SHAPE FUTURE

IN THE CENTER OF ECS DEVELOPMENT TO FURTHER BOOST THE TRANSFORMATION OF MOBILITY, TOWARDS ZERO EMISSION & ZERO FATALITIES.

D7.2 Broad Strategies for Stakeholders engagement & Initial dissemination and communication plan

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Executive Summary

This deliverable outlines the comprehensive dissemination and communication strategy for the ***ShapeFuture*** project, which aims to drive advancements in Electronic Components and Systems (ECS) for highly automated vehicles. The strategy is designed to maximize awareness, engagement, and impact among stakeholders, including academia, industry, government, and the general public.

Key components of the dissemination and communication approach include the establishment of a **strong visual identity**, a **dedicated project website**, and **active engagement across multiple social media channels**. These elements serve as primary tools for promoting project updates, achievements, and future objectives.
A **sentiment analysis tool** has also been incorporated to monitor public perception, allowing for real-time adjustments in communication strategies to address audience feedback effectively.

Furthermore, this strategy sets measurable **key Performance Indicators** (KPIs) for tracking the progress of engagement activities. By focusing on both quantitative metrics, such as reach and engagement rates, and qualitative insights from sentiment analysis, the project team aims to optimize its dissemination efforts throughout the ***ShapeFuture*** lifecycle.

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Abstract

This deliverable outlines the comprehensive dissemination and communication strategy for the ***ShapeFuture*** project. The project's primary goal is to revolutionize Electronic Components and Systems (ECS) for highly automated vehicles.

Aligned with the project's objectives, this strategy ensures effective dissemination throughout the ***ShapeFuture*** lifecycle. It provides a framework for sharing project work and results, both during and after completion. Furthermore, it serves as a guide for project partners, offering common tools that require active engagement from all participants.

The defined dissemination activities are designed to achieve two key objectives: **raising public awareness and engaging targeted stakeholders.** These activities will highlight the ***ShapeFuture*** project's objectives, activities, and outcomes.

To reach a diverse audience, the partners will utilize a variety of dissemination tools and activities. These include a dedicated website, social media platforms, newsletters, press releases, published articles, and presentations at conferences, events, and workshops. Additionally, a specialized **Sentiment Analysis** toolkit for research and innovation will be developed.

Shape Future Overview

1.1 Project Outline

The ***ShapeFuture*** project aims to revolutionize Electronic Components and Systems (ECS) for highly automated vehicles by developing innovative solutions that enhance safety, security, reliability, and performance.

While significant advancements have been made in ECS technology, there are still challenges to overcome in areas such as perception, cognition, AI-enabled decision-making, resilient automation, and communications. Current systems may face limitations in terms of accuracy, robustness, efficiency, and integration with human-machine interfaces.
To address these challenges, ***ShapeFuture*** proposes a comprehensive approach that involves:

- **Developing innovative ECS solutions:** Creating new ECS components and systems that surpass existing capabilities in terms of performance, efficiency, and reliability.
- **Enhancing perception and cognition:** Improving the ability of ECS to accurately perceive and understand the environment, including objects, people, and other vehicles.
- **Advancing AI-enabled decision-making:** Developing AI algorithms that enable ECS to make intelligent and timely decisions in complex and dynamic environments.
- **Ensuring resilient automation:** Designing ECS systems that are robust and reliable, capable of operating in challenging conditions and recovering from failures.
- **Improving communications:** Enhancing the communication capabilities of ECS to enable seamless and secure data exchange between vehicles, infrastructure, and other systems.

Key Objectives:

- Advance vehicle safety, security, and reliability.
- Lead European ECS development and supply.
- Improve ECS accuracy, robustness, and efficiency.
- Create cognitive ECS with enhanced human interaction.
- Enable resilient automation and communication.
- Foster technology adoption and business sovereignty.

By addressing these key areas, ***ShapeFuture*** aims to drive innovation in ECS technology and contribute to the development of safer, more efficient, and sustainable highly automated vehicles. Additionally, the project will help to ensure European ECS value chain sovereignty by strengthening the region's position in this critical industry.

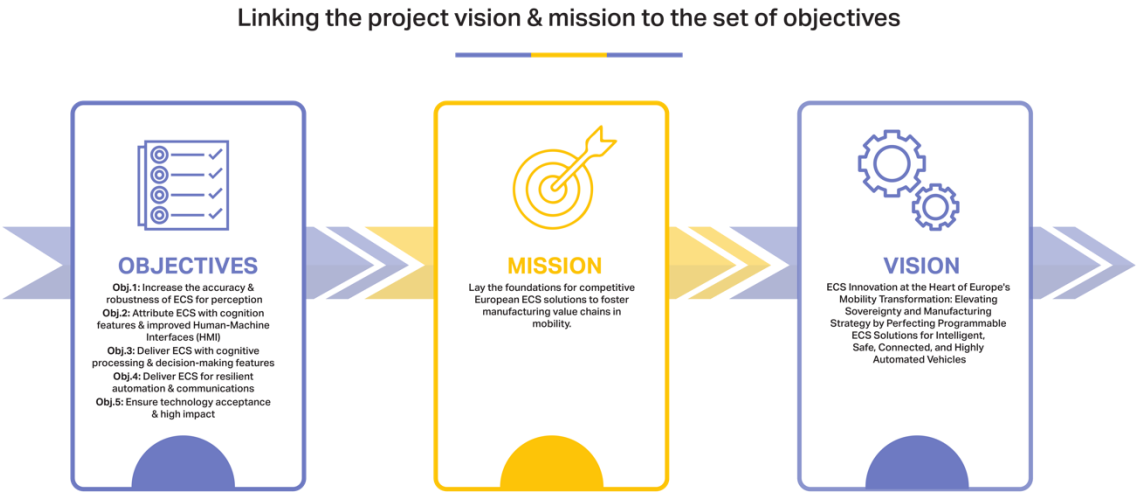


Figure 1: The Shape Future Project overview

The table below presents additional descriptive information about the Shape Future project, intended to be communicated to the project's target groups & stakeholders.

Table 1: The ShapeFuture Project

***ShapeFuture* Project Description**
Shapefuture in the center of ECS development to further boost the transformation of mobility, towards zero emission & zero fatalities.
Expected outcomes
• Enhanced safety, security, and reliability • Leading-edge ECS development and supply • Improved ECS accuracy, robustness, and efficiency • Cognitive ECS with enhanced human interaction • Resilient automation and communication • Technology adoption and business sovereignty
Expected Impacts of *ShapeFuture* Project Activities
• Incorporation of novel ECS in various applications, development of new AI-based methods and tools, increased user acceptance of new perception systems. • Development of compact MEMS scanner modules for HMIs, demonstration of enhanced performance and KPIs through laser beam scanning. • Application of MARL-based strategies for decision making, integration of enriched sensor data from roadside units, use of non-von Neumann-based programmable hardware platforms, exploration of FPGA accelerators for safety-critical scenarios, combination of Bayesian Neural Networks for enhanced robustness, feature extraction, and true 3D cognition. • Deployment of AI-based channel selection algorithms for C-V2X communication, use of AI and computer vision components for environment perception, development of automated approaches for security and decision-making. • Increased stakeholder acceptance of ***ShapeFuture*** technologies through various identified channels.

Direct Users

- **Original Equipment Manufacturers (OEMs):** Companies that design and manufacture vehicles, such as car manufacturers.
- **Tier 1 and Tier 2 Suppliers:** Companies that supply components and systems to OEMs, including those involved in the development of ECS.
- **Research institutions:** Universities and research organizations that conduct research on ECS technology and its applications.
- **Government agencies:** Government departments and agencies involved in transportation, technology, and safety.

Shape Future Major project results

- **Enhanced Safety, Security, & Reliability:** Improved in-vehicle systems, increased resilience to cyber threats, and enhanced system reliability.
- **Advanced ECS for European Automotive Supply Chain:** Availability of leading-edge ECS components and systems, positioning Europe at the forefront of technology development.
- **Improved Perception Capabilities:** Increased accuracy and robustness of ECS for perception, smaller form factors, and lower power consumption.
- **Cognitive Features and Enhanced HMI:** Integration of cognitive capabilities, improved human-machine interfaces for a seamless user experience.
- **Cognitive Processing and Decision-Making:** Advanced cognitive capabilities for complex decision-making tasks, enhanced ability to learn and adapt.
- **Resilient Automation and Communications:** Resilient ECS systems, improved communication capabilities for seamless data exchange.
- **Increased Technology Acceptance & Business Sovereignty:** Widespread adoption of innovative ECS technologies, strengthened European business sovereignty.

1.2 Organizing the Dissemination and Communication efforts

The ***ShapeFuture*** project recognizes the importance of effective communication and dissemination in achieving its core objectives. This strategy serves as a roadmap for project partners to navigate the identification of target audiences and determine the content and timing of messages necessary for project success.

Communication as a Strategic Tool:

By strategically utilizing communication tools, ***ShapeFuture*** will actively contribute to achieving its project goals.

Roles and Responsibilities:

- **Communication Managers:** Each partner organization will designate a communication manager responsible for implementing the communication plan at their organizational level.
- **Lead Partner and Communication Group:** Innovation Dis.Co (Vasiliki Chatzidogiannaki and Panagiotis Terzopoulos) will act as the Lead Partner, overseeing the coordination of communication activities across the entire project.
- **Project Communication Group:** Together with the communication managers from each partner, they will form the ***ShapeFuture*** project communication group. This group will facilitate collaboration and ensure a unified communication approach throughout the project.

Dissemination & Communication Strategy & Target Audience

1.3 Quintuple Helix Innovation Model

To achieve optimal communication and dissemination results for the Shape Future project, we will employ a tailored approach based on the **Quintuple Helix Innovation Model**. This model establishes an ecosystem that fosters collaboration and interaction between five key actors:

- Academia
- Government
- Industry
- Natural Environment
- Media and Culture-Based Public

By engaging with these actors within the Quintuple Helix ecosystem, we aim to create a more comprehensive and impactful dissemination and communication strategy based on the following Levels:

1. **On-Demand Level:** We will utilize a **Sentiment Analysis Tool** to monitor the general audience's sentiments and responses towards the project's priorities. This tool will enable us to **align our dissemination and communication efforts** more effectively, increasing their efficiency and impact.
2. **Supply Level:** The ***ShapeFuture*** communication strategy will be specifically tailored to address **key target groups and audiences** within the Quintuple Helix ecosystem. We will adopt a **multi-stakeholder approach**, focusing on essential players and stakeholders involved in the development and deployment of highly automated vehicles.

The ***ShapeFuture*** project targets a diverse range of Stakeholders:

- **Academia:** Research institutions and universities involved in ECS technology and related fields.
- **Government:** Regulatory bodies, transportation authorities, and government agencies involved in technology and innovation.
- **Industry:** OEMs, Tier 1 and Tier 2 suppliers, and other companies involved in the automotive industry.
- **Natural Environment:** Organizations and individuals concerned with the environmental impact of transportation and technology.
- **Media and Culture-Based Public:** Journalists, bloggers, social media influencers, and other public figures who can help disseminate information about the project.

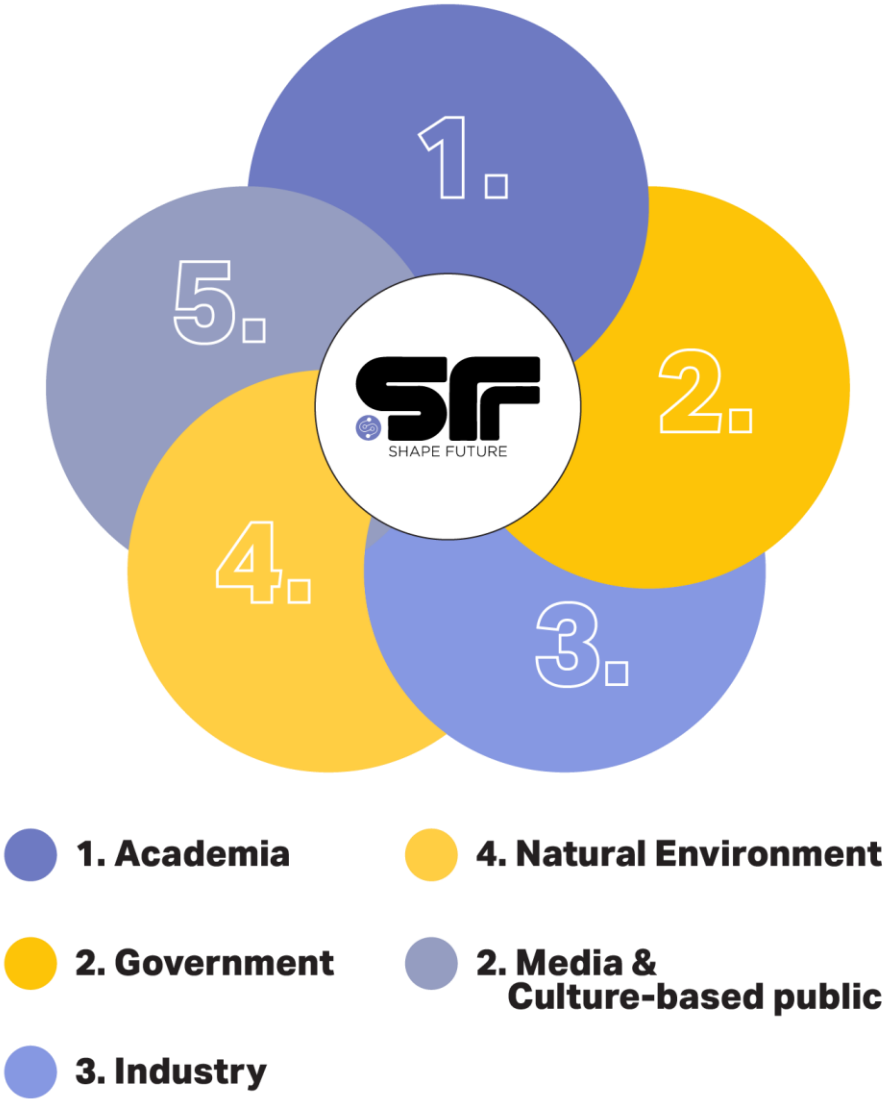


Figure 2: The Quintuple Helix Model

1.4 Tailored Messages

We will develop tailored messages for each target group, highlighting the specific benefits and implications of the ***ShapeFuture*** project for their respective interests and concerns. These messages will be disseminated through various channels, including:

- **Website and social media:** Our dedicated project website and social media channels will provide up-to-date information about the project's progress, achievements, and outcomes.
- **News releases and media outreach:** Press releases will be issued to announce key milestones and achievements, and media outreach efforts will be conducted to generate news coverage.
- **Presentations and conferences:** Project representatives will participate in conferences, workshops, and other events to present the project's goals, progress, and results to relevant audiences.

- **Publications and articles:** Research papers, articles, and other publications will be produced to disseminate the project's findings and insights to the academic and scientific community.
- **Stakeholder engagement:** Regular engagement with stakeholders will be conducted to gather feedback, address concerns, and build support for the project.

By adopting this comprehensive approach, we aim to optimize our communication and dissemination efforts, ensuring they resonate with our target audiences and have a significant impact on the development and adoption of ECS technology for highly automated vehicles.

1.5 A tailormade Sentiment Analysis Tool for research and innovation

A key pillar of ***ShapeFuture's*** dissemination and communication strategy is the integration of a **tailored Sentiment Analysis Tool**, specifically designed to **bridge the gap between public perception, stakeholder expectations, and the project's technological objectives.** The purpose of this tool extends far beyond simply tracking online opinions or collecting engagement metrics. Instead, it acts as a strategic decision-support system that continuously informs how the project communicates, how stakeholders are engaged, and ultimately, how new Electronic Components and Systems (ECS) solutions for automated vehicles are accepted and adopted in the real world.

1.5.1 Purpose and Strategic Role

The rationale for embedding sentiment analysis into ***ShapeFuture*** is to ensure that dissemination and communication activities are not isolated promotional exercises but are instead evidence-based, stakeholder-driven, and impact-oriented. In practice, this means the tool serves four core strategic purposes:

1. **Understanding Perceptions to Drive Technology Acceptance:**

The introduction of highly automated systems and advanced ECS technologies depends heavily on societal trust, industry readiness, and regulatory alignment. Sentiment analysis allows the project to continuously capture how these diverse stakeholder groups perceive technological advances, including their hopes, fears, and expectations. By mapping these perceptions, ***ShapeFuture*** can anticipate resistance points (e.g., data privacy, safety concerns, cost) and actively address them through targeted messaging, outreach campaigns, or policy dialogues.

2. **Informing Stakeholder-Specific Communication Strategies:**

Different stakeholders have different priorities and decision-making drivers. OEMs and Tier-1 suppliers are primarily concerned with integration complexity and ROI, policymakers focus on regulatory and safety implications, while citizens may prioritise ethical AI use and data protection. The sentiment analysis tool supports segmented analysis by stakeholder group, enabling the consortium to tailor communication narratives and engagement formats accordingly, for instance, providing more technical detail to industry partners while emphasizing trust and transparency in communications aimed at the public.

3. **Enabling Dynamic, Adaptive Communication:**

Public attitudes and stakeholder positions evolve over time, especially in emerging technology fields such as autonomous mobility. By monitoring changes in sentiment

continuously across social media, news media, forums, and other online channels, the tool allows ***ShapeFuture*** to adapt its messaging strategies in real-time. This ensures that project communication remains relevant, impactful, and aligned with evolving societal discussions and expectations throughout the project lifecycle.

4. **Supporting Impact Pathways and Policy Uptake:**

Sentiment insights also contribute to the project's broader impact strategy by identifying which narratives and communication approaches are most effective in accelerating technology uptake. Moreover, understanding how policymakers, media, and the general public frame the debate around ECS technologies provides valuable intelligence for aligning ***ShapeFuture's*** dissemination outputs with regulatory priorities and policy trends, increasing the project's visibility and influence in standardisation and legislative processes.

1.5.2 Why Sentiment Analysis Matters for *ShapeFuture*

Traditional dissemination approaches often rely on quantitative metrics, such as reach, impressions, or event attendance, which, while useful, do not explain how the audience perceives and why they react in certain ways. Sentiment analysis closes this gap by adding a qualitative dimension to communication strategy. It enables the consortium to measure not only how many people are reached but also how they feel about the technology, what narratives dominate the discussion, and how these narratives affect adoption trajectories.

Furthermore, by systematically analysing barriers and enablers to acceptance, such as trust in AI decision-making, perceived safety risks, cost concerns, ethical considerations, or environmental benefits, the project can integrate these insights into its exploitation, standardisation, and stakeholder engagement strategies. This approach ensures that dissemination is not merely reactive but strategically proactive, shaping public and industry conversations to support long-term adoption and scaling of ***ShapeFuture's*** innovations.

1.5.3 Integration into the Dissemination Strategy

The Sentiment Analysis Tool is therefore positioned as a **core intelligence layer** within ***ShapeFuture's*** broader communication and stakeholder engagement framework. It informs key dissemination activities, including:

- Message design and audience targeting for different stakeholder segments.
- Selection of communication channels and content formats based on sentiment trends.
- Prioritisation of topics and narratives for public engagement, media outreach, and policy communication.
- Evidence-based refinement of KPIs and engagement strategies as stakeholder perceptions evolve.

Through this continuous feedback loop, **sentiment analysis transforms communication from a static dissemination activity into a dynamic engagement process**, one that actively shapes the conditions necessary for successful technology acceptance, societal adoption, and commercial deployment of ***ShapeFuture's*** outcomes.

1.5.4 Extracting Insights from Diverse Media Sources

The Sentiment Analysis Tool analyzes both **traditional and electronic media sources**. This includes news articles, social media posts, online forums, and other forms of public

discourse. By analyzing these diverse sources, we gain a comprehensive understanding of the general audience's sentiment towards the project's priorities.

1.5.5 Optimizing Communication Through Sentiment Analysis

1. Monitoring Sentiment: The tool monitors the public's reactions and responses to ***ShapeFuture's*** goals and developments. This real-time sentiment analysis allows us to:

    - Identify key concerns and areas of interest: By understanding public perception, we can tailor our communication strategy to address specific needs and interests.
    - Track public opinion over time: Monitoring trends in sentiment helps us assess the effectiveness of our communication efforts and adjust them as needed.

2. Aligning Dissemination and Communication: Based on the insights gained from the Sentiment Analysis Tool, we can adapt our dissemination and communication outputs to better resonate with the audience. This leads to:

    - Increased Efficiency: The tool helps us target our communication efforts more effectively, maximizing the impact with fewer resources.
    - Enhanced Impact: Tailored messaging based on sentiment analysis encourages deeper engagement with the public and stakeholders, leading to a more significant project impact.

Innovation Dis.Co brings extensive experience in utilizing cutting-edge communication practices and AI algorithms for European Commission projects.
This expertise plays a key role in:

- Identifying **Key Pathways for Stakeholder Engagement**: By analyzing sentiment data, we can identify the most effective ways to engage with different stakeholders, fostering collaboration and support for the project.
- Achieving Optimal Communication Outcomes: Utilizing the Sentiment Analysis Tool and our communication expertise, we aim to optimize communication with stakeholders and the public, maximizing the project's overall impact.

In conclusion, the ***ShapeFuture*** project's tailored Sentiment Analysis Tool is a valuable asset in our dissemination and communication strategy. It allows us to gather crucial insights from the public, refine our messaging, and ultimately achieve optimal communication outcomes for the project.

1.6 Theoretical Background

Over the past years, Social Network Analytics (SNA) has emerged as a crucial and strategic tool for decision-makers worldwide. Electronic, traditional, and social media platforms have transformed into **valuable sources of user insights**, offering valuable information on technology and community trends. The ever-growing usage of social media has resulted in a vast amount of data scattered across the network. Particularly in the research and innovation field, maintaining a constant awareness of consumer demand and acceptance of new technologies, initiatives, and trends provides a significant competitive edge in designing and implementing a successful communication and dissemination plan that caters to the specific needs of the general audience.

However, the sheer volume of data, combined with their diverse formats such as videos, images, and text, necessitates the implementation of advanced data mining and analytics algorithms to process and extract useful information and insights. Our framework encompasses the following pillars:

- Social Influence
- Text mining and topic detection
- Sentiment Analysis

These pillars are further detailed in the subsequent subsections. For more comprehensive information on the theoretical approach, please refer to Annex 1.

1.6.1.1 Social Influence

Social Influence pertains to the impact that individuals have on each other's behavior within a network. It is a widely recognized and intuitive phenomenon in social networks [1]. The strength of social influence is influenced by several factors, including the strength of relationships between network users, the distance between users in the network, temporal effects, and the characteristics of both the network and its individuals. In the context of a social network, it is represented as a graph G = {V, E}, where V represents the set of nodes and E represents the set of edges. At a local level, social influence is a directional effect from node A to node B, associated with the strength of the edge connecting them. On a global level, certain nodes may possess intrinsic influence due to the network's structure. These global measures typically pertain to nodes rather than edges [2].

Social influence analysis aims to measure the influence of one person qualitatively and quantitatively on others. As social networking continues to play an increasingly significant role in the lives of millions of individuals, practical applications of social influence analysis are expected to grow. Influence in electronic and social media can be observed through changes in social action patterns, which encompass user behaviors within the social network. Recent research [3] has explored the learning of influence degrees based on historical user actions, while other studies [4][5] examine how social actions evolve within the network and how they are influenced by social influence factors [6].

1.6.1.1 Text mining and detection

Text mining encompasses a knowledge-intensive process where a user interacts with a collection of documents using various analysis tools over time. Like data mining, text mining's goal is to extract valuable information from data sources by identifying and exploring interesting patterns. However, in text mining, the data sources are

document collections, and interesting patterns are discovered within the unstructured textual data found in these documents.
Text mining draws inspiration and guidance from foundational research in data mining, resulting in high-level architectural similarities between text mining and data mining systems. Both types of systems rely on preprocessing routines, pattern discovery algorithms, and presentation-layer components such as visualization tools to facilitate the exploration of result sets. Additionally, text mining incorporates many of the specific types of patterns from data mining research into its core knowledge discovery operations.
While data mining assumes that data is already stored in a structured format, much of its preprocessing focuses on tasks like data scrubbing, normalization, and creating numerous table joins. In contrast, text mining preprocessing operations revolve around identifying and extracting representative features from natural language documents. These operations transform unstructured data stored in document collections into a more explicitly structured intermediate format, which is not typically a concern for most data mining systems.
Furthermore, due to the central role of natural language text, text mining leverages advancements made in other computer science disciplines that deal with natural language processing. Notably, text mining incorporates techniques and methodologies from information retrieval, information extraction, and corpus-based computational linguistics.

1.6.1.2 Sentiment Analysis

The task of categorizing an opinionated document as expressing an overall positive or negative sentiment is known as sentiment polarity classification or sentiment analysis. Sentiment analysis has mainly been explored in reviews, such as assigning "thumbs up" or "thumbs down" to movie reviews. However, there are other scenarios where the interpretation of "positive" and "negative" sentiments may have subtle differences. While evaluations in the review context are often subjective, there are cases where the classification of "positive" and "negative" sentiments differs in meaning.
Sentiment classification is not limited to strictly opinionated input. For instance, classifying a news article as good or bad news is considered a sentiment classification task in literature. However, a piece of news can be categorized as good or bad without being subjective or expressive of the author's personal states. For example, a statement like "the stock price rose" provides objective information that is considered good news in appropriate contexts. It is important to note that our main intention is not to provide a definitive definition for "sentiment polarity classification" problems. Nonetheless, the following points are worth mentioning:

- When determining the sentiment polarity of opinionated texts, where authors explicitly express their sentiment with statements like "this laptop is great," objective information such as "long battery life" is often taken into consideration to determine the overall sentiment.
- Assessing whether a piece of objective information is good or bad is still distinct from classifying it into topic-based classes, and therefore inherits the challenges associated with sentiment analysis.
- The differentiation between subjective and objective information can be nuanced and requires careful consideration.

1.6.2 The Methodology

We utilize advanced big data analysis and AI-based algorithms to gather and analyze real-time data from both electronic and traditional media. By incorporating the aforementioned theories and methodologies, our objective is to uncover valuable insights for the ***Shape Future*** project. These insights focus on the following aspects:

- Identifying the topics of discussion surrounding the Electronic Components and Systems (ECS) for highly automated vehicles.
- Understanding the sentiments and concerns expressed by individuals regarding these topics.
- Identifying influential individuals and their connections within the field of discussion.

To address these questions, we employ an AI-supported methodology that leverages machine learning algorithms specifically designed to effectively analyze text. Our approach is tailored to the industry in question, ensuring context-aware analysis that aligns with the sector under investigation.
By conducting sentiment analysis on the collected data, we gain valuable insights that inform the most effective dissemination and communication of the project results. This allows us to make timely and user-centric decisions. Specifically, we aim to address the following:

- Identifying the main obstacles and opportunities related to the adoption of the ***ShapeFuture*** project.
- Determining the channels through which people engage in discussions about the project's objectives.
- Creating content that addresses the identified needs, obstacles, and opportunities.
- Identifying key media outlets and influential individuals whose involvement can maximize the impact of the dissemination and communication plan.
- Constantly measuring people's sentiments throughout the project serves multiple purposes. It helps us better understand the needs of the general audience and provides continuous input regarding technology needs and demands (demand pull). This dynamic and insightful feedback allows us to continuously improve the effectiveness of our dissemination and communication plan.

The methodology underpinning ***ShapeFuture's*** **Sentiment Analysis Tool** is designed to deliver a robust, systematic, and actionable understanding of stakeholder perceptions toward the project's core technologies, including Electronic Components and Systems (ECS), AI-enabled decision-making, and autonomous mobility. Unlike generic social media listening approaches, this methodology is tailored to the following objectives:

- supporting technology acceptance
- accelerating adoption
- informing dissemination, communication, and exploitation decisions throughout the project lifecycle

At its core, the methodology follows a multi-layered process built around four main stages: (1) data acquisition and preprocessing, (2) stakeholder segmentation and classification, (3) sentiment and topic analysis, and (4) synthesis and strategic interpretation. This process is continuous and iterative, enabling the consortium to refine strategies dynamically as stakeholder attitudes evolve over time.

1. Data Acquisition and Preprocessing

The first step involves collecting and processing data from a diverse range of online and offline sources to ensure a representative understanding of stakeholder sentiment. This includes:

- Digital and social media: Twitter (X), LinkedIn, YouTube, blogs, forums, and discussion boards where industry experts, policymakers, and the public exchange opinions on mobility technologies.
- Traditional media: News articles, press releases, and policy papers that shape public narratives and influence policymaker perspectives.
- Academic and technical sources: Research publications, conference presentations, and white papers to capture expert-level discourse.
- Regulatory and policy communications: Statements, consultations, and regulatory updates from EU and national bodies that reflect governmental attitudes and directions.

Preprocessing involves **filtering noise, normalizing language** (e.g., handling synonyms and domain-specific terminology), and preparing the text for computational analysis through techniques such as **tokenisation, lemmatisation, and stop-word removal**. This ensures the data is clean, consistent, and relevant for subsequent analytical stages.

2. Stakeholder Segmentation and Classification

A critical enhancement to the methodology, is **the segmentation of sentiment data according to key stakeholder groups**. This approach recognises that different stakeholders have different priorities, influence levels, and roles in shaping technology adoption.

The segmentation layer classifies data into the following categories, based on metadata (e.g., author profile, organisation type, platform, and language) and contextual cues:

- **Industry stakeholders (OEMs, Tier-1/Tier-2 suppliers)**: Focused on technology maturity, integration complexity, cost, and return on investment.
- **Research and academia:** Interested in scientific advancements, validation, and collaborative opportunities.
- **Regulators and policymakers:** Concerned with safety, standardisation, ethical implications, and compliance frameworks.
- **Investors and financial ecosystem:** Evaluating market readiness, business models, and scalability potential.
- **Civil society and public users:** Focused on societal impact, privacy, safety, accessibility, and ethical concerns.
- **Media and influencers:** Shaping public narratives and framing perceptions of risk, opportunity, or disruption.

This segmentation is essential for identifying **who is driving conversations**, **what their main concerns and motivations are, and how they influence adoption decisions**. It also enables ***ShapeFuture*** to quantify the relative weight of each group's opinion and target its communication and engagement strategies with far greater precision.

3. Sentiment and Topic Analysis

Once segmented, the data undergoes a dual-layered analytical process:

Sentiment Analysis: Using natural language processing (NLP) models and machine learning classifiers, the system determines **the polarity** (positive, negative, neutral) and **intensity** (strongly or weakly expressed) of opinions within each stakeholder group. This includes detecting **emotional tone** (e.g., trust, fear, optimism, scepticism) and associating it with specific technologies or topics.

Topic Modelling and Trend Detection: Advanced topic-modelling algorithms (e.g., Latent Dirichlet Allocation – LDA) identify the most frequently discussed themes (e.g., safety, cybersecurity, cost, regulation, societal impact). Time-series analysis then tracks how these topics evolve, indicating shifts in attention, emerging concerns, or growing acceptance over time.
Together, these analyses generate a **multi-dimensional picture of stakeholder sentiment**, allowing ***ShapeFuture*** to see not only what people think, but also why they think it, and how those perceptions change across different contexts and timelines.

4. Synthesis and Strategic Interpretation
The final step of the methodology **transforms raw sentiment data into actionable intelligence for project partners**. This includes:
Barrier and driver mapping: Identifying key enablers (e.g., trust in AI safety mechanisms, perceived environmental benefits) and obstacles (e.g., data privacy fears, infrastructure readiness) that influence adoption trajectories.
Stakeholder impact scoring: Prioritising groups based on their influence on technology acceptance and tailoring communication campaigns accordingly.
Engagement strategy calibration: Informing decisions on message framing, tone, and channel selection for each stakeholder segment.
Feedback into exploitation planning: Feeding insights into business models, go-to-market strategies, and policy engagement plans to enhance the likelihood of adoption and scale-up.

Sentiment analysis within ***ShapeFuture*** is not a one-off exercise but an ongoing intelligence function. Analysis is updated periodically (initial, intermediate, and final reports) and presented to the consortium for discussion and strategic decision-making. Each new cycle provides richer longitudinal data, highlighting evolving stakeholder expectations and enabling the consortium to continuously adapt communication, dissemination, and exploitation actions for maximum impact.
By linking real-time stakeholder insights directly to project decision-making, this methodology ensures that ***ShapeFuture's*** communication is not only descriptive but strategically proactive, anticipating challenges, shaping narratives, and accelerating the societal, regulatory, and market conditions necessary for the successful adoption of ECS innovations and autonomous systems.

1.6.3 Implementation Roadmap

The successful integration of sentiment analysis into the ***ShapeFuture*** project relies not only on robust methodology but also on a **clear, phased implementation roadmap** that ensures the insights generated are continuously translated into **strategic action**. This roadmap spans the entire project lifecycle and is closely aligned with the project's communication, dissemination, and exploitation activities. Its primary objective is to create an **evidence-driven feedback loop** between public perception, stakeholder expectations, and project decision-making, enabling ***ShapeFuture*** to remain responsive, impactful, and adoption-focused from start to finish.

The implementation is structured into four main phases: **Initial Baseline Analysis, Continuous Monitoring, Periodic Strategic Reviews, and Final Evaluation & Exploitation Integration.**

Phase 1: Initial Baseline Analysis

The process begins during the early stages of the project with a comprehensive baseline sentiment analysis. This initial phase is crucial for establishing a reference point against which future sentiment dynamics and stakeholder attitudes can be measured. Key actions include:

- Stakeholder Mapping and Segmentation: Identifying and categorising the main stakeholder groups (industry, academia, regulators, investors, public, media, etc.) according to their influence on technology acceptance and adoption.
- Topic and Concern Identification: Analysing discourse around ECS technologies, autonomous mobility, AI decision-making, data security, and related areas to detect prevailing narratives, recurring themes, and emerging issues.
- Sentiment Benchmarking: Measuring baseline sentiment polarity (positive, neutral, negative) for each stakeholder group and mapping perceptions to specific factors such as safety, regulation, cost, privacy, and societal impact.
- Opportunity and Risk Assessment: Highlighting early opportunities for stakeholder engagement and potential risks or misconceptions that require targeted communication interventions.

The outcome of the first phase is a foundational report summarising public and stakeholder sentiment, identifying adoption barriers and enablers, and outlining key communication priorities for the first 12–18 months of the project.

Phase 2: Continuous Monitoring and Data Collection

Following the baseline analysis, sentiment tracking enters a continuous monitoring phase. This involves regular (monthly or quarterly) data collection and analysis to capture evolving perceptions, new trends, and emerging stakeholder concerns. This phase ensures that communication strategies remain agile and responsive. Key components include:

- Real-Time Sentiment Tracking: Automated data collection from online and traditional media to capture fluctuations in public and stakeholder attitudes in near real-time.
- Stakeholder-Specific Dashboards: Generation of dynamic dashboards that visualise sentiment evolution per stakeholder group, allowing partners to identify shifts in perception and adapt engagement tactics accordingly.
- Early Warning Signals: Detection of negative sentiment spikes or misinformation trends that could influence adoption trajectories, triggering rapid response campaigns or targeted outreach.
- Influencer and Opinion Leader Mapping: Identifying key voices and communities shaping public opinion and assessing their potential role in accelerating or hindering technology adoption.

The outcome of this phase is a continuous intelligence flow into the communication and dissemination work plan, enabling rapid strategic adjustments and proactive engagement to support technology acceptance.

Phase 3: Periodic Strategic Reviews and Adaptive Communication

At critical milestones (typically every 12 months), the consortium may conduct in-depth strategic sentiment reviews. These reviews consolidate continuous monitoring data into actionable insights and link them directly to project activities. Each review includes:

- Evaluating how each group's attitudes have shifted and identifying what factors (e.g., safety demonstrations, policy developments, media narratives) contributed to these changes.
- Identifying persistent obstacles to acceptance (e.g., regulatory uncertainty, privacy concerns, infrastructure limitations) and recommending targeted communication, policy engagement, or exploitation actions to address them.
- Refining messaging, tone, and channel strategies to better resonate with each stakeholder group, based on updated sentiment patterns.
- Strategic Alignment with Policy and Exploitation Plans: Ensuring that communication activities align with evolving policy agendas and market conditions, supporting downstream exploitation and commercialisation objectives.

The outcome of this phase is a sentiment report delivered to the consortium, forming the basis for updated dissemination and exploitation roadmaps and ensuring continued alignment with stakeholder expectations.

Phase 4: Final Evaluation and Exploitation Integration

The final phase of the roadmap focuses on synthesising the full body of sentiment data collected throughout the project into a comprehensive evaluation that informs ***ShapeFuture's*** legacy strategies and post-project activities. This phase includes:

- **Sentiment Evolution Analysis**: Assessing how stakeholder perceptions have changed from project inception to completion, and how these shifts correlate with project milestones, demonstrations, and external events.
- **Technology Acceptance Scorecards**: Creating evidence-based scorecards that evaluate the readiness and acceptance level of ***ShapeFuture*** technologies among each stakeholder group. These scorecards can inform business models, policy recommendations, and future R&I strategies.
- **Integration with Exploitation Plans**: Translating sentiment insights into concrete exploitation strategies, including recommendations for commercial positioning, go-to-market messaging, standardisation contributions, and regulatory advocacy.
- **Post-Project Recommendations**: Delivering a set of best practices and strategic recommendations for future communication and dissemination activities, ensuring sustained visibility, impact, and stakeholder support beyond the project's lifetime.

The outcome of the last phase is a final Sentiment and Stakeholder Perception Report that not only measures communication success but also provides actionable intelligence to support exploitation, market introduction, and continued stakeholder engagement.

A defining feature of the implementation roadmap is its feedback-driven structure. Insights generated from sentiment analysis continuously flow back into ***ShapeFuture's*** communication, dissemination, and exploitation work. This iterative process allows the project to:

- Adjust key messages to address evolving concerns or emphasise emerging benefits.
- Reallocate resources to focus on channels and stakeholder groups with the highest impact potential.
- Adapt exploitation strategies based on shifting market sentiment and regulatory landscapes.
- Influence policy dialogues and public narratives to create more favourable conditions for technology deployment.

1.7 Initial Sentiment Analysis

The initial sentiment analysis conducted in the early phase of ***ShapeFuture*** provides a foundational understanding of public and stakeholder perceptions surrounding the project's core technological domains, including Electronic Components and Systems (ECS), autonomous vehicle innovation, AI-enabled decision-making, European mobility sovereignty, and the evolving automotive supply chain. This baseline assessment is a crucial input to ***ShapeFuture's*** dissemination and engagement strategy, serving as the first diagnostic layer in a continuous cycle of perception monitoring, strategic communication adjustment, and adoption-focused stakeholder engagement.

1.7.1 Objectives of the Initial Sentiment Analysis

The objectives of the first sentiment assessment include:

- Establishing a Perception Baseline: Determining how stakeholders perceive the project's main thematic areas and where existing narratives stand on the spectrum from optimism to scepticism.
- Identifying Adoption Barriers and Enablers: Detecting early signs of resistance or enthusiasm. such as concerns over data privacy or excitement about environmental benefits, that will directly influence future uptake.
- Guiding Communication Priorities: Providing evidence to fine-tune initial messaging, outreach campaigns, and media engagement.
- Supporting Stakeholder-Specific Strategies: Highlighting differences in perception across key stakeholder groups to enable more effective, targeted engagement approaches.

1.7.2 Stakeholder Segmentation and Analysis Approach

The initial sentiment data was analysed through a stakeholder-segmented lens to reveal how attitudes vary across different groups and to identify their likely impact on technology acceptance. This segmentation is crucial for designing tailored communication strategies and prioritising engagement efforts.
The analysis focused on the following groups:

- **Industry (OEMs, Tier 1 & Tier 2 suppliers):** Conversations focused on technological maturity, integration challenges, cost, and time-to-market. Positive sentiment was high around European leadership and business potential, while concerns were noted about integration complexity and standardisation.
- **Policy and Regulatory Stakeholders:** Discussions often centred on safety, liability, and regulatory readiness. Although sentiment was largely neutral-to-positive, a significant share highlighted the need for robust legal and ethical frameworks.
- **Research and Academia:** Strongly positive sentiment was observed here, focusing on innovation potential, collaborative opportunities, and scientific advances.
- **Civil Society and End-Users:** Sentiment was mixed, enthusiasm about increased safety, accessibility, and environmental benefits was tempered by concerns over privacy, data use, and trust in autonomous decision-making.
- **Media and Public Opinion Leaders:** Media narratives were generally positive but occasionally alarmist, particularly around cybersecurity and employment disruption due to automation.

This segmentation reveals that while enthusiasm and optimism dominate in the research and industrial spheres, public trust and regulatory confidence remain critical challenges that must be addressed through targeted messaging, policy engagement, and transparent communication.

1.7.3 Key Findings and Quantitative Indicators

The first wave of sentiment data, collected from May 2024 to September 2024 across social media, online news, and forums, provided the following:

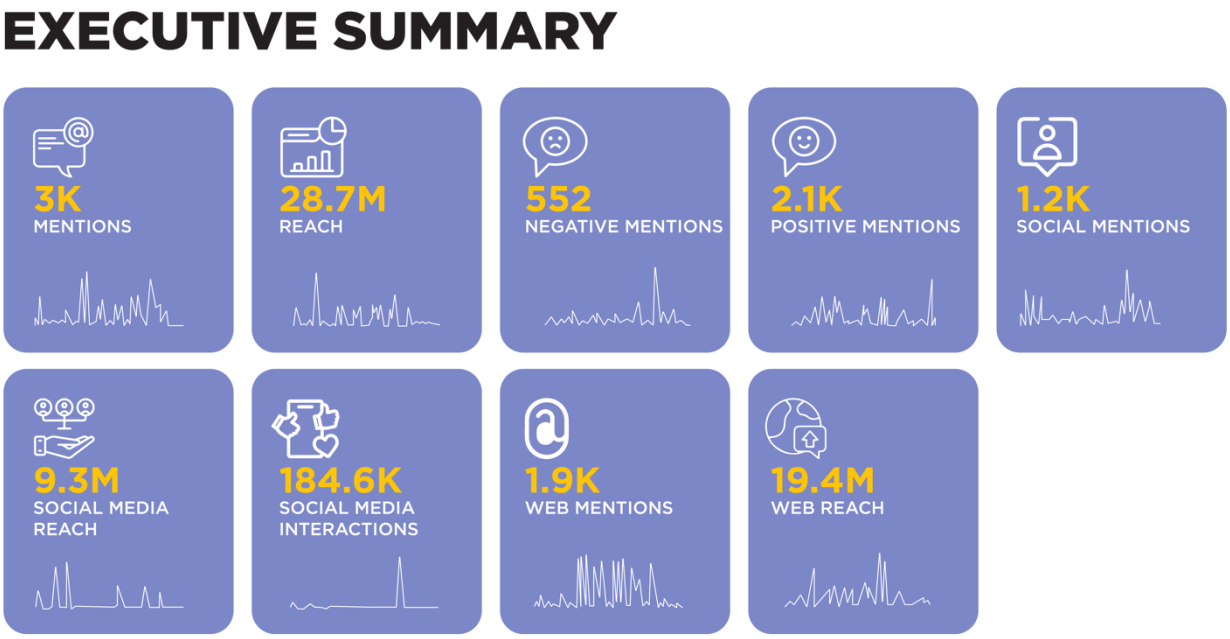


Figure 3: 1st Sentiment Analysis Summary

The first Executive Summary as shown in Figure 3 above, provides a comprehensive overview of the digital footprint, reach, and sentiment of the people cocnerning the innovations in Electronic Components & Systems (ECS) since May 2024 when the ***ShapeFuture*** project started. Key metrics include:

1. **Mentions**: A total of 3,000 mentions, indicating significant visibility and engagement across various platforms.
2. **Total Reach**: With a reach of 28.7 million, the project's topic concerns a wide audience, reflecting strong dissemination and message spread.
3. **Sentiment Analysis**:
    - **Negative Mentions**: Out of the total mentions, 552 were identified as negative, representing a small portion of the overall sentiment but indicating areas for potential improvement or clarification.
    - **Positive Mentions**: With 2,100 positive mentions, the campaign saw a favorable response from a majority of the audience.
4. **Social Mentions**: There were 1,200 social mentions, highlighting the public interest across platforms.

5. **Social Media Reach and Interactions**: Social media reach was 9.3 million, and interactions totaled 184,600, showcasing strong engagement from the audience and indicating that the topic interests social media users.
6. **Web Mentions and Web Reach**: A total of 1,900 web mentions were identified with a web reach of 19.4 million, illustrating robust online presence and visibility of the topic of Electronic Components and Systems (ECS) for highly automated vehicles beyond social media channels.

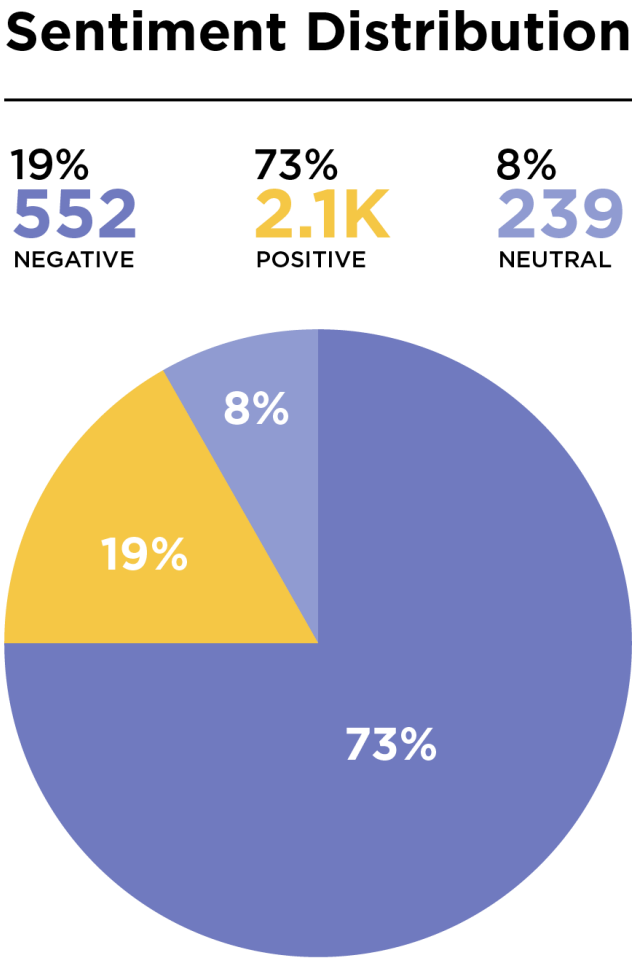


Figure 4: Sentiment Distribution

The **sentiment analysis** breakdown as shown in Figure 4, illustrates the proportions of positive, negative, and neutral responses based on the main keywords selected for the project:

- Positive (73%): Focused on Europe's leadership in ECS innovation, sustainability, improved mobility, and job creation.
- Negative (19%): Concentrated around safety risks, data privacy, job displacement, and infrastructure readiness.
- Neutral (8%):Reflecting factual reporting or balanced debate without strong opinion.

- Engagement Indicators: 1,200 social mentions, 184,600 interactions, and 19.4 million web reach show robust audience engagement.

This distribution demonstrates an encouraging initial public reception but also highlights areas that require strategic communication interventions to mitigate misconceptions and address trust gaps. This sentiment breakdown supports the understanding that the project's main keywords achieved favorable audience perception while also highlighting areas for targeted improvement. Together, the Executive Summary and Sentiment Distribution provide a holistic view of the project's impact, reach, and audience perception.

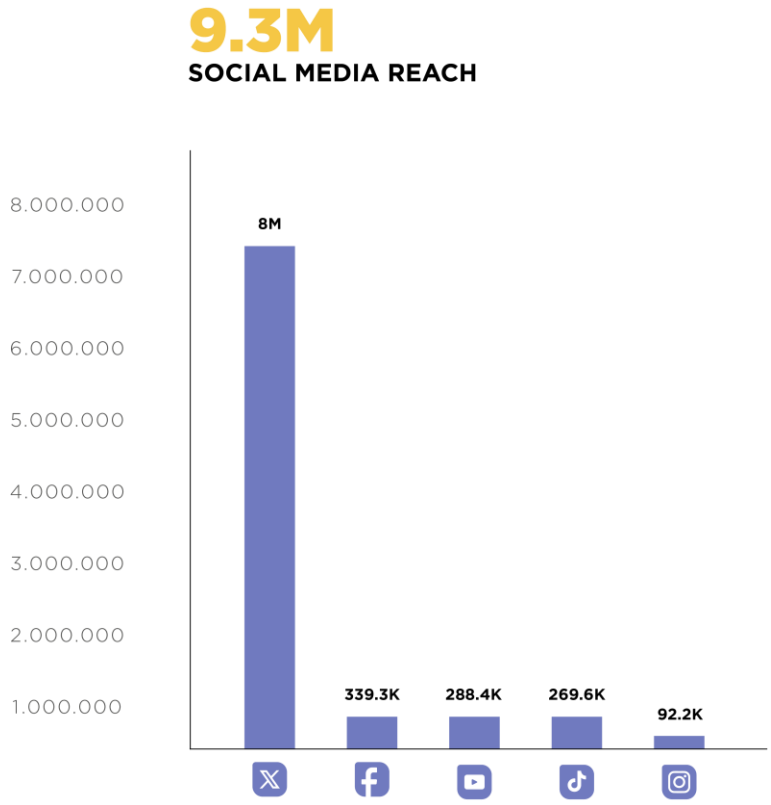


Figure 5: Social Media Reach

This chart provides a breakdown of social media reach across different platforms from May 2024 to the present. The total social media reach achieved is 9.3 million, with notable differences in platform-specific engagement:

1. **Platform Reach Distribution**:
    - **X (formerly Twitter)**: Dominated the reach with approximately 7 million, showing that this platform was the primary driver of visibility concerning our main keywords.
    - **Facebook, YouTube, TikTok, and Instagram**: Each had considerably lower reach, with Facebook and YouTube reaching similar levels just under 1 million each. TikTok and Instagram contributed smaller portions, indicating limited engagement on these platforms relative to X.
    - **LinedIn**: Does not seem to be a significant communication channel for the specific topic.

This distribution highlights the strong presence and performance on X, making it the most impactful social media channel for the project's topic.

1.7.4 Topic-Level Insights: Barriers and Enablers

The below table shows examples of topics of **positive** and **negative** sentiment that arise concerning the ***ShapeFuture*** project, with a focus on ECS Innovation, Automated Vehicles, European Mobility, AI-Enabled Decision Making, and the EU Automotive Supply Chain:

Table 2: Examples of positive & negative topics analyzed on web

Positive topics	Negative topics
• **Enhanced Safety and Reliability**: Positive feedback on advancements that improve the safety, security, and reliability of automated vehicles through ECS innovation. • **Environmental Impact**: Appreciation for the project's focus on sustainable mobility, reducing emissions, and supporting the EU's climate goals. • **Technological Leadership in Europe**: Positive sentiment about Europe leading in ECS technology, strengthening its automotive supply chain and creating economic opportunities. • **Improved Mobility and Accessibility**: Support for the role of automated vehicles in enhancing public mobility, particularly for the elderly and people with disabilities. • **AI-Enabled Decision Making**: Positive reactions to the use of AI to improve decision-making processes in automated vehicles, leading to safer and more responsive systems. • **Job Creation in Tech and Innovation**: Optimism regarding new job opportunities in AI, automotive technology, and ECS development in Europe.	• **Job Loss in Traditional Automotive Roles**: Concerns about the impact of automation and AI on traditional automotive jobs, with potential job losses in manufacturing and driving roles. • **Privacy and Data Security**: Worries about data privacy and security in automated vehicles, particularly regarding AI-enabled decision-making and data collection. • **Technological Reliability and Safety Risks**: Fears about the reliability of ECS and AI in critical situations, especially in cases of system failure or hacking. • **Cost of Innovation**: Criticism of the high cost of ECS innovation and automated vehicle development, and concerns that it could increase vehicle prices or require significant public investment. • **Environmental Concerns Regarding ECS Production**: Negative sentiment around the environmental impact of ECS production and electronic waste from advanced automotive systems. • **Lag in Infrastructure Development**: Frustration over the potential mismatch between the pace of innovation in automated vehicles and the slower progress in necessary infrastructure, such as smart roads and charging networks.

These findings provide an **early map of the psychological and practical landscape** that will shape stakeholder decisions over the coming years. They underscore the

need for continuous monitoring and proactive communication strategies tailored to address these issues head-on.

1.7.5 Implications for Communication and Adoption Strategy

The initial sentiment analysis is not a static report, it is a strategic input into the project's dissemination and exploitation planning. It informs several key strategic directions for the next phases:

- **Targeted Messaging:** Future campaigns will address specific concerns (e.g., privacy, safety, cost) directly and transparently, building trust and confidence.
- **Stakeholder Prioritisation:** Engagement strategies will focus on groups whose perceptions most influence adoption, namely, policymakers, end-users, and industry decision-makers.
- **Policy Dialogue:** Findings will shape the project's approach to regulatory engagement, contributing to discussions on standards, ethics, and liability.
- **Exploitation Readiness:** Early sentiment indicators will guide market-entry planning, helping partners design value propositions that resonate with customer and societal priorities.
- **Trust-Building Initiatives:** Continuous communication, public demonstrations, open data policies, and participatory workshops will be developed to address scepticism and increase acceptance.

1.7.6 Next Steps: Towards a Dynamic Sentiment Intelligence Framework

This initial analysis represents the starting point of an evolving intelligence cycle. Future iterations will include deeper sentiment segmentation, real-time monitoring dashboards, and longitudinal studies of opinion dynamics.

As ***ShapeFuture*** progresses, sentiment analysis will serve not just as a measurement tool but as a strategic driver of adoption, informing decisions across communication, dissemination, exploitation, and policy impact activities.

Ultimately, the insights gained from the initial sentiment analysis underscore the importance of a stakeholder-centred, evidence-based approach to communication. By understanding how different actors perceive ***ShapeFuture*** technologies, and why, the project can tailor its actions to reduce resistance, amplify support, and accelerate the path from technological innovation to real-world adoption.

1.8 Dissemination Roadmap

The ***ShapeFuture*** project was launched in May 2024 with an introductory kick off meeting. A critical phase in the project's dissemination strategy involved the development and implementation of the project's website. The website mockups were designed by Innovation Dis.Co to visually represent the project's goals, methodology, and expected outcomes. In collaboration with our OTH partner, these mockups were transformed into a fully functional website. As the project unfolds, 3 dissemination plans will be executed, including the presentation of the dissemination strategy, project KPIs, the project's brand identity and the project's publications and dissemination activities. These activities will ensure the project's impact reaches a diverse audience, including researchers, policymakers, industry professionals, and the general public. The final dissemination event, scheduled for April 30, 2027, will mark the completion of these efforts, providing a platform to share the project's achievements and future prospects.

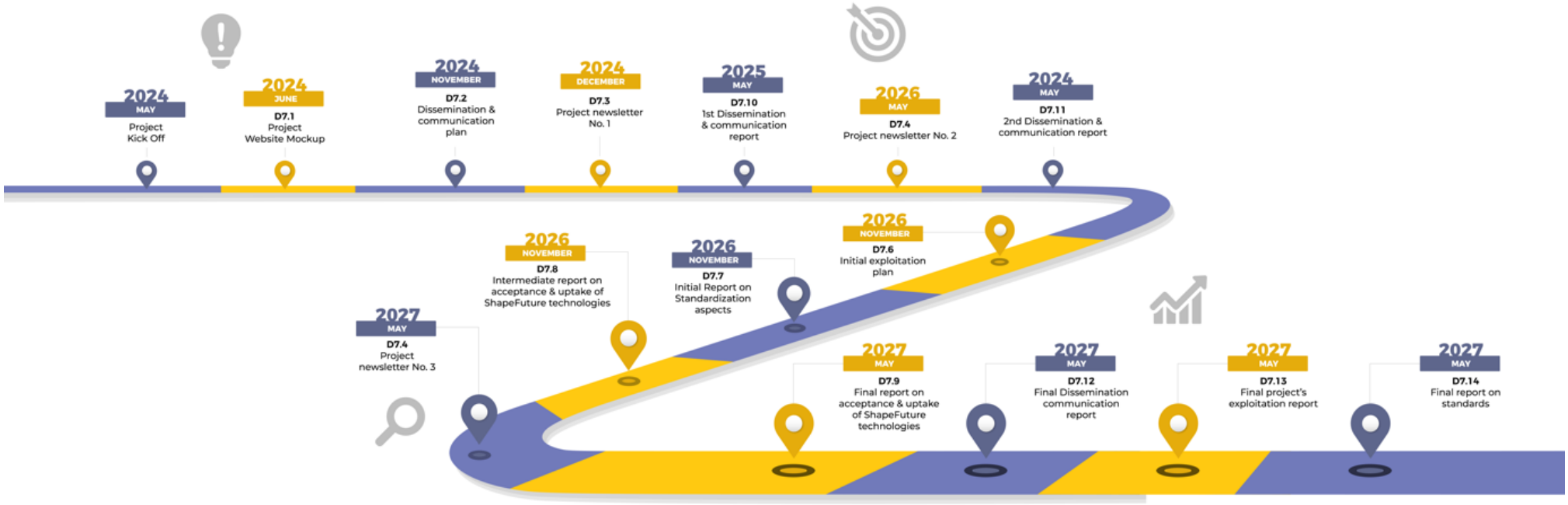


Figure 6: Dissemination & Communication Roadmap

Project Visual Identity

The visual identity package consists of the project's logo versions, colour palette, visualizations, typefaces, branding ideas, and Templates for Minutes and PowerPoint presentations.

1.9 Project's Logo

The project's logo has been created in different formats to serve different purposes.

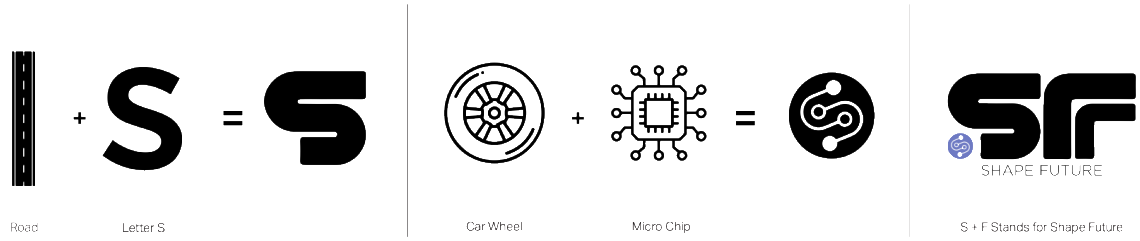


Figure 7: The Project logo and inspiration

1.10 Color Palette

A palette based on purple, yellow, black & white has been chosen as shown below:

Figure 8: Color Palette

1.11 Visual Examples

In the project's Brand Book, some visual examples are included in order to explain the way posts in the social media channels and news will be presented, having a coherent look and feel according to the suggested colors and typefaces:

Figure 9: Visual examples

1.12 Typefaces

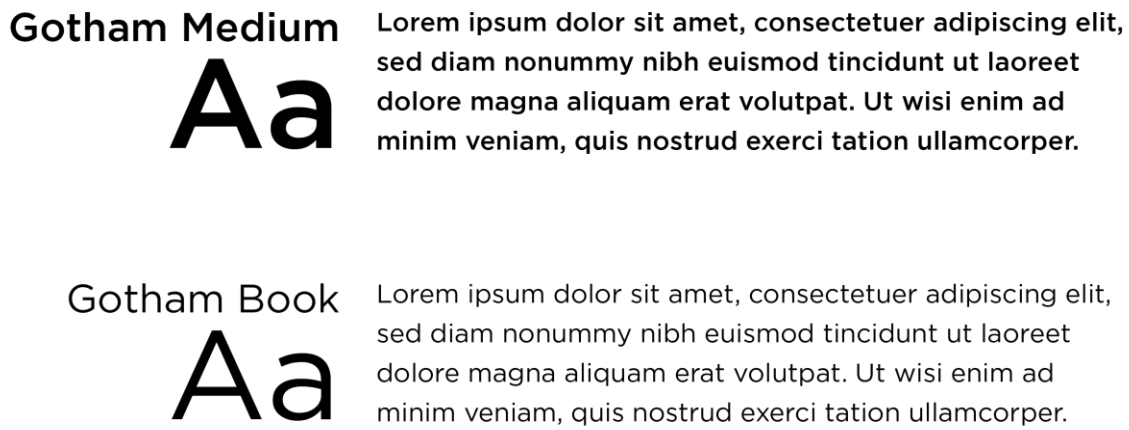


Figure 10: Typefaces

Project Website

The ***ShapeFuture*** project has taken the initial steps towards establishing a strong online presence by developing a website. The project website mockups, designed by Innovation Dis.Co, provide a blueprint for the website's visual elements, content structure, and user experience. In collaboration with OTH, these mockups are being transformed into a fully functional website, ensuring a cohesive and informative online platform.

1.13 Structure of the website

This section presents the pages that comprise the website, as displayed in the Main Navigation Panel (Header).

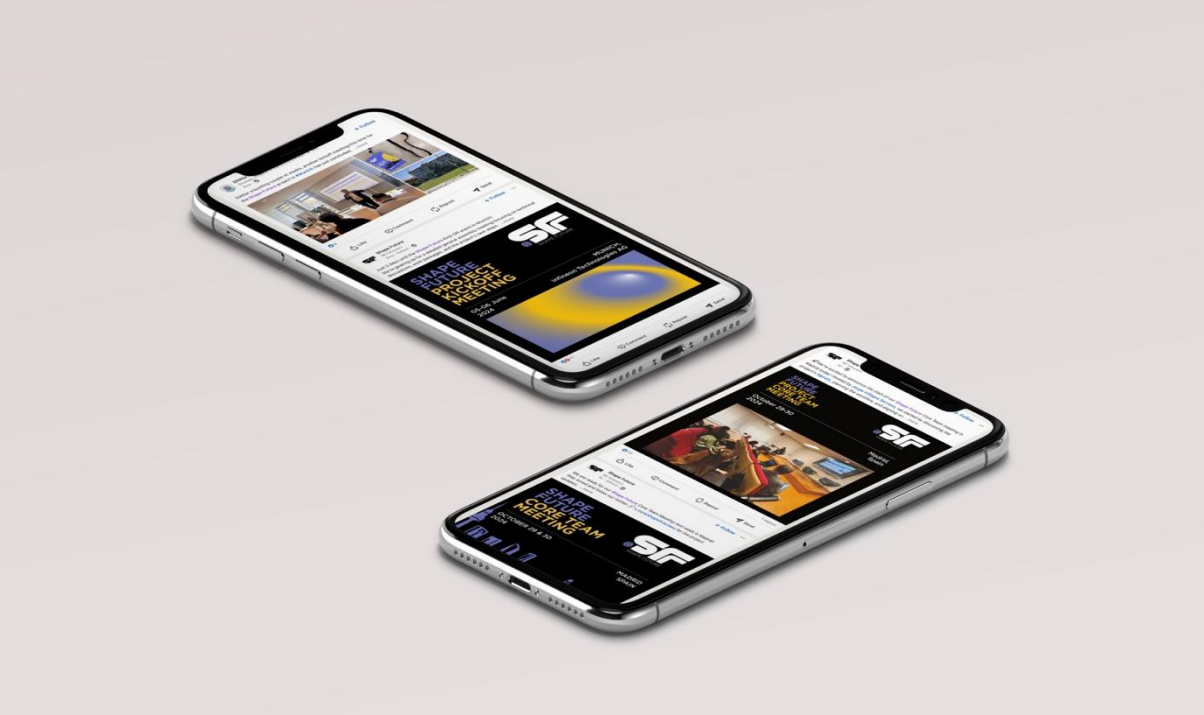
1.13.1 Home Page

The website's public landing page displays the project logo, the project's vision and partner count, along with an overview of the project's primary objective. Also, by scrolling down, the visitor can be informed by the project's news section.

Figure 11: Project's Website

Shape Future Social Media

The ***ShapeFuture*** project recognizes the importance of a strong online presence to effectively communicate project information and engage with a diverse audience. By utilizing social media platforms, the project aims to increase visibility, foster collaboration, and encourage public participation.



5.1 Social Media Strategy

The proposed social media strategy for the ***ShapeFuture*** project is well-aligned with the project's goals and target audience, focusing on LinkedIn, YouTube, and X (Twitter), platforms popular among professionals, researchers, and the public. This strategy is further strengthened with Innovation Disco's team of experts.

The emphasis on creating high-quality content aligns perfectly with Innovation Disco's expertise. We will work closely with the project team to develop engaging content across all platforms, fostering a strong community around the Shape Future project.

Our Strategy includes the following Social Media Platforms are are the most popular concerning the topic of our project:

LinkedIn offers a professional network ideal for reaching project stakeholders. It is a valuable platform for the ***ShapeFuture*** project as it allows for networking, sharing industry-related content, and engaging in relevant discussions. By utilizing LinkedIn, ***ShapeFuture*** can connect with key stakeholders, such as researchers, policymakers, and industry leaders, building a professional community interested in the project.

Innovation Dis.Co will help establish the project and its team through regular articles, newsletters, blog posts, and insightful participation in relevant groups. While organic reach limitations exist, Innovation Dis.Co has experience in crafting compelling

content and utilizing targeted advertising strategies to maximize audience engagement.

YouTube provides a powerful platform for highlighting the project's visual aspects. This platform allows for engaging storytelling and can effectively communicate the project's goals, progress, and impact to a wider audience. Additionally, YouTube's searchability and shareability make it a powerful tool for reaching new viewers and increasing brand exposure.

Innovation Dis.Co's team of video production experts will handle everything from shooting and editing to promotion and audience engagement. This ensures high-quality videos optimized for search, driving organic traffic, and increasing project visibility.

We understand the importance of real-time updates on **X (Twitter)**. By using hashtags and engaging with industry influencers, S***hapeFuture*** can increase its visibility and reach a larger audience. Twitter also allows for real-time interactions, making it a valuable tool for engaging with the target audience and addressing queries or feedback promptly.

We will collaborate with the project team to share timely news and updates, strategically utilizing relevant hashtags to maximize reach. Innovation

The proposed strategy acknowledges the potential challenges of each platform, such as organic reach limitations on LinkedIn and the competitive nature of YouTube. Innovation Dis.Co's expertise lies in mitigating these challenges through creative content strategies, targeted advertising, and ongoing analytics monitoring. By continuously analyzing the effectiveness of the strategy, we will make data-driven adjustments to optimize performance on each platform.
In conclusion, the proposed social media strategy offers a solid structure to effectively reach the ***ShapeFuture*** project's target audience, build brand awareness, and achieve project goals.

1.14 Social Media Platforms

By utilizing the following social media platforms as part of the marketing strategy, ***ShapeFuture*** can effectively connect with its target audience, increase brand awareness, and drive engagement and traffic to its website.

Table 3: Social Media Platforms

Social Media Channel	Direct link
Linkedin	https://www.linkedin.com/company/shape-future-project
Twitter	https://x.com/shapefutureeu
YouTube	https://www.youtube.com/channel/UCd5C3Wm_zs6njsx9jdWLcoQ

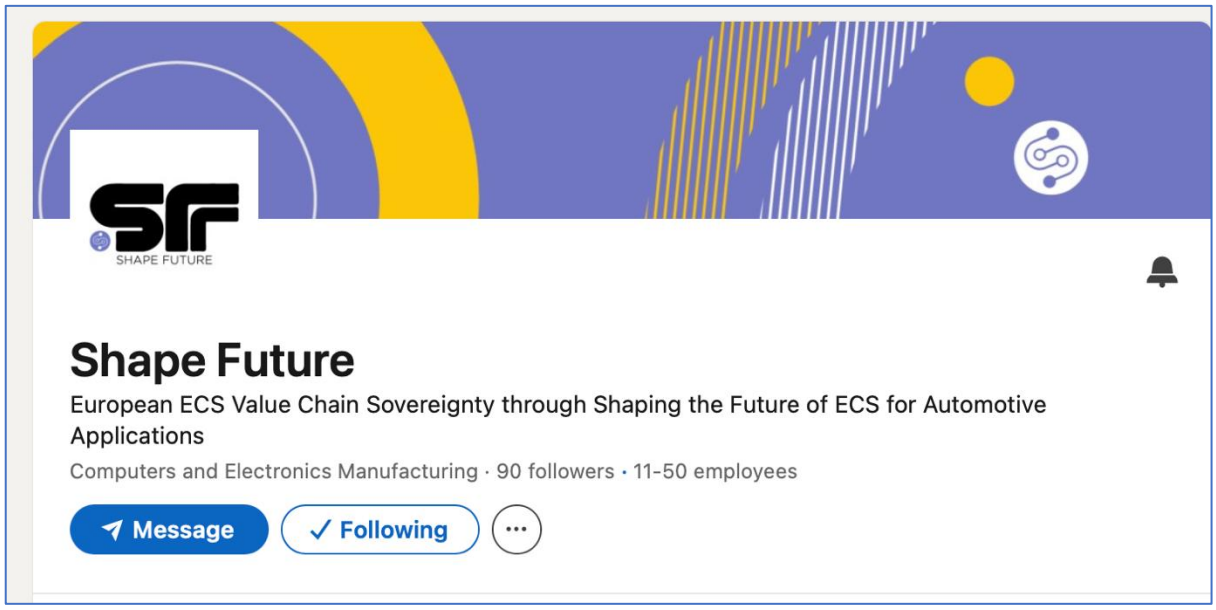


Figure 11: Project's LinkedIn Channel

Figure 12: Project's X (Twitter) Channel

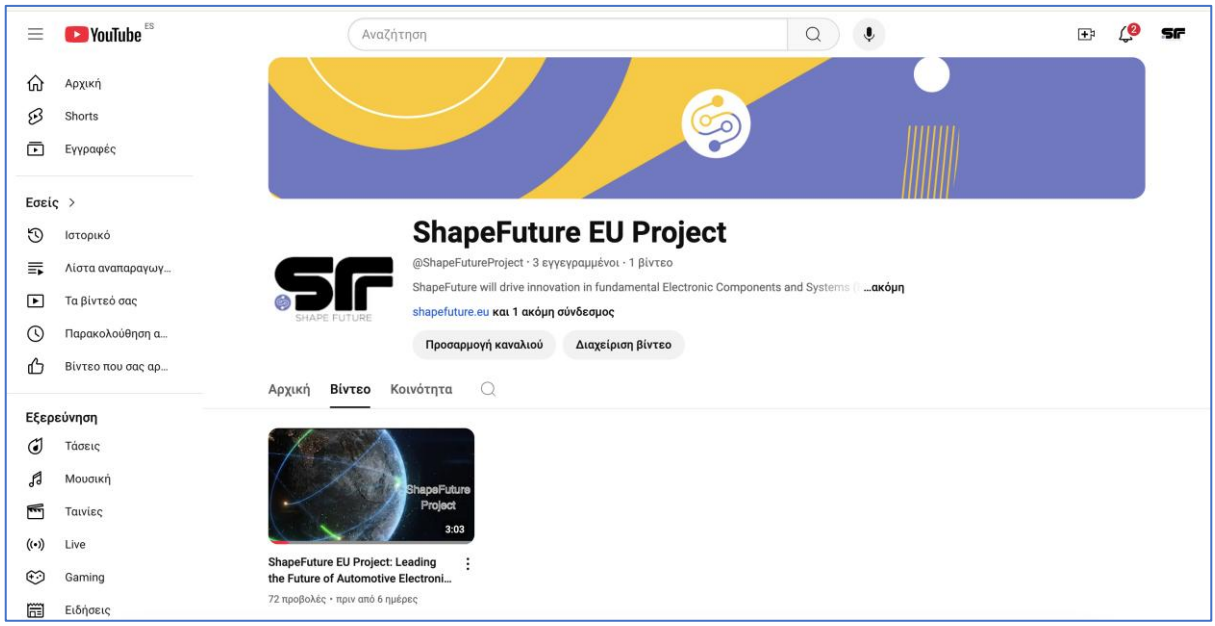


Figure 13: Project's YouTube Channel

1.15 Social Media Guidelines

The purpose of the guideline is to provide a comprehensive overview of the various components and recommended applications of the ***ShapeFuture*** identity. It is designed for both internal and external use, aiming to ensure that all members adhere to the correct implementation of the identity. This fosters a sense of unity in communication among all members and enhances overall visibility.

1.15.1 LinkedIn

LinkedIn provides an excellent opportunity to connect with a specific and growing user base. Therefore, the target audience for ***ShapeFuture*** will primarily consist of sector-specific groups such as technical groups, researchers, academia, professional associations etc. As LinkedIn has a more formal nature, it is important to use language that is relevant to the S***hapeFuture*** project.

To maximize engagement and reach, it is recommended to use relevant hashtags whenever possible. Additionally, mentioning the ***ShapeFuture*** project in all communication and posts can help encourage engagement through comments and notifications to your connections. This allows for the following benefits:

1. Increased visibility: By mentioning the ***ShapeFuture*** project, our connections will be notified and more likely to engage with our posts, thereby increasing the visibility of your content.

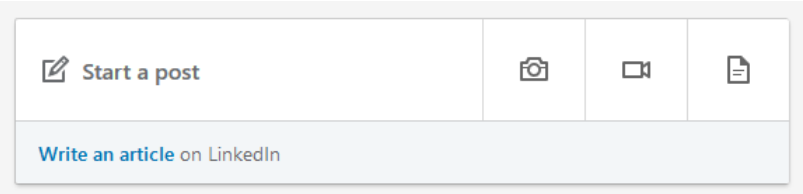
2. Enhanced networking: Connecting with individuals who have an interest in the ***ShapeFuture*** project can lead to valuable networking opportunities and potential collaborations.

3. Targeted communication: By focusing on the ***ShapeFuture*** project in our LinkedIn communication, we can ensure that our message reaches a relevant audience who are interested in the initiative.

Overall, LinkedIn offers a platform to connect with a specific audience and leveraging the project in our communication can help drive engagement and expand our network.

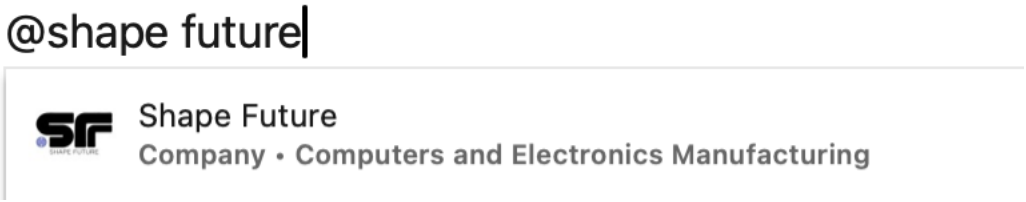
To include a mention of the ***ShapeFuture*** project in a post, it is recommended to follow these steps:

1. A post or an article should be written on a LinkedIn personal or company profile. This can be done by:
    - starting a new post/article



    - reposting/commenting someone else's post/article

2. Typing "@" and then begin typing a name ***ShapeFuture*** project in the box. Choosing the ***ShapeFuture*** project profile from the list and continue/finish typing the message.



1.15.1.1 Use of LinkedIn hashtags

Including hashtags in LinkedIn posts and articles increases the chance of being discovered by LinkedIn members who follow or search for those specific hashtags. Here is a step-by-step guide on how we use hashtags to a LinkedIn update:

1. We write a post or article on our LinkedIn personal or company profile.
2. We Identify words or phrases that we want to highlight as search criteria.
3. We add the # symbol in front of these words or phrases to turn them into hashtags. For example, in case we want to highlight the word "technology," you would write it as " #technology".
4. We continue writing our post or article, incorporating these hashtags where appropriate.
5. Once we publish our update, LinkedIn members who follow or search for these hashtags will have a higher chance of discovering our post or article.

By utilizing hashtags on LinkedIn, we can increase the visibility and reach of our content to a targeted audience who are interested in the topics we are discussing.

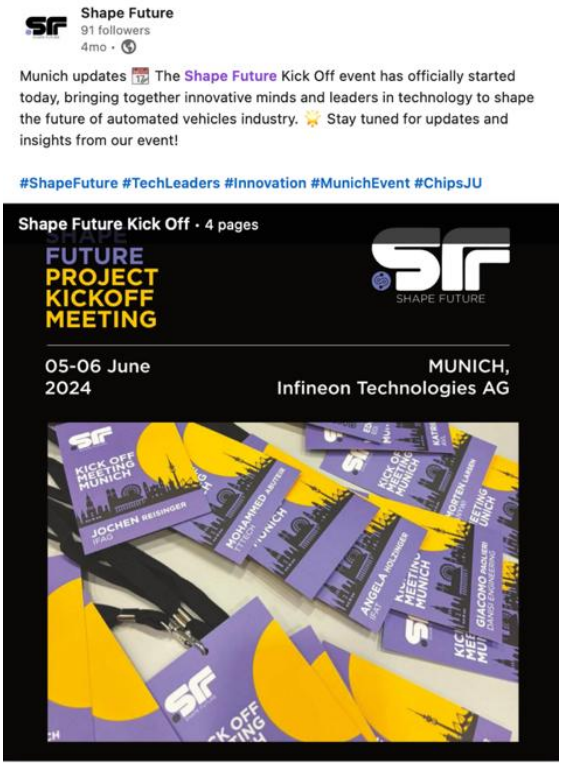


Figure 14: Visual Example of hashtags

1.15.2 Twitter (X)

X provides an ideal platform for connecting with a wide range of target audiences, including the public and professionals. The primary objective is to attract followers who are interested in relevant topics, while also keeping the consortium informed about Electronic Components and Systems (ECS) for highly automated vehicles trends. This approach facilitates effective communication and dissemination of project activities. Given the nature of the X platform, it is important to keep posts concise. Additionally, including images or videos to support the content is highly recommended. Hashtags (#) should also be included in tweets to help categorize and increase visibility, such as using #ShapeFutureproject for posts related to the project. Relevant posts mentioning the ***ShapeFuture*** project may also be retweeted to further amplify their reach.

To mention the iproject and add hashtags to X posts, we follow the same steps mentioned in the chapter about LinkedIn. This includes writing our tweet, adding relevant hashtags, and incorporating the ***ShapeFuture*** project in our communication to engage with your audience effectively. By leveraging these strategies, we can maximize the impact of our X presence and effectively reach our target audience.

YouTube

So far we have uploaded a video titled "*ShapeFuture* EU Project: Leading the Future of Automotive Electronic Components & Systems" on our YouTube channel. This video serves as an introduction to the project, highlighting its mission to revolutionize the future of mobility. By showcasing the groundbreaking innovations in Electronic Components & Systems (ECS), the video aims to engage a wider audience, including researchers, industry professionals, and policymakers. This visual representation of the project's vision and goals will help attract potential partners and inspire future advancements in the automotive industry.

Figure 15: Project's 1st YouTube video

Concerning our video strategy, a number of **video interviews** will be created during the project's lifetime, to inform project's audience on all technical aspects of the project.
A number of **general videos** will be created as well, presenting all the project's meeting and showcasing the project's progress.
The above videos are planned to be promoted through paid campaigns on project's social media platforms.

1.15.2.1 Hashtag Strategy

Developing a hashtag strategy for ***ShapeFuture*** is crucial to effectively reach and engage the target audience on social media platforms. Here are some key considerations we have considered while developing the hashtag strategy for the ***ShapeFuture*** project:

1. Research and Analysis: We conduct thorough research to identify popular and relevant to the project hashtags. Analyse the performance and engagement levels of these hashtags to determine their effectiveness in reaching the target audience.

2. Brand-Specific Hashtags: We create unique and memorable hashtags specifically for the ***ShapeFuture*** project. These can include the project name or a catchy phrase that aligns with the project's objectives. We encourage the target audience to use these hashtags when discussing or sharing content related to ***ShapeFuture***. This helps in building brand recognition and fostering a sense of community.

3. Industry-Specific Hashtags: We utilize industry-specific hashtags that are commonly used by professionals, influencers, and organizations in the field. These hashtags can help increase the visibility of ***ShapeFuture*** content among relevant communities and attract industry-specific engagement.

4. Trending and Event-Related Hashtags: We stay updated with trending topics, events, conferences, or industry-specific discussions. We incorporate these trending hashtags into ***ShapeFuture*** content when relevant to increase visibility

and join relevant conversations. This strategy helps in capitalizing on current trends and expanding the reach of ***ShapeFuture*** content beyond the existing audience.

5. Hashtag Consistency: We ensure consistent use of hashtags across different social media platforms and content types. This helps in creating a recognizable and cohesive brand presence. We regularly monitor the performance and engagement levels of different hashtags to assess their effectiveness and adjust if needed.

6. Engagement and Community Building: We actively engage with users who use ***ShapeFuture*** related hashtags by liking, commenting, and sharing their content. This helps in building relationships, increasing visibility, and fostering a sense of community around the ***ShapeFuture*** project.

Here are some relevant hashtags for the ***ShapeFuture*** project and its related topics:

#ShapeFuture #technology #EU #horizonEU #supplychain #innovation #collaboration #researchproject #EUfunding #ShapeFutureproject #ECSInnovation #AutomatedVehicles #EuropeanMobility #AIEnabledDecisionMaking #futureofmobility #smartmobility #autonomousvehicles #mobilityinnovation #EUmobilitypolicy

These hashtags can help categorize and increase the visibility of our tweets and posts related to the ***ShapeFuture*** project and its various aspects. We use them strategically and in conjunction with relevant content to engage our target audience effectively.

1.15.3 Audience Engagement

Engaging the audience is crucial for the success of the ***ShapeFuture*** project. Here are some key actions we have taken to enhance audience engagement:

- Creating Interactive Content: We develop content that encourages audience participation and interaction. This can include polls related to #AutomatedVehicles. We encourage the audience to share their opinions, experiences, and ideas related to the topics discussed.

- Responding Promptly: We actively monitor social media platforms and website comments to respond promptly to audience queries, feedback, and comments. We whow genuine interest in their concerns and provide helpful and informative responses. This helps in building trust and fostering a positive relationship with the audience.

- Encouraging User-Generated Content: We motivate the audience to create and share their own content related to ***ShapeFuture.*** This can include testimonials, success stories, photos, videos, or blog posts. We repost and share user-generated content to highlight the engagement and involvement of the audience.

- Engaging in Social Listening: We monitor social media platforms, industry forums, and online communities to identify conversations and discussions

related to ***ShapeFuture*** relevant topics. We engage in these discussions by providing valuable insights, answering questions, and sharing relevant content. This helps in establishing ***ShapeFuture*** as a trusted source of information and encourages further engagement from the audience.

- Collaborating with Influencers: We collaborate with industry influencers, thought leaders, and experts to co-create content, participate in interviews, or host joint webinars. Their endorsement and involvement can attract their followers and increase engagement with the ***ShapeFuture*** project.

- Personalizing Communication: We tailor communication and content to suit the interests and preferences of different segments within the ***ShapeFuture*** target audience. This can be achieved by analyzing audience data, understanding their behavior, and creating content that resonates with their specific needs.

By implementing these strategies, ***ShapeFuture*** can enhance audience engagement and build a loyal community.

1.15.4 Performance tracking and analysis

Tracking and analysing the performance of the project is essential to evaluate its effectiveness, identify areas for improvement, and make data-driven decisions.
Here are some key aspects we considered for performance tracking and analysis:

1. Setting Clear Objectives: We clearly define the objectives and key performance indicators (KPIs) for the project. These can include metrics such as website traffic, social media engagement, lead generation, conversion rates, and brand awareness. We aligned the tracking and analysis efforts with these objectives to measure success accurately.

2. Website Analytics: We utilize website analytics tools like Google Analytics to track and analyse various metrics such as monitor website traffic, user behaviour, conversion rates, and engagement on different pages. We analyse the sources of traffic, bounce rates, time spent on the website, and conversion funnels to understand user preferences and optimize the website accordingly.

3. Social Media Metrics: We track and analyse social media metrics such as followers, engagement rates, reach, impressions, and click-through rates. We assess the performance of different social media platforms and content types to identify the most effective channels and strategies for audience engagement. We finally, use social media analytics tools or the built-in analytics features of each platform to gather data.

4. Content Performance: We analyse the performance of several types of content created for the project, including news posts, videos and infographics. We track metrics such as views, shares, comments, and engagement rates to identify the most popular and effective content.

5. Campaign Analysis: We evaluate the performance of specific campaigns or initiatives within the ***ShapeFuture*** project. We monitor campaign-specific

metrics such as reach, engagement, click-through rates, and conversion rates. We compare the performance of different campaigns to identify successful strategies and areas for improvement.

6. Audience Sentiment Analysis: We utilize audience insights and demographics data to gain a deeper understanding of the target audience. We analyse audience behaviour, preferences, and engagement patterns to tailor content and communication strategies accordingly. We identify key segments within the audience and develop targeted approaches to improve engagement and conversion rates.

By consistently tracking and analysing the performance of the project, it becomes possible to identify areas of success, areas for improvement, and make data-driven decisions to optimize our strategy and achieve project objectives.

LinkedIn Analytics

Below, there is an overview of the first analytics for LinkedIn and the website:

The ***ShapeFuture*** LinkedIn page has seen positive engagement. Over the past period, the page has garnered **165** reactions and gained **92** new followers, bringing the total to **96**. Additionally, the page has attracted **224** new unique visitors. These metrics indicate growing interest in the project and its mission.

Figure 16: LinkedIn analytics

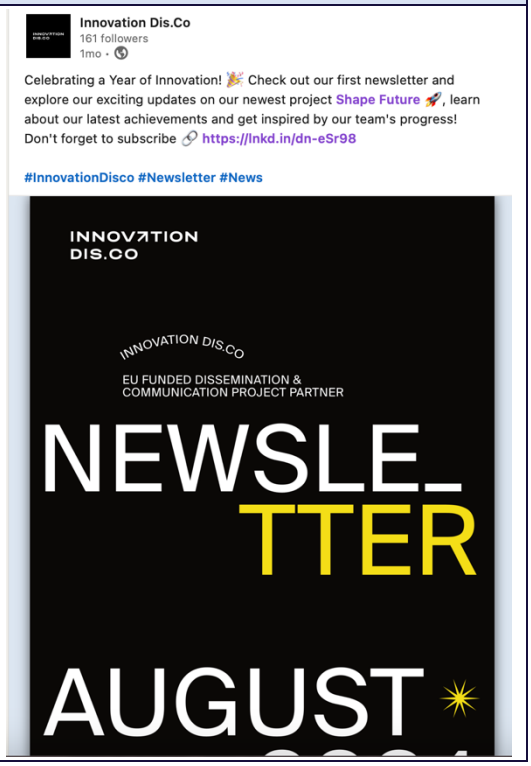
1.15.5 Social Media activities report

The below table, includes several social media posts in all different social media platforms, together with a link leading to the specific posts:

Table 4: Social Media Activity Report

Date	Topic	Material
31/5	Welcome to Shape Future project!	
3/06	Just 2 days until the Shape Future Kick Off	

5/06	Munich updates	
6/06	It's a wrap!	

30/07	latest Shape Future news!	
5/09	Check out our first newsletter	

18/09	Just wrapped up the WP1 #ShapeFuture	
24/10	We are ready for our Shape Future Core Team Meeting	

Dissemination and Communication Tools and Plan

1.16 Key Performance Indicators for dissemination and communication

The ***ShapeFuture*** project has identified key performance indicators (KPIs) to help set, track, and evaluate goals. These KPIs serve as measurable targets that guide the project's progress. By actively participating and supporting the project, all partners contribute to achieving these goals efficiently. The collective effort of the consortium partners will accelerate the project's success and ensure the desired outcomes are realized in a timely manner.

Channel	KPI	Method of measurement	Frequency	Threshold
Events - Up to 25 participants (Shape Future - organized events, international workshops, dissemination visits) Events - 25-100 participants	Number of events	Manually	End of project	>=40
	Number of audience contacts	Surveys	On schedule	At least 50% of the participants
	Number of participants Interested on *ShapeFuture* project	Surveys	On schedule	At least 40% of the participants
	Number of events	Manually	End of project	>=20
(professional events with	Number of audience contacts	Surveys	On schedule	At least 30% of the participants
relevant end-users and authorities, international	Number of participants interested on *ShapeFuture* project	Surveys	On schedule	At least 20% of the participants
Scientific workshops) Events - more than 100 participants (Conferences - Shape Future relevant)	Number of events	Manually	End of project	>=10
	Number of participants for Shape Future section contacted	Surveys	On schedule	At least 50% of the participants
	Number of participants for Shape Future section interested in the project	Surveys	On schedule	At least 40% of the participants
Journal publications	Number of journal publications by Shape Future partners	Direct reporting	End of project	>=60
Presentations in International Conferences	Number of conference presentations by *ShapeFuture* partners (persons involved)	Direct reporting	End of project	>=300

1.17 *ShapeFuture* e-Newsletters

The ***ShapeFuture*** project will disseminate information through regular newsletters. These newsletters, provide updates on project milestones, upcoming events, and relevant industry news. By adopting a reader-friendly format and incorporating engaging visuals, the newsletters aim to foster a deeper connection with our stakeholders. So far we have created one newsletter, posted on our website news, LinkedIn and shared via email.

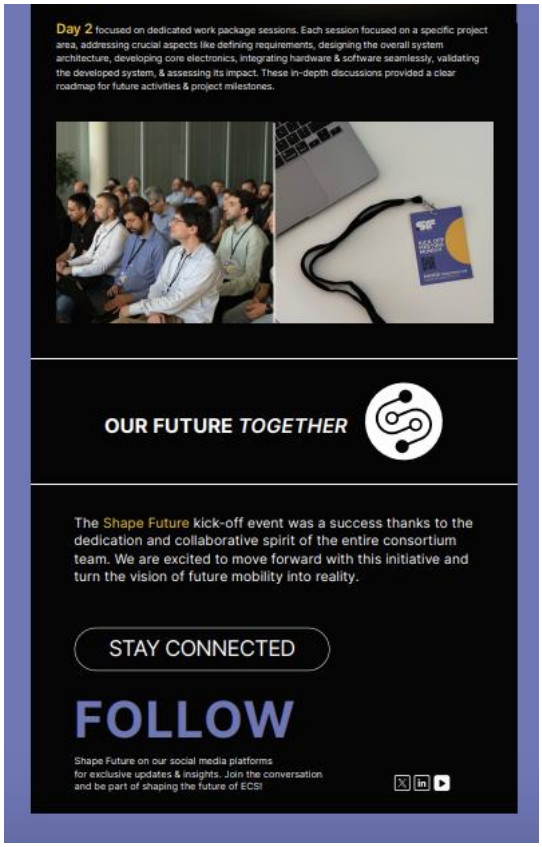


Figure 17: Newsletters

1.18 Shape Future Templates

The project document templates, are designed to ensure a consistent and professional representation of the Project across all communication and documentation facets. These templates adhere to the project's branding guidelines, embodying a coherent visual identity.

Figure 18: PowerPoint template

Figure 19: Meeting minutes & Deliverable templates

1.19 Shape Future promotional material

1.19.1 Roll up Banners and posters

The roll-up banners and posters serve as a visually appealing medium to engage & inform stakeholders during events, conferences, and other outreach activities, thus amplifying the project's visibility & impact.

Figure 20: Roll-up banners & posters

1.19.2 Project's Information card & Brochure

The project's information card and brochures again serve as a visually appealing medium to engage & inform stakeholders during events, conferences, and other outreach activities, thus amplifying the project's visibility & impact.

Figure 21: Project's Info Card & Brochure examples

1.19.3 Linktree

The project's QR code as shown below, redirects to a *Linktree* list of all project accounts (website, social media, YouTube channel). The *Linktree* list acts as a digital hub, consolidating all essential links and resources related to the Project.

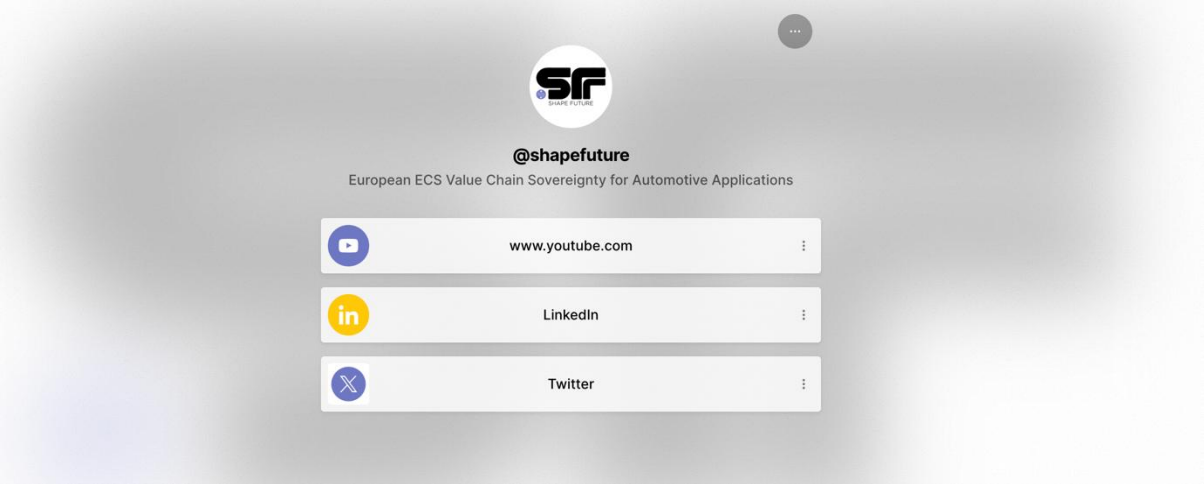


Figure 22: Project Linktree and QR code

1.20 *ShapeFuture* Publications

Scientific publications are a crucial component of the ***ShapeFuture*** project's dissemination strategy, as they enable the project team to share findings, methodologies, and innovations with the academic and scientific community. By publishing in reputable journals and presenting at international conferences, the project aims to contribute to the body of knowledge surrounding Electronic Components and Systems (ECS) for highly automated vehicles. These publications serve as a platform to validate research outcomes, promote the project's advancements, and engage with researchers, experts, and stakeholders in related fields.

Furthermore, scientific publications support the project's objectives by fostering collaborations, encouraging knowledge exchange, and positioning ***ShapeFuture*** as a leader in ECS innovation. Through these efforts, ***ShapeFuture*** not only amplifies its scientific impact but also strengthens the broader adoption and recognition of its technological contributions within the academic and industrial communities.

Below there is a list of the first 3 publications of the project until today:

Table 5: Project's Scientific Publications

Scientific Publications			
No	Title	Authors	Partner
1	On the Latency Performance of Mobile Mapping Services: towards Vulnerable Road Users Safety	Luca Bedogni, Carlo Augusto Grazia & Raoul Scalise	UNIMORE
2	Open Challenges in the Formal Verification of Autonomous Driving	Paolo Burgio, Angelo Ferrando & Marco Villani	UNIMORE
3	Evidential Semantic Lane-Grid for Unknown Space Analysis & High-Level Representation of Dynamic Occupancy Grids	Victor Jiménez-Bermejo, Vinicius Trentin, Antonio Artuñedo, Jorge Villagra	CSIC

Conclusions

After six months of coordinated efforts, the ***ShapeFuture*** project has successfully established a foundation for effective stakeholder engagement and communication. Key accomplishments include the launch of a fully functional project website and the creation of a cohesive brand identity that will enhance the project's visibility across multiple platforms.

Initial dissemination efforts, including the utilization of social media channels and sentiment analysis, have demonstrated positive audience engagement and a growing interest in the project.

As the project progresses, the ongoing use of tailored messages and stakeholder-specific communication strategies will ensure that ***ShapeFuture's*** objectives and achievements are conveyed effectively. These efforts are expected to increase stakeholder acceptance, foster collaborations, and contribute to the project's overarching goal of transforming mobility through advanced ECS technologies.

Looking forward, the project team is committed to building upon these foundations to further expand the project's impact on the future of automated vehicle systems in Europe.

Annex I

Social influence refers to the behavioral change of individuals affected by others in a network. Social influence is an intuitive and well-accepted phenomenon in social networks. The strength of social influence depends on many factors such as the strength of relationships between people in the networks, the network distance between users, temporal effects, characteristics of networks and individuals in the network.

Influence Related Statistics

A social network is modeled as a graph G = {V, E}, where V is the set of nodes, and E is the set of edges. As is the convention, the links correspond to actors (people) and the links correspond to social relationships. At the local level, social influence is a directional effect from node A to node B, and is related to the edge strength from A to B. On a global level, some nodes can have intrinsically higher influence than others due to network structure. These global measures are often associated with nodes in the network rather than edges. We next present the concepts and measures at a local and global level respectively.

Edge Measures

Edge measures relate the influence-based concepts and measures on a pair of nodes. Such measures explain simple influence-related processes and interactions between individual nodes.

- **Tie Strength** According to Granovetter's seminal work, the tie strength between two nodes depends on the overlap of their neighborhoods. In particular, the more common neighbors that a pair of nodes A and B may have, the stronger the tie between them. If the overlap of neighborhoods between A and B is large, we consider A and B to have a strong tie. Otherwise, they are considered to have a weak tie.
- **Weak Ties** When the overlap of the neighborhoods of A and B is small, the connection A — B is considered to be a weak tie.
- **Edge Betweenness** measures the total amount of flow across the edge. Here, we assume that the information flow between A and B are evenly distributed on the shortest paths between A and B.

Node Measures: Node-based centrality is defined in order to measure the importance of a node in the network. A node with high centrality score is usually considered more highly influential than other nodes in the network. The main principle in categorizing the centrality measures is the type of random walk computation involved. In particular, centrality measures can be grouped into two categories: radial and medial measures.

- **Degree** The first group of the centrality measures is that of the radial and volume- based measures. One way of interpreting the degree centrality is that it counts the number of paths of length 1 that starts from a node.
- **Closeness centrality:** It measures the centrality by computing the average of the shortest distances to all other nodes.
- **Node Betweenness:** As is the case for edges of high betweenness, nodes of high be¬tweenness occupy critical positions in the network structure, and are therefore able to play critical roles.

Structural holes In a network, we call a node a structural hole if it is connected to multiple local bridges.

Social Similarity and Influence

A central problem for social influence is to understand the interplay between similarity and social ties. A lot of research has tried to identify influence and correlation in social networks from many different aspects: social similarity and influence; marketing through social influence, influence maximization; social influence model and practice through conformity, compliance and obedience ,and social influence in virtual worlds.

- **Homophily** Homophily is one of the most fundamental characteristics of social networks. This suggests that an actor in the social network tends to be similar to their connected neighbors or "friends".The phenomenon of homophily can originate from many different mechanisms:
  - **Social influence:** This indicates that people tend to follow the behaviors of their friends. The social influence effect leads people to adopt behaviors exhibited by their neighbors;
  - **Selection:** This indicates that people tend to create relationships with other people who are already similar to them;
  - **Confounding variables:** Other unknown variables exist, which may cause friends to behave similarly with one another.

These three factors are often intertwined in real social networks, and the overall effect is to provide a strong support for the homophily phenomenon. Intuitively, the effects of selection and social influence lead to different applications in mining social network data. In particular,recommendation systems are based on the selection/social similarity, while viral marketing is based on social influence. To model these different factors, several models have been proposed.

Influence and Actions in Social Media

Influence is usually reflected in changes in social action patterns (user behavior) in the social network. Recent work has studied the problem of learning the influence degree from historical user actions, while some other workinvestigates how social actions evolve in the context of the network, and how such actions are affected by social influence factors. Before introducing these methods, we will first define the time-varying attribute augmented networks with user actions.

Time-varying attribute-action augmented network: The time-varying attribute- action augmented network is denoted as $G(t) = (V(t),E(t),X(t),Y(t))$, where $V(t)$ is the set of users and $E(t)$ is the set of links between users at time t, $X(t)$ represents the attribute matrix of all users in the network at time t and $Y(t)$ represents the set of actions of all users at time t. For all actions, they define a set of action tuples as $Y = (v,y,t)$, where v e $V(t)$,t e $\{1,... ,T\}$, and y e $Y(t)$.

Influence and Interaction

Besides the attribute and user actions, influence can be also reflected by the interactions between users. Typically, online communities contain ancillary interaction information about users. For example, a Facebook user has a Wall page, where her friends can post messages. Based on the messages posted on the Wall, one can infer which friends are close and which are acquaintances only. Similarly, one can use follower and following members on Twitter to infer the strength of a relationship. Xiang et al propose a latent variable model to infer relationship strength based on profile similarity and interaction activity, with the goal of automatically distinguishing strong relation- ships from weak ones. The model attempts to represent the intrinsic causality of social interactions via statistical dependencies. It distinguishes interaction activity

from user profile data, and integrates two types of information by considering the relationship strength to be the hidden effect of user profile similarities, as well as the hidden cause of the interactions between users. The input to the problem can be considered an attribute-augmented network G = (V, E, X) with interaction information mj C M between users, where mj is a set of different interactions between users Vj and Vj . The model also uses continuous latent variable z, but for each link rather than action. The latent variable can be further treated as the strength of the social influence. There are some methods aiming to model social influence using a link analysis method. The basic idea is similar to the concept of random walks. Java et al. employ such a method to model the influence in online social networks.

Topic mining

Probabilistic **topic modeling** approaches [48] share the fundamental assumption that documents within a corpus can be formulated as mixtures of topics, where each topic is modeled as a probability distribution over words. A topic model may be interpreted as a generative model for documents since it specifies a simple probabilistic procedure according to which new documents emerge. In this context, a dataset is a collection D of n documents such that D □{*d*1, *d*2 ,□, *dn*}, where each document *d* □D is is a collection words. Therefore, the generative model, provided by LDA, aims at describing the underlying procedure according to which, each document obtains its words. Initially, let's assume the knowledge of T topic distributions for our dataset corresponding to T multinomials containing V elements each, where V stands for the number of terms in our corpus. Therefore, our corpus is composed by a set of unique words that form a vocabulary indexed by{1,□,*V*}. Words within the vocabulary are represented as unit-basis vectors having a single component equal to one and all other components equal to zero. Thus, through the utilization of superscripts in order to denote components, the v-th word in the vocabulary is represented by a V-vector w□{0,1}^{V} such that w^u □ 1and w^u □ 0,□*u* □ *v* . According to the same rationale, a document in the corpus constitutes a sequence of N words which can be denoted by w = [w1, w2 ,.., wN], where wn is the n-th word in the sequence.

Under the light of the previous declarations and assumptions, the document generation process may be decomposed into the following steps:

1. for each document *d* □D :
    a. draw a topic distribution, □$_d$ ~ *Dir*(□) , where *Dir*(□) is a draw from a uniform Dirichlet distribution with scaling parameter a;
    b. for each word in the document:
        i. Draw a specific topic $z_{d,n}$ ~ *multi*(□$_d$) , where *multi*(·) is multinomial;
        i. Draw a word, $w_{d,n}$ ~ □$_z$.

A draw from a T-dimensional Dirichlet distribution returns a T-dimensional multinomial, θ in this case, where the T values must sum to one. The normalization requirement for θ ensures that θ lies on a (k — 1)-dimensional simplex and has the probability density:

$$p(\theta \mid \alpha) = \frac{\Gamma(\sum_{i=1}^{T} \alpha_i)}{\prod_{i=1}^{T} \Gamma(\alpha_i)} \prod_{i=1}^{T} \theta^{\alpha_i - 1}$$

Where □ is the parameter of the Dirichlet distribution. Technically □ □[□1,□2 ,□,□T], but unless otherwise noted, all elements of□ will be the same, so that□ corresponds to a simple number. z represents a vector of topics, where if the i-th element of z is 1 then w draws from the i-th topic. β on the other hand, is a T x V word-probability matrix for each topic and each term such that □ □ $p(w^j \square 1 \mid z^i \square 1)$.

$$p(\theta, \mathbf{z} \mid \mathbf{w}, \alpha, \beta) = \frac{p(\theta, \mathbf{z}, \mathbf{w} \mid \alpha, \beta)}{p(\mathbf{w} \mid \alpha, \beta)}$$

Subsequently, a step-wise procedure is employed for each individual document, so that the probability of the entire corpus can be acquired by multiplying the individual document probabilities, based on the assumption of independence. The decomposition process for the numerator yields:

$$p(\theta, \mathbf{z}, \mathbf{w} \mid \alpha, \beta) = p(\mathbf{w} \mid \mathbf{z}, \beta)\, p(\mathbf{z} \mid \theta)\, p(\theta \mid \alpha)$$

where $p(\mathbf{w} \mid \mathbf{z}, \square)$ represents the probability of observing a document with N words given a topic vector which assigns a topic to each word from the T x V probability matrix β. It is possible to decompose this quantity into the product over each individual word probability according to the following equation:

$$p(\mathbf{w} \mid \mathbf{z}, \beta) = \prod_{n=1}^{N} \beta_{z_n, w_n}$$

Sentiment analysis
Methodology
"What other people think" has always been an important piece of information for most of us during the decision-making process. Long before awareness of the World Wide Web became widespread, many of us asked our friends to recommend an auto mechanic or to explain who they were planning to vote for in local elections, requested reference letters regarding job applicants from colleagues, or consulted Consumer Reports to decide what to buy. But the Internet and the Web have now (among other things) made it possible to find out about the opinions and experiences of those in the vast pool of people that are neither our personal acquaintances nor well-known professional critics - that is, people we have never heard of. And conversely, more and more people are making their opinions available to strangers via the Internet.
The user hunger for and reliance upon online advice and recommendations that the data above reveals is merely one reason behind the surge of interest in new systems that deal directly with opinions as a first-class object. But, Horrigan reports that while a majority of American internet users report positive experiences during online product research, at the same time, 58% also report that online information was missing, impossible to find, confusing, and/or overwhelming. Thus, there is a clear need to aid consumers of products and of information by building better information-access systems than are currently in existence. ?The interest that individual users show in online opinions about products and services, and the potential influence such opinions wield, is something that vendors of these items are paying more and more attention to .

Contrasts with Standard Fact-Based Textual Analysis

The increasing interest in opinion mining and sentiment analysis cannot be exclusively attributed to its potential applications but it is more importantly based on the new intellectual challenges that the field presents to the research community since the task of text evaluation is significantly different from "classic" text mining and fact-based analysis. Traditionally, text categorization seeks to classify documents by topic. There can be many possible categories, the definitions of which might be user- and application- dependent; and for a given task, we might be dealing with as few as two classes (binary classification) or as many as thousands of classes (e.g., classifying documents with respect to a complex taxonomy). In contrast, with sentiment classification, we often have relatively few classes (e.g., "positive" or"3 stars") that generalize across many domains and users. In addition, while the different classes in topic-based categorization can be completely unrelated, the sentiment labels that are widely considered in previous work typically represent opposing (if the task is binary classification) or ordinal/numerical categories (if classification is according to a multi- point scale). In fact, the regression-like nature of strength of feeling, degree of positivity, and so on seems rather unique to sentiment categorization (although one could argue that the same phenomenon exists with respect to topic-based relevance).

There are also many characteristics of answers to opinion-oriented questions that differ from those for fact-based questions. As a result, opinion-oriented information extraction, as a way to approach opinion-oriented question answering, naturally differs from traditional information extraction (IE) . Interestingly, in a manner that is similar to the situation for the classes in sentiment-based classification, the templates for opinion- oriented IE also often generalize well across different domains, since we are interested in roughly the same set of fields for each opinion expression (e.g., holder, type, strength) regardless of the topic. In contrast, traditional IE templates can differ greatly from one domain to another - the typical template for recording information relevant to a natural disaster is very different from a typical template for storing bibliographic information.

These distinctions might make our problems appear deceptively simpler than their counterparts in fact-based analysis, but this is far from the truth since sentiment can often be expressed in a more subtle manner, making it difficult to be identified by any of a sentence or document's terms when considered in isolation.

Classification and Extraction

Problem Formulations and Key Concepts Motivated by different real-world applications, researchers have considered a wide range of problems over a variety of different types of corpora. We now examine the key concepts involved in these problems. This discussion also serves as a loose grouping of the major problems, where each group consists of problems that are suitable for similar treatment as learning tasks.

Sentiment Polarity and Degrees of Positivity One set of problems share the following general character: given an opinionated piece of text, wherein it is assumed that the overall opinion in it is about one single issue or item, classify the opinion as falling under one of two opposing sentiment polarities, or locate its position on the continuum between these two polarities. A large portion of work in sentiment-related classification/regression/ranking falls within this category. Euchar and Lavrenko point out that the polarity or positivity labels so assigned may be used simply for summarizing the content of opinionated text units on a topic, whether they be positive or negative, or for only retrieving items of a given sentiment orientation (say, positive).

The binary classification task of labeling an opinionated document as expressing either an overall positive or an overall negative opinion is called sentiment polarity classification or polarity classification. Although this binary decision task has also been termed sentiment classification in the literature, as mentioned above, in this survey we will use "sentiment classification" to refer broadly to binary categorization, multi-class categorization, regression, and/or ranking.
The input to a sentiment classifier is not necessarily always strictly opinionated. Classifying a news article into good or bad news has been considered a sentiment classification task in the literature. But a piece of news can be good or bad news without being subjective (i.e., without being expressive of the private states of the author): for instance, «the stock price rose" is objective information that is generally considered to be good news in appropriate contexts. It is not our main intent to provide a clean-cut definition for what should be considered ¨sentiment polarity classification¨ problems, but it is perhaps useful to point out that:

- In determining the sentiment polarity of opinionated texts where the authors do explicitly express their sentiment through statements like "this laptop is great," (arguably) objective information such as "long battery life" is often used to help determine the overall sentiment;
- the task of determining whether a piece of objective information is good or bad is still not quite the same as classifying it into one of several topic-based classes, and hence inherits the challenges involved in sentiment analysis; and
- The distinction between subjective and objective information can be subtle.

Subjectivity Detection and Opinion Identification Work in polarity classification often assumes the incoming documents to be opinionated. For many applications, though, we may need to decide whether a given document contains subjective information or not, or identify which portions of the document are subjective. Early work by Hatzivassiloglou and Wiebe examined the effects of adjective orientation and gradability on sentence subjectivity. The goal was to tell whether a given sentence is subjective or not judging from the adjectives appearing in that sentence. A number of projects address sentence-level or sub-sentence-level subjectivity detection in different domains. Wiebe et al. present a comprehensive survey of subjectivity recognition using different clues and features.
Wilson et al. address the problem of determining clause-level opinion strength (e.g., "how mad are you?"). Note that the problem of determining opinion strength is different from rating inference. Classifying a piece of text as expressing a neutral opinion (giving it a mid- point score) for rating inference does not equal classifying that piece of text as objective (lack of opinion): one can have a strong opinion that something is "mediocre" or "so-so." Recent work also considers relations between word sense disambiguation and subjectivity.
Subjectivity detection or ranking at the document level can be thought of as having its roots in studies in genre classification.

Joint Topic-Sentiment Analysis One simplifying assumption sometimes made by work on document- level sentiment classification is that each document under consideration is focused on the subject matter we are interested in. This is in part because one can often assume that the document set was created by first collecting only on-topic documents (e.g., by first running a topic-based query through a standard search engine). However, it is possible that there are interactions between topic and opinion that make it desirable to consider the two simultaneously; for example, Rilof et al. find that "topic-based text filtering and subjectivity filtering are complementary" in the context of experiments in information extraction. Also, even a

relevant opinion-bearing document may contain off- topic passages that the user may not be interested in, and so one may wish to discard such passages.

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