermore, this knowledge introduced by developing new AI/ML and NLP methods during the project can be transferred to other projects and products			

3.2. Top 8 cumulative project achievements

1	Standardisation	Contribution	Study for Standardization	1
Summary		The Turkish consortium prepared a joint document on the related existing standards that are related to OMD.		
Impact		use-cases involved (quantification: 3)		
Partners		Experteam, DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ, ARD GROUP		

2	Dissemination	Conference	Dissemination of OMD at the PODays 2024, poster and presentation	1
Summary		A five minute pitch of all involved subprojects was prepared and poster presented.		
Impact		people presented (quantification: 50)		
Partners		Experteam, Hiperlink Eğitim İletişim Yayıncılık Gıda San. Paz. ve TIC. LTD. STI., DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ		

3	Exploitation	New library	Enhanced Question Answering with LLM and RAG Integration	1
Summary		By combining Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) for sophisticated question answering, Dogus Technology made tremendous strides. RAG models were utilised to increase real-time information retrieval and classification accuracy, while LLMs, like ChatGPT, were used to improve data		

	quality and produce rich training datasets. This method greatly improved customer support and slashed ticket resolution times.
Impact	At Dogus Technology, the combination of LLMs and RAG models produced improvements of 68% in single-label classification and 64% in multilabel tasks. (quantification: 1)
Partners	DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ

4	Exploitation	New product	USP of Equality in Justice (A part of Multi-domain assignment tool)	1
Summary	"OCAS" is the tool available for assigning lawyers, utilized by 39 Bar Associations. While OCAS relies on traditional rule-based approaches, our advanced 3-step legal tech solution leverages the latest AI technologies. Our state-of-the-art optimization solution creates a robust and scalable environment for the legal domain.			
Impact	Our solution will ensure that assignments are made more fairly, transparently, and optimally. (quantification: 50)			
Partners	ARD GROUP			

5	Exploitation	New product	USP of IT support	2
Summary	Tickota predicts completion times (ticket resolution times) of ITSM task, and classifies the priority / urgency of an incoming ticket to ensure quality, minimizing response times and reducing SLA penalties. The goal is to route the ticket to the most appropriate expert.			
Impact	Improvement in ticket resolution time (quantification: 15)			
Partners	Experteam			

6	Exploitation	New product	Reference Architecture for Multi-domain assignment tool	1
Summary	The tool shall be able to combine data from different sources across multiple domains. It shall generate assignments based on the selected domain information and platform. Such a tool will be particularly useful for users who work across multiple domains, as they will be able to create assignments based on data obtained from various domains.			
Impact	The described tool can bring significant benefits to the companies, such as increased efficiency, improved customer satisfaction, competitive advantage, and potential for expansion. (quantification: 8)			
Partners	Experteam, Hiperlink Eğitim İletişim Yayıncılık Gıda San. Paz. ve TIC. LTD. STI., DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ, ARD GROUP, Caretronic d.o.o., FTP - Com. Equip. Inf. Lda, Strategy Big Data, FrontEndART Software Ltd.			

7	Exploitation	New product	AI/ML models scaled effectively for improved performance and efficiency.	1
Summary	The proposed approach involves agents and user preferences to assign tickets based on related goals in different use cases.			
Impact	Develop and Improvement new models (quantification: 0)			

Partners	Experteam, Hiperlink Eğitim İletişim Yayıncılık Gıda San. Paz. ve TIC. LTD. STI., DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ, ARD GROUP

8	Exploitation	New product	Optimal Software Maintenance Task Assignment module	1
Summary		Based on the AI model developed for Optimal Software Maintenance Task Assignment, an OMD software module will be implemented (either as a library or a deployable subsystem).		
Impact		The module will enable the integration of Optimal Software Maintenance Task Assignment feature into the management systems of the FrontEndART. (quantification: 100)		
Partners		FrontEndART Software Ltd.		

3.3. Achievements

Dissemination	Exploitation	Standardisation	New company	Patent	Human capital
Total: 12	Total: 29	Total: 1	Total: 0	Total: 0	Total: 0

4. Project progress during the reporting period

4.1. Project progress and issues during the reporting period

4.1.1. Top 4 technical achievements during the reporting period

1. AI Model Development

Designing an artificial intelligence (AI) model involves several key steps, from problem definition and data collection to model selection, training, and evaluation. In our project we will continue AI model design based on best practices which are described below.

· Model Training

· Model Evaluation

· Fine-tuning and Optimization

· Deployment and Monitoring

In the forthcoming period, where the partners are targeting the integration of AI models into products, the optimization of models for production run is planned.

Dogus Technology is proceeding well with the following steps:

- (evaluation) Initiate an annotation study to evaluate NLP model efficacy in handling consumer electronics complaints using labelled data from sikayetvar.com, an online platform that collects customer issues. This research aims to refine AI customer service tools by analysing real-world feedback for more accurate and user-focused responses.
- (exploration) Conduct research aimed at exploring the integration of reinforced learning with human feedback mechanisms in artificial intelligence (AI) systems.

2. Classification

Dogus Technology concentrated on improving the categorisation models in the first half of 2024 in order to better prioritise demand, with the aim of precisely identifying the significance of tickets that are entering the system for the first time. The study question, "Can we improve the classification of customer complaints by enhancing the training data using LLM?" was one we investigated as part of our efforts. By using fresh approaches and analyses, significant advancements were realised.

We are improving our classification models by retraining and fine-tuning them using recently released data, especially in the agent assignment domain. This also incorporates future enhancements like feature space expansion, better data processing, and integration-related modifications. Using real-world data from sites such as Sikayetvar.com, where 100 complaints were manually labelled by five professionals in a multilabel classification exercise, the efficacy of these models was evaluated. When the agreement between titles and descriptions was assessed, it was found that 27 out of 100 samples had differences. These findings informed subsequent efforts to train the model.

The study also included creating models that incorporate synthetic data generated by LLM in order to address the overfitting problems that were seen in previous BERT-based classifiers. When evaluated on real-world data, the models' performance drastically decreased (to about 25–30%) despite demonstrating great accuracy (up to 95%) with training data. This prompted the investigation of alternate strategies including few-shot/zero-shot learning and enhancements to the calibre of training data. Additionally, as our test results show, retraining models on actual customer data resulted in substantial F1 score improvements.

Additionally, Dogus Technology has started a research project to improve multilabel classification methods, specifically to handle the complexity of client complaints, which sometimes involve several problems. Our goal is to improve response effectiveness and efficiency by improving AI models to precisely identify and classify many issues contained in a single complaint. Using retrieval-augmented generation (RAG) models, for example, we were able to improve the accuracy of classification, particularly in multilabel jobs. Success rates increased from 20% to 68% for single-label and 64% for multilabel classifications on Sikayetvar data.

Further optimisations in the future will evaluate the performance of the retrieval model, retrieve more documents, and improve symptom name identification even further. Our research in this field has produced encouraging findings, especially when it comes to merging several data sources for more comprehensive classification coverage.

The ultimate objective of these developments is to expedite response times, shorten the time it takes to handle tickets, and enhance overall customer happiness. These goals will be regularly tracked using operational data and consumer surveys.

3. API Development

Partners are targeting the full integration of AI modules to their individual products. API development to access the newly developed services through the common OMD platform is also a technical target for the next period.

The consumer electronics use-case implements an on-demand model file I/O loading system, coupled with the development of a consumer layer that queues request, maintains them in memory, and incorporates multiple security layers. Additionally, the deployment of the application to the server and the definition of DevOps processes are planned. This approach is designed to streamline operations, enhance security measures, and improve overall system efficiency through optimised resource management and automated deployment practices.

4. Performance Assessment/KPIs

During this reporting period, we made progress in improving and developing our KPIs. Workflow optimization reduced the time required for key processes such as appointments and approvals. Improvements in sales efficiency also brought us closer to our targets. In addition, our efforts to increase SLA compliance will lead to better resolution of issues within timeframes. Finally, the groundwork has been laid to improve the fix time for software tasks and further improvements are expected.

4.1.2. Top 4 next technical targets

1. Integrate all submodules to the main OMD platform

Hiperlink has started to develop a common infrastructure architecture for all partners used throughout the project. This architecture is enriched with various technical components to ensure high performance and reliability:

Microservices Architecture and Docker/Kubernetes Utilization: The infrastructure is designed in accordance with the principles of microservices architecture. Thanks to this structure, each service (e.g. data collection, preprocessing, model training, etc.) is run as an independent microservice. Using Docker containers, these microservices are isolated and Kubernetes is used to manage and orchestrate the containers. This increases scalability and fault tolerance.

Using Redis for Queue Management: Redis queue structure was used to manage high-volume data flows during data processing and AI model training. Redis provides a lightweight and fast queue management system to avoid congestion during data processing. This system improves overall processing efficiency by simultaneously collecting, processing and distributing data sets.

API Integration and Security: API integrations are a critical component for data exchange and communication with other partners in the project. Hiperlink has integrated keycloak to make API integrations more reliable and secure. This solution is used to authenticate API requests, manage authentication and authorization processes, and protect against data leaks.

Development of Configuration Infrastructure: A configuration management infrastructure has been developed to ensure that the architecture is flexible and configurable. This infrastructure provides a dynamically configurable system for different environments and usage scenarios. Configuration files and parameters are stored on a central configuration server and services pull configuration information from this server. This allows for quick changes and updates without interruption of services.

2. Driving Excellence in OMD Through Collaborative Dissemination & Exploitation Networks

Emphasizing the creation of knowledge-sharing networks for the dissemination and use of project results, increasing the awareness of the OMD project worldwide.

During the last quarter of 2024 and the first quarter of 2025, each partner will produce a publication to raise awareness of the OMD project. These publications can be academic works such as conference papers, articles, books, etc. In addition, a visual and social media campaign will be organised to direct people to the OMD demonstration studies.

3. Development of optimization models

Hiperlink is also responsible for optimization studies in the project. In this context, based on the available synthetic and real data sets, it worked on an SLA calculation model to respond to incoming tickets within the optimal SLA (Service Level Agreement) time.

Optimization Model and SLA Calculation: A more advanced AI-based optimization model was developed using Google OR-Tools to ensure that incoming tickets are responded to by the most appropriate staff within the SLA time. This model provides the most appropriate task assignment by considering ticket category, staff skills, past performance scores and SLA requirements.

Optimization Models and Evaluation

While developing the optimization model, various optimization techniques were experimented with:

- Linear Programming (LP)
- Mixed Integer Programming (MIP)
- Constraint Programming (CP)

The performance of the model is evaluated by calculating the total score of the assignment results and ensuring SLA compliance. A successful optimization result is defined as an assignment that maximizes the score while satisfying all SLA constraints.

4. Completion of studies for the integration of the models into the end-user front-end

Demo Frontend Enhancement: In addition, a demo frontend has been developed to demonstrate the project and its operation. This frontend will visually demonstrate how the AI models and infrastructure architecture work. This demo will be presented at the next ITEA conference and will be used to promote the project.

4.1.3. Top 4 issues

1. Trends in LLM

Details:

While concerns about data quality have long been a major obstacle, new developments in large language models (LLMs), like ChatGPT, have helped allay these worries by offering contextually validated and enhanced data for AI model training. By assisting in the creation of clear and cohesive datasets, these LLMs lessen reliance on manually sourced raw data that may contain errors. ChatGPT and similar tools have proved very helpful in automatically managing data enrichment, enhancing standardisation, and completing missing information. Data collection techniques for the creation of AI models are changing as a result of this move to AI-driven data processing.

Impact:

Using LLMs more effectively speeds up the training of AI models by supplying more dependable and extensive datasets. This enhancement lowers the amount of manual labour needed to clean and standardise incoming data, improves ticket management systems, and aids in achieving higher forecasting accuracy.

Mitigation action:

Implement cutting-edge LLMs (such as ChatGPT) for continuous data augmentation and context validation as a mitigating measure. Reduce problems with data quality and enhance the training process by using automated pipelines for data collecting, such as web scraping, API integrations, and other data sources.

2. Resource-related Problems

Details:

Project schedules and development quality are still being impacted by difficulties in obtaining enough qualified workers, financial limitations, and computational resources. The complexity of AI models increases the demand for advanced infrastructure and specialised knowledge.

Impact:

Limited resources may cause projects to run longer than planned, innovate less, or compromise on software features or model performance, which may have an adverse effect on the project's objectives as a whole.

Mitigation action:

Partners can target new prospective markets and expedite the commercialisation of AI-driven solutions and other goods, in order to overcome resource constraints. Developing into sectors like retail, banking, healthcare, and telecommunications that demand advanced customer support solutions can bring in more money. The money made from this can then be used to expand computing capacity and recruit experts.

Furthermore, we may draw in more companies seeking to optimise customer service by pitching these AI solutions as value-adding tools that boost productivity and save operating expenses. This will enable us to offer scalable solutions that meet the demands of the business while meeting resource constraints.

3. Problems with the Propensity Model

Details:

Due to the complexity of consumer behaviours and market dynamics, developing reliable propensity models is still difficult. By 2024, some of these problems have been lessened thanks to the availability of more detailed customer datasets obtained through enhanced AI-driven data collection techniques.

Impact:

Inaccurate propensity models can still result in poor decision-making and targeting, which lowers potential income and engagement.

Mitigation action:

The use of cutting-edge analytical methods and ongoing model improvement based on insights from real-time data is essential. To ensure accuracy, domain-specific experts must continue to be used for data validation and annotation. Propensity models are further enhanced by integration with LLMs, which offers deeper behavioural insights.

4. Team member turnover

Details:

Particularly in technically challenging AI projects, a high turnover rate among key team members causes continuity issues and knowledge gaps.

Impact:

Project delays, higher training expenses, and a loss of institutional knowledge are caused by turnover; these factors may reduce productivity and have an effect on the general quality of the project.

Mitigation action:

In 2024, efforts will be directed at keeping valuable employees by presenting chances for professional advancement, cultivating a positive work atmosphere, and outlining distinct career trajectories on Generative AI. Improved onboarding procedures guarantee a more seamless transfer and reduce disturbance in the event of employee turnover.

4.1.4. Status of deliverables

[Planned] What is the total number of deliverables in the project?

There are twenty-four deliverables defined in the overall project.

[Planned] How many deliverables are supposed to be finalised (from the start of the project until the end of this reporting period)?

The following deliverables below were supposed to be finalised.

D1.1 - Project Progress Report - PPR1	Jun 2022
D2.1 - State-of-the-art Analysis	Jun 2022
D2.2 - Scenarios and Use cases	Jun 2022
D2.3 - Legal, ethical and Acceptance analysis	Sep 2022
D2.4 - Requirement analysis	Sep 2022
D3.1 - General system architecture	Dec 2022
D1.2 - Project Progress Report - PPR2	Dec 2022
D1.3 - Project Progress Report - PPR3	Jun 2023
D1.4 - Project Progress Report - PPR4	Dec 2023
D5.1 - Specification of Evaluation Metrics	Apr 2024
D3.2 - Data Pipelines and Preprocessing Design	Jun 2024
D3.3 - AI models design	Jun 2024
D3.4 - Optimization Models Design Report	Jun 2024
D4.1 - Data pipelines and preprocessing modules	Jun 2024
D4.3 - Optimization modules	Jun 2024
D1.5 - Project Progress Report - PPR5	Jun 2024

[Actual] How many deliverables have already been finalised (from the start of the project until the end of this reporting period)?

We finalised the following nine deliverables.

D1.1 - Project Progress Report - PPR1	Jun 2022
D2.1 - State-of-the-art Analysis	Jun 2022
D2.2 - Scenarios and Use cases	Jun 2022
D2.3 - Legal, ethical and Acceptance analysis	Sep 2022
D2.4 - Requirement analysis	Sep 2022
D3.1 - General system architecture	Dec 2022
D1.2 - Project Progress Report - PPR2	Dec 2022
D1.3 - Project Progress Report - PPR3	Jun 2023
D1.4 - Project Progress Report - PPR4	Dec 2023
D5.1 - Specification of Evaluation Metrics	Apr 2024
D3.2 - Data Pipelines and Preprocessing Design	Jun 2024
D3.3 - AI models design	Jun 2024
D3.4 - Optimization Models Design Report	Jun 2024
D4.1 - Data pipelines and preprocessing modules	Jun 2024
D4.3 - Optimization modules	Jun 2024
D1.5 - Project Progress Report - PPR5	Jun 2024

[Delayed] Are there any deliverables delayed more than 2 months in this reporting period? If so, please explain why.

There are no delayed deliverables.

4.1.5. Statement on project progress during the reporting period

In this period, Project works are conducted well-structured with project committees. We have done technical monitoring workshops, demo structure discussions, management activities, deliverable documents initiation and coordination with partners. Representation activities (i.e. disseminations, publications, events etc.) have been carried out by partners.

Four out of seven milestones are almost achieved. WP1 is 80% complete, with four reports on the national and international side. WP2 and WP3 are %100 complete, with the last period of the project. WP4 is 80% complete, and WP5 has progressed 75%. WP6 has reached 80% complete.

ID	Description	Month of completion
MS1	Specification of use cases, State-of-the-art Analysis. Deliverable D2.1, D2.2 are released.	M6
MS2	Definition of requirements. Deliverable D2.3, D2.4 are released.	M9
MS3	Definition of general system architecture. Deliverable D3.1 is released	M12
MS4	Specification of evaluation metrics. Deliverable 5.1 is released.	M28
MS5	System Architecture Design and AI Models Development, System Development and Integration, Realisation of Use Cases tasks outputs. Deliverable D3.2, D3.3, D3.4, D4.1, D4.3, D5.2 are released.	M30
MS6	UI and Reporting Interfaces Development, Integration, Test, and Validation tasks outputs. All use cases successfully installed with OMD. Deliverable D4.2, D4.4, D5.3 is released.	M36
MS7	OMD Dissemination and exploitation tasks. Deliverable D6.1, D6.2, D6.3 are released.	M36

4.2. Details of progress per Work Package

WP 1: Project Management

Technical progress meetings have been organized and managed. In these monthly meetings, the integration and design of the demo were discussed for this period. Support was provided to companies regarding the management and monitoring of deliverables and the completion of modules. The new Itea report was initiated, and actions were resolved. Preparations for the next StG review were started, the date and schedule were created / shared with partners.
Tasks and project management activities determined for the Tickota product development processes were carried out. Team management and coordination were conducted through weekly status meetings.
Discussions were held on optimization and product design within the national consortium.
The poster and the leaflet preparations were supported. Explitation partners are looked for.
Preparation towards the PO Exhibition days is supported.

WP 2: Use Case Requirements and Business Models

WP2 was completed in June 2023. The deliverables related to this work package have been uploaded to the ITEA portal under the corresponding work package section. Although this work package has been completed, KPI tracking continues to ensure the success of the use cases.

WP 3: System Architecture Design and AI Models Development

WP3 has been completed in this period. Pipelines and AI models have been designed and implemented to provide improved tools for matching agents, customers and telemarketing campaigns.
The design of the different modules and services associated to the identified components has been carried out, generating an overview that allows the orchestration and coordination of the whole system:
The models have been designed for the acquisition of data from different sources, such as databases, structured and unstructured data sources; the establishment of data pipelines and data preprocessing modules that are of critical importance for the quality and performance of the machine learning models.
To manage and utilize unstructured data effectively, we have followed a systematic approach, including data collection and text preprocessing. Public datasets and internally recorded human speech audio are utilized for training the AI algorithms, while data on care activities and patient care plans are collected through dedicated devices and stored securely on a central server.
We have made a structured approach to designing and implementing AI models for handling both unstructured and structured data. This includes text classification and named entity recognition models, which utilize advanced natural language processing techniques to accurately categorize and extract information from legal documents
We also focused on integrating various models into a unified system to optimize the efficiency and effectiveness of data processing

WP 4: System Development and Integration

During this period, significant progress has been made in advancing both the development and integration of AI models and optimization tools. The partners have worked in coordination to ensure that the ongoing efforts remain aligned with the overall objectives of the project.

An AI-powered recommendation model has been developed to prioritize customer support requests and predict their completion times based on past records. Using NLP techniques, requests are analyzed and routed to the appropriate expert to maintain customer satisfaction and ensure compliance with SLA constraints. Experimental results have been obtained using advanced machine learning models.

Work on the Reference System Architecture continued, adopting a microservices approach for easier integration across various platforms. Additionally, efforts have been focused on implementing a Named Entity Recognition (NER) model to extract and categorize key information from legal texts, aiding in decision-making processes.

Further research on Multi-label Classification and NER has achieved strong performance metrics, with continued exploration of advanced models. The development also includes APIs that utilize techniques such as Entity Linking and Fuzzy Word Matching to enhance real-world applications.

In addition, technical workshops have been conducted, and technical committees were established to guide the development and testing processes. Demo preparations are also underway for upcoming presentations. Optimization efforts are focused on SLA calculations and improving ticket assignment efficiency using optimization algorithms like Mixed Integer Programming (MIP).

WP 5: Demonstration

Over the first half of 2024, significant progress has been made in WP5. The OMD framework modules and web services from WP4 were successfully integrated and applied to the use cases defined in WP2. Extensive testing and evaluation of the system were conducted across different use case environments, providing valuable insights into its performance under various conditions and workloads.
Efforts were made to optimize the solution based on end-user feedback, ensuring it better meets their needs. The development of a complete and market-ready prototype of the OMD system is near completion. Furthermore, the groundwork for future sustainability and exploitation of the OMD results has been established, ensuring a smooth path for adoption by a wide range of stakeholders post-project. This progress ensures that the project remains on track to achieve its objectives.

WP 6: Dissemination&Exploitation

Coordination of outreach activities, mainly focusing on individual exploitation plans and joint exploitation plan using business model canvas.
Partner worked on identifying Potential Users in order to determine who can benefit from the project results and how they can be applied. Also, we developed business plans and created strategies for commercializing project outcomes.

We engaged with industry partners and collaborated with businesses to explore practical applications of the research.
Market analysis and studies were conducted to understand the market potential and demand for the project's results.
The project was presented at events such as Hannover Messe 2024, Romenvirotec 2024, Bucharest Tech Week 2024, EuCNC 2024, European Manufacturing Conference 2024, EUSEW 2024.

4.3. Per partner progress during the reporting period

4.3.1. Partners' main contribution and effort

Partner	Planned effort (Project start~ end of reporting period)	Actual effort (Project start ~ end of reporting period)	Contact
Experteam	4.73	4.72	Demet Seyhan
	Main contributions during the reporting period: We coordinated both national and international consortia. Internally we developed AI models in this period. In the field of NLP models, we established infrastructures for running machine learning and NLP models with real data, advancements in integrating models to work with each other, transforming data from complex company databases and feeding it into machine learning algorithms via pipelines, observing the performance of artificial intelligence models in real-life data environment.		
	Discrepancy explanation: -		
ARD GROUP	5.10	4.82	Arda Ödemiş
	Main contributions during the reporting period: As the technology provider, we developed the Recommendation Model. This AI system uses text classification, NER, and cosine similarity to match user queries with the most appropriate case-lawyer matching. NER and cosine similarity results are integrated with the LLM-RAG model to enhance lawyer assignments accuracy and transparency. We also authored a paper titled 'Named Entity Recognition for Lawyer Assignment in Justice Cases,' advancing legal AI through automation and text analysis.		
	Discrepancy explanation: The actual effort was achieved according to the national funding criteria. There are not relevant discrepancies between the planned effort and the actual one.		
Strategy Big Data	10.54	10.54	IGOR CASADO MORENO
	Main contributions during the reporting period: The affinity prediction tool and the generation of a socio-cultural profile of potential customers, as well as affinity prediction, have been developed. At the same time, the usefulness of NLP models at the sentiment level has been validated. Models have been designed for data acquisition from different sources, such as databases, structured and unstructured data sources; the data pipelines and data preprocessing modules are of critical importance for the quality and performance of ML molels.		

	Discrepancy explanation: The current state of progress of the project is 80%.		
Hiperlink Eğitim İletişim Yayıncılık Gıda San. Paz. ve TIC. LTD. STI.	3.23	3.23	Hilmi Oğuz
	Main contributions during the reporting period: During this period, we have played an active role in the technical meetings and committees of WP4. In June, we prepared a presentation for the OMD project's poster, which was showcased in Istanbul as part of the Eurostar program. Additionally, we continued coding the infrastructure we provided for the reference architecture, with significant progress made in microservice architecture. Furthermore, in the area of optimization, we implemented enhancements to facilitate the calculation of SLAs (Ser		
	Discrepancy explanation: there is no discrepancy		
University of Szeged	1.74	2.53	László Vidács
	Main contributions during the reporting period: In this semester, USZ mainly worked on the integration part of the AI solution developed during the prevous semesters. USZ also developed a web service based framework to use the AI modules independently. USZ also worked on a manuscript that summarizes one part of the development work and submitted it for publication to the conference PROFES 2024.		
	Discrepancy explanation: The discrepancy comes from multiple sources. First, we are rolling some extra effort from past semesters. Furthermore, both the development work with integration and wiriting a manuscript were more complex tasks than planned earlier. The last source of the extra effort is the fact that the University also applied students in this project, and the extra effort was required for the less experienced developers to finish the tasks.		
Caretronic d.o.o.	8.50	8.50	Simona Brezar
	Main contributions during the reporting period: The main contributions during the reporting period include the development and implementation of an advanced healthcare recommendation system, aimed at improving decision-making processes in nursing homes. This system was integrated with a Speech-to-Service (S2S) module to enhance service delivery by predicting and recommending actions based on data from existing nursing home databases. Caretronic worked on the exploitation of OMD at international fairs and trades.		
FrontEndART Software Ltd.	1.85	1.75	Tibor Bakota
	Main contributions during the reporting period:		
BEIA GmbH	1.88	1.10	George Suciu
	Main contributions during the reporting period: BEIA had an advisory role contributing to the dissemination and exploitation of the use cases		
	Discrepancy explanation: BEIA is participating self-funded in the project since we did not receive funding from the national agency.		
FTP - Com. Equip. Inf. Lda	6.16	6.16	Germano Fernando Santos Pinto

	Main contributions during the reporting period: We left the project in June 2023. Our national funding ended on June 2023		
Instituto Superior de Engenharia do Porto (ISEP)	8.70	8.70	Goreti Marreiros
	Main contributions during the reporting period: We left the project in June 2023. Our national funding ended on June 2023.		
DOGUŞ BILGI ISLEM VE TEKNOLOJI HİZMETLERİ	3.26	3.43	Setenay Gemici
	Main contributions during the reporting period: Created models with synthetic data produced by LLMs to overcome overfitting problems observed in earlier BERT-based classifiers. Advanced RAG models-based multilabel classification techniques that use data from Sikayetvar.com platforms can boost accuracy from 20% to 68% for single-label and 64% for multilabel tasks.		

4.3.2. Actual vs. planned effort overview

Report	Planned effort up to reporting period (PY) - total: 66.03 PY	Reported actual effort up to reporting period (PY)
2024 Semester 1	55.68 (84% of total)	55.48
2023 Semester 2	45.32 (69% of total)	45.25
2023 Semester 1	33.54 (51% of total)	33.18
2022 Semester 2	19.94 (30% of total)	23.52
2022 Semester 1	9.06 (14% of total)	9.37

5. Additional feedback to previous STG remarks (optional)

To STG reviewers: This chapter is meant to provide additional information on the status of actions, in addition to the information on the online action tool (the information is exported on the Excel file). The project consortium uses this chapter to provide longer and more detailed information that are too exhaustive for online action tool and the Excel export.

Following actions have been commented on and marked as done on the platform.

Number	Action	Status by PL	Deadline
ACTION-063	Highlight technological novelty with respect to the state of the art for targeted innovations #1 and #4	Done	Next PPR
ACTION-064	Elaborate KPI #1 to provide more details on how this KPI measures project progress, linked to the innovation goals and use case	Done	Next PPR
ACTION-065	Specify the "technical achievements" in terms of used techniques and methodologies for achievements #1 and #2	Done	Next PPR

ACTION-063 Highlight technological novelty with respect to the state of the art for targeted innovations #1 and #4

This improvement is now made in the related section above (top 4 innovations).

ACTION-064 Elaborate KPI #1 to provide more details on how this KPI measures project progress, linked to the innovation goals and use case

The goal of the project was to reduce the assignment duration by optimizing our demand management processes through improved selection of the experts. In case of ITSM this is to increase the customer satisfaction and to reduce costs due to SLA constraints. In our jira system we are able to measure and monitor this entity called “assignment duration” by the intervention duration (initial assignment) and historical assignment data. In our workflow this corresponds to status change of a ticket from “created” to another status.

ACTION-065 Specify the "technical achievements" in terms of used techniques and methodologies for achievements #1 and #2

The achievements 1 and 2 in PPR 2023 H2 was:

1. Information Enrichment

2. AI models design and optimization

1.Information Enrichment

Classifying a customer involves using all the information available for this purpose in the company's systems. Generally, this data corresponds to data collected from operations based on previous contacts and their results.

Developing an affinity model implies going further and adding new variables that provide a new perspective on the customer. We are talking about the application of: NLP models, based on sentiment and the impact this has on the conversation, if we have had previous contact.

Extraction of additional potentially usable information that is publicly available. Given the existing data protection limitations, it is as important to know which sources are accessible as those that are not.

- Identification of key sources

- Information Extraction. Methods and Processes Availability and Variability of the same.

- Compliance with the RGPD policy. Acceptance of customer use.

Information enrichment is the basis for the development of any predictive model, regardless of the inference techniques applied: ML, classical inference, etc. An analysis of Open Data information sources has been developed, as well as the availability of information in Social Networks. This last point has been discarded due to legal and information integrity limitations due to the impossibility of guaranteeing the unitary assignment of the client. The following sources have been used for the Open Data work

External data are collected to help the model provide accurate predictions when the amount of information provided by the client is not rich enough. Even if the client provides many useful variables, it is always useful to have this external data to help model the target population.

External data come from different sources:

- INE (National Statistics Institute)

- Tax Agency

- Cadastre (housing information)

The data collection process for all of the above sources is quite similar. The data sources are obtained through a process of research on which websites contain potentially useful information and the feasibility of obtaining this data.

If a web page is deemed to contain needed information, a crawler must be built for this source. Each crawler is different and must be customized for each web page. These crawlers traverse websites retrieving all the information in an iterative manner.

Web pages often deny requests from the same source/ip if a large number of requests are received in a short period of time. This makes the process of scraping a web site terribly slow, so a pool of proxies is used to be able to perform a large number of requests in a short period of time.

Once this data is collected, it is cleaned and transformed into a tabular format so that it can be stored in a structured SQL database. Again, this module is independent for each data source, as the way your data is structured is totally independent. This process can be quite complex as will be seen later.

The different data sources are updated with different periodicity. Therefore, each channel has its own cron job that triggers its execution. One of the most complex pipelines is the one in charge of processing cadastral data. Cadastral data is really important, as it allows obtaining information about the target customer's home and its surroundings. Census units are also related to this and their information is combined in the following process

We are talking about the processing of more than 200 million processed records, the normalization of addresses and the estimation of housing prices and rental prices: 10 million households. All this makes up more than 200 socio-demographic variables analyzed, always anonymized.

NLP SENTIMENT

First of all, it should be noted that SBD already has its own S2T model. As a complement to it, a research process has been developed on the best technique for assigning sentiment to texts of transcribed conversations in a call center. The conclusion has been the importance of combining lexical models with semantic models.

Lexical models allow accurate recognition of word patterns, and semantic models capture meaning using language models that have been built on neural networks trained on large volumes of text.

In the case of sentiment identification, there is the constraint of short texts, a particularly difficult area of work in NLU given the few existing words (tokens) to identify and label the associated sentiment. This scenario is particularly complex vs. the calculation of sentiment in texts of medium or long length (more than 500 - 1000 tokens), since with only 3 - 10 tokens, associating a sentiment value is an operation with much more imprecision and variability.

In addition to the above, we must reflect the high variability of content and situation that occurs in different projects or campaigns, being very different or not comparable the sentiment in a customer support campaign, from that of a portability campaign or telemarketing calls.

Therefore, the selected model is a combination of lexical and semantic, being the lexical part based on pattern discovery of regular expressions, and the semantic part on DEEP AVERAGING NETWORKS, a type of model that allows working with short text in a robust way.

Thanks to the word dropout that we applied in the training for the DAN type models, the impact of having short text is minimal, in turn, it generates a robust technique that makes the models generalize in the best possible way.

As a result of the combination of technology choice (lexical + semantic DAN), we are able to give the sentiment at the level of text fragments, but also by words, having these positive or negative valences influencing the set of predicted text fragments.

Finally, for a correct development of the model, it has been necessary to train on multiple datasets.

SBD has a labeling tool for model training. The requirements set for the development of this functionality have been the following:

Sentiment labeling will be performed using three categories. An excerpt from the internal labeling guide serves as an example:

- Positive: Any sentence that includes a positive opinion or point of view of the product, service or attention received will be considered.

GDPR Impact on processing

On April 14, 2016 the European Parliament approves the General Data Protection Regulation (GDPR) legislation, coming into force on May 25, 2018. This regulation combines the privacy laws of the 28 member states and establishes a set of 99 articles in defense of the rights and protection of individuals and fully impacts customer communication via telemarketing.

- Right of access: data subjects can consult the data that organizations store about them.

- Right to be forgotten: users can request the removal of their personally identifiable information from an organization's storage. The latter may refuse requests if it can demonstrate a legal basis for the decision.

- Right to object: users can refuse permission to collect, process or use their personal data. Again, the organization can ignore the refusal only after providing a sufficient legal reason for the decision.

- Right of portability: users can access and transfer their data.

- Right to rectify: users expect correction of inaccurate data.

Data controllers must obtain authorization to transfer personal data to an international organization or to another country.

Finally, it should be noted that the GDPR imposes the same responsibility on processors and data controllers. It means that a non-compliant third-party processor affects an organization's compliance status. The law also has strict requirements for reporting breaches up the chain.

All information processed in this project contains the authorization of its owners to that effect. The developments undertaken are based on strict compliance with current legislation.

2.AI models design and optimization

Techniques for Multilabel Classification: Dogus Technology concentrated on improving models for multilabel classification in order to confront the complexity of client complaints, where a single issue may encompass several issues. This required fine-tuning models to increase classification accuracy, especially when dealing with customer data that had overlapping problems. Initially, a number of models were created, including BERT-based classifiers, but after testing them on actual data, adjustments were made to prevent overfitting.

Models of Retrieval-Augmented Generation (RAG):

A major step towards increasing model accuracy and managing complicated, real-world data—like consumer complaints from Sikayetvar.com—was the switch to RAG models. With a jump from 20% to 68% for single-label classification and 64% for multilabel classification, the RAG model contributed to higher classification success rates, indicating the model's capacity to handle more complex data sets.

LLM Integration and Optimisation: To overcome the problem of inadequate or low-quality training datasets, Dogus Technology used large language models (LLMs) to produce synthetic data for training. To improve the resilience of AI models, methods including few-shot learning and data augmentation were investigated. Furthermore, the ability of pre-existing models to generalise beyond artificial inputs was enhanced by refining them using real-world data.

Data Governance and AI for Decision Making: One of the major accomplishments of the Smartfix solution was the incorporation of AI models, which were intended to enhance decision-making and give priority to data governance. This was crucial for employing AI-driven insights to automate customer care activities like ticket classification and issue identification (Euromonitor).

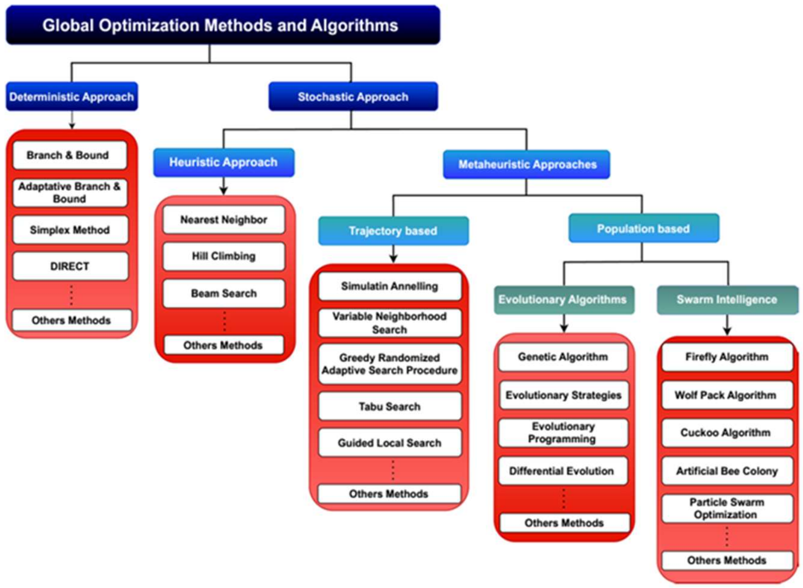
Evaluation of the Model's Performance: A number of performance indicators were employed to assess the model's performance, including average agreement rates between the outputs of the AI model and human labellers and macro F1 scores. These measurements indicated regions in which feature space expansion or retraining of the models could lead to improvements.

Designing Optimization Models

Machine learning (ML) algorithms are commonly used in many application areas such as advertising, recommender systems, computer vision, natural language processing and user behavior analytics. This is because they are general and perform well on data analytics problems. Different machine learning algorithms are suitable for different types of problems or datasets. In general, building an effective machine learning model is a complex and time-consuming process that involves determining the appropriate algorithm and obtaining an optimal model architecture by tuning its hyper-parameters (HPs).

Parameters: These are the parameters that the algorithm adjusts according to the provided dataset.

Hyperparameters: These are the high-level parameters that you set manually before you start training, based on characteristics of the data and the algorithm's learning capacity.



Tickota has a prediction model that includes various regression algorithms. The best algorithm is selected based on the results of evaluation metrics. For example, the decision tree regression algorithm is one of them. optimization is done by hyperparameters in the decision tree regression algorithm.

Here are the hyperparameters:

- Algorithm: As mentioned before, this algorithm decides the priority of the features and hence their order in the tree structure.

- Tree Depth: This defines the depth layer. This can definitely affect both the structural and time complexity of the tree. We can remove unimportant nodes and reduce the depth.

- Minimum Instance Split: This is an integer value that defines the minimum number of instances required to split an internal node.

- Minimum Instance Leaf: This defines the minimum number of instances in the leaf. This hyperparameter can help reduce overfitting by reducing the depth of the tree.

Furthermore, the optimization of an AI-powered system that provides expert recommendation for Tickota can provide effective results by integrating multi-criteria decision making (MCDM) methods such as Analytic Hierarchy Process (AHP) and PROMETHEE. Here is a general outline of such a system:

1. Requirements Analysis

- Training Needs: By analyzing the current situation of the company, it should be determined in which areas there are training needs. For example, needs can be identified in areas such as software development, data analytics, cyber security.

- Criteria: Criteria such as type of training (online/on-site), cost, training duration, experience of the trainer, certificate programs are determined.

2. Data Collection

- Training Opportunities: Data should be collected from different training providers and courses. This data can be categorized according to criteria such as content, duration, cost, experience of the trainer.

- Employee Profile: The current skills and training needs of the company's employees should be collected.

3. Integration of AHP and PROMETHEE

- AHP (Analytic Hierarchy Process):

o Criteria Weights: The weights of the criteria determined by the AHP method are calculated. For example, how important is the impact of cost on the success of education?

o Comparison of Alternatives: A hierarchy is created between training programs and alternatives are evaluated according to this hierarchy.

- PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations):

o Ranking of Alternatives: Training programs are ranked using PROMETHEE method with the weights from AHP. This method allows you to choose between alternatives according to criteria.

o Visual Support: PROMETHEE's tools such as GAIA plane can be used to visually compare alternatives.

4. Artificial Intelligence Supported Recommendation System

- Machine Learning: Machine learning models can be used to improve the recommendation system using the company's past training data and employee performance.

- Natural Language Processing (NLP): By analyzing training requests and feedbacks, training suggestions can be offered in accordance with the needs of employees.

- Recommendation Engine: Based on the data collected from training providers and AHP/PROMETHEE results, a recommendation engine can be developed that offers customized training recommendations to employees.

5. User Interface

- Dashboard: An interface that visually presents training recommendations, criteria weights and the decision process.

- Filtering and Sorting: Options that allow users to filter and sort recommendations based on criteria.

- Reporting: Reports summarizing the selected training programs and explaining why they were selected.

6. Feedback and Development

- Feedback Collection: Users can leave feedback on the system after their training and the system can improve itself according to this feedback.

- Continuous Learning: The AI-supported recommendation engine is constantly trained with new data and makes its recommendations more accurate.

7. Technology Stack

- Backend: Languages like Python, R, or Java can be used to run AHP and PROMETHEE algorithms and machine learning models.

- Frontend: Modern frameworks like Angular, React or Vue.js can be used to develop the user interface.

- Database: Relational databases like PostgreSQL, MySQL or NoSQL databases like MongoDB can be used for data storage.

- API: RESTful API or GraphQL can be used to communicate data between backend and frontend.

This system will ensure that the needs of the expert to be selected are analyzed effectively and the most suitable expert for the company is determined. Furthermore, the integration of methods such as AHP and PROMETHEE will make it possible to make decisions in a more objective and multidimensional way.