Austrian Lab for AI Trust* Dossier 5

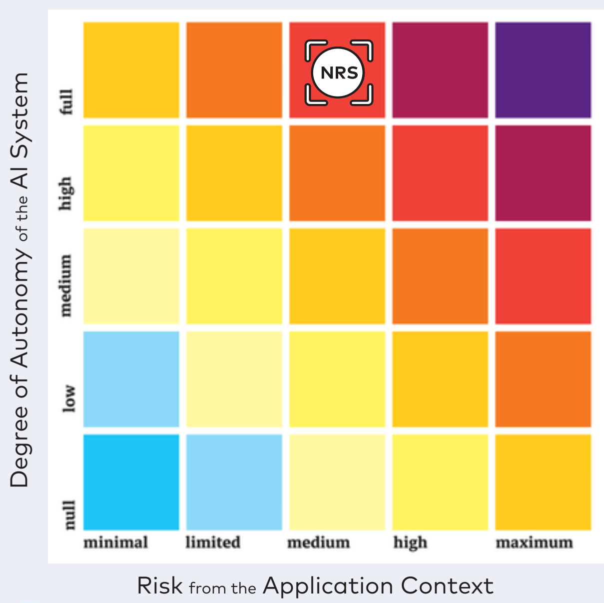
News Recommendation Systems: AI-Based Personalization in Digital News Services

Executive Summary

Nowadays, the internet and social media have become primary sources of information for many people. To help users navigate the vast amount of available information, social media and news platforms use news recommender systems. These systems filter information based on users' preferences, determined by their past search and click behavior. Ideally, users then only receive news that aligns with their interests. While this filtering function is convenient, it also poses significant challenges at the individual and societal levels. First, the algorithms of news recommendation systems are designed to keep users engaged for as long as possible. The longer users stay on a platform, the more advertising revenue is generated. Highly emotional and negative news captures attention and is therefore suggested more frequently. Ultimately, this can lead to a craving for more news and, in the worst case, news addiction—a phenomenon that has become a major problem among young people and is referred to as „doomscrolling." Furthermore, distortions occur at the individual level. Events around us are perceived one-sidedly due to the filtering of certain news, which promotes the spread of misinformation. Societally, this creates ***echo chambers*** and ***filter bubbles***, where people consume similar news, reinforce each other's opinions, and amplify them. Exchange of differing opinions and nuanced information is prevented, ultimately leading to polarization in society.

The ALAIT Risk Radar classifies the use of news recommendation systems as „high risk" (red; see illustration). However, according to the ***EU AI Act***, the risk associated with these systems is classified as „medium" (level 3) on the ALAIT Risk Radar. In terms of ***degree of autonomy***, these systems are mostly fully autonomous because they operate independently with minimal or no human intervention. Human involvement is limited to long-term oversight, such as through audits (Level 5). Platforms and users can reduce risk by implementing the risk mitigation measures outlined at the end of this dossier. In principle, greater news diversity and the development of democratic, fair systems are crucial (see page 6). ***Transparent*** and explainable systems, as well as human oversight, are recommended to avoid ***biases*** and political polarization.

ALAIT Risk Radar for News Recommendation Systems: AI-Based Personalization in Digital News Services



AI Applications in News Recommendation Systems

The ALAIT Risk Radar is a scientifically developed risk analysis tool for artificial intelligence (AI) that classifies AI applications based on context and taking into account their degree of technical autonomy, thereby making the risk landscape visible to users at a glance. The following principle applies: The higher the operational risk arising from the application context and the greater the degree of autonomy of the AI system with regard to decision-making, the riskier the use is classified. An expanded bracket indicates a range within the risk classification. A low degree of autonomy in an AI system does not mean one can sit back and relax. It requires a strong role for the people who use it. (For details on the tiered model, see p. 9f.)

**ALAIT is a research project initiated by the Federal Ministry of Innovation, Mobility, and Infrastructure (BMIMI) aimed at developing a novel form of technology assessment for AI technologies using scientific methods.*

Introduction

In recent years, social media and online news platforms have grown in popularity.1 At the same time, users are exposed to so much news that it is difficult for them to keep track of it all and identify news items that interest and concern them. News platforms and social media have found a solution to this problem in personalized recommendation systems, also known as news recommender systems. These systems' algorithms learn users' preferences from their reactions and can thus predict which news, information, products, or services are of particular interest to the individual.[3,4,5] Such personalized news services can identify users' needs and preferences and optimize the platform's user experience.

When it comes to news recommender systems, it's important to distinguish between social media and traditional news platforms. Although both use algorithms to suggest content, they operate under different incentives, datasets, and regulatory conditions. Social media platforms are based on an attention economy, so their news recommendation systems are optimized to keep users on the platform for as long as possible, allowing for more ad displays. They prioritize „shareability" and „virality".[36] This often rewards emotional, polarizing, or sensational content because it generates the most clicks and comments.[36,38] News platforms likewise want to drive engagement, but their primary goal is customer retention and loyalty.[37] A news platform relies on its reputation as an accurate source of information to gain subscribers. Therefore, their news recommendation systems are often constrained by editorial guidelines to avoid damaging the platform's credibility.

Many news sources and agencies, such as CNN, the BBC, and ORF, provide access to the latest news at any time and from anywhere through their online portals. To attract more visitors, these portals increasingly use recommendation systems designed to improve the user experience. „Improved user experience" refers to characteristics such as usability, utility, efficacy, and satisfactory interaction with the system.[5] MModern news recommendation systems adapt content flexibly to context and individual needs. They optimize the format and length for the respective device, consider accessibility (e.g., screen readers), and deliver location-based news. For example, the NZZ has specific regional editions for Germany and Switzerland[2,] , and the ORF uses AI-powered recommendations on its video platform, ORF ON, to suggest targeted content. Other European media outlets also follow a public service approach. For instance, the Finnish broadcaster Yle is developing a „public service algorithm" that combines personalization with public surplus value. These recommendations aim to be personally relevant while also offering diverse perspectives and exposing users to surprising content outside their ***filter bubbles***. Yle emphasizes ***transparency*** and user ***autonomy***; users can understand why content is recommended and control their personalization.[7]

Despite these positive examples, news platforms also face risks and challenges. While users benefit from personalized recommendations, these can also undermine their freedom of choice and jeopardize their privacy. Values such as privacy, safety, consumer protection, accountability, solidarity, equality, fairness, ***transparency***, and democratic oversight often conflict with the economic interests embedded in the platform's architecture. Since news recommendation systems determine which content is highlighted or hidden, they can influence public opinion and restrict human autonomy.[8] Therefore, it is important to carefully weigh these and other factors when evaluating news recommendation systems.

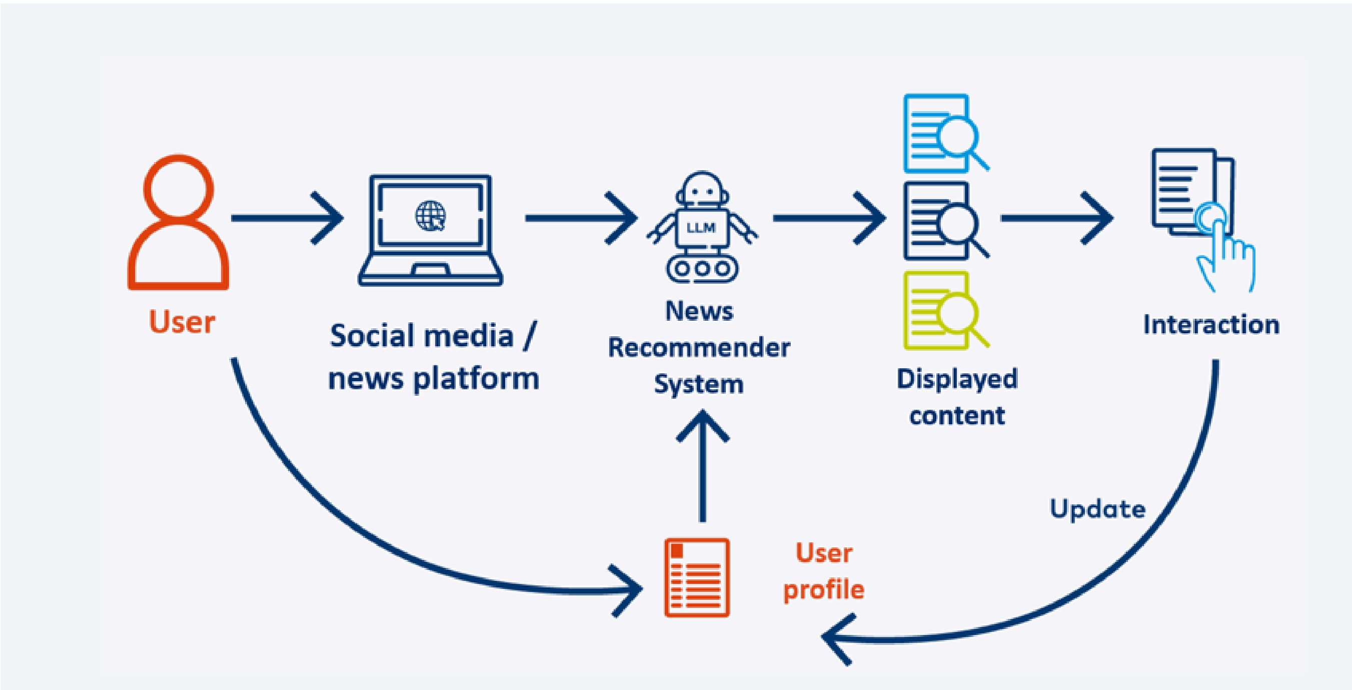
Recommendation systems on social media go a step further because they use virtual profiles of users that may contain sensitive data, such as age, address, and personal interests. With this „social profiling," platforms can influence users without their knowledge. Although this practice is prohibited in the European Union, it is difficult to control.[6] Additionally, news addiction, or „doomscrolling", has become one of the biggest problems for young people in recent years.

Technology Description

A news recommendation system selects articles from among the many available ones that might be of the greatest interest to a specific person. When a user opens a social media platform, the system uses their profile to determine their preferences. If a profile hasn't been created yet, the system uses previous clicks, reading habits, location, and cookies to create a temporary profile.[1,5] Based on this profile, the system selects and displays suitable articles. When a user clicks on or reads an article, their profile is updated. Consequently, the system is constantly learning and can tailor its recommendations more effectively.

This „modeling" of users is inherently challenging.[4] One of the greatest challenges of recommendation systems is the dynamic nature of users' interests. An accurate recommendation system must continuously track these changes and adjust the profile accordingly.[5,17] Another problem with user modeling is the lack of direct feedback. Many users do not rate or comment on articles. Therefore, the system must learn from indirect cues, such as clicks or reading time.[4,5]

The following diagram illustrates the basic principle:



There are two main types of news recommendation systems:

1. Collaborative Filtering (CF): This approach uses user feedback, such as likes, dislikes, or ratings, to identify preferences. Based on this feedback, the system recommends articles that other users with similar behaviour have liked

2. Content-Based Filtering: In this approach, articles are compared with one another based on their characteristics (e.g., text or multimedia content). The system recommends content similar to articles that users have already read or rated positively.

Depending on the application, both approaches have advantages and disadvantages. Hybrid systems, which combine collaborative filtering and content-based filtering, are often used to balance these out. These systems integrate the two approaches to compensate for their respective limitations. They can better address the „cold start" problem – the difficulty of providing relevant recommendations for new users or content due to a lack of usage data – and data scarcity. Additionally, they provide more precise and diverse recommendations because they simultaneously consider the relationships between users and content.

Current news recommendation systems rely on advances in machine learning, particularly in natural language processing, which deals with textual content. At its core, this technology involves training algorithms using large sets of labeled data (***supervised learning***) to categorize news articles

Deep learning (DL), on the other hand, is based on artificial neural networks and can learn important features and patterns directly from raw data without having to define them manually beforehand.

DL models are now considered the state of the art for news recommendation systems because they

1. achieve higher ***accuracy*** when processing text, images, or videos;
2. better capture the complex interactions between users and content;
3. also account for time-varying user behavior through sequential modeling; and
4. mitigate typical challenges of conventional systems, such as cold start or insufficient rating data.

DL models can solve these problems by automatically extracting useful information from user and content data, enabling more accurate recommendations. Graph-based recommendation systems (GRS) build on this by modelling the complex relationships between users, items and other factors within a multirelational graph. This enables them to identify latent interests that conventional models might overlook.[32]

Opportunities

For Users (Readers):

- **Personalized recommendations and a better user experience**: Personalized recommendations reduce the complexity of the information landscape and thus improve the user experience. The goal is not to limit the volume of news artificially, but rather to facilitate the selection process. A well-tuned system acts as a digital curator, helping readers quickly access relevant topics. This reduces the overwhelming volume of information, decreases information complexity, and increases user satisfaction.[3,4]

- **Accessibility and Context Sensitivity**: Modern news recommendation systems are increasingly able to adapt to specific usage scenarios and accessibility needs. These systems can detect if a user is on a smartphone or PC and provide content tailored to the device, whether it be longer or shorter text, or visually structured content. These systems can also take into account regional language variants, local news interests, and accessibility requirements, such as screen reader-compatible text for visually impaired users.[2]

For Platforms:

- **Improved Click-Through Rates and User Retention**: A well-optimized news recommendation system increases the relevance of the displayed content, leading to higher engagement rates. This results in longer session durations and a greater willingness of users to return.[3,4,15] Studies show that news recommendation systems can increase click-through rates on news portals by more than 30%.[9,15] By monitoring click behavior, recommendation systems can automatically identify users' needs and preferences, create a preference profile, and use this information for targeted advertising.

Challenges and Risks

Despite the promise of delivering significant benefits to users and platform operators, news recommendation systems pose a wide range of risks and challenges at both the individual and societal levels.

Individual Level:

- ***Data Protection:*** DThe performance of a news recommendation system is directly linked to the amount of data processed. However, this can lead to data privacy issues, as some news platforms and social media sites use information such as users' geographic location.[2,4] If this data is stolen or misused, it could have serious implications for the privacy and security of those affected.

- **News Addiction:** : This refers to the compulsive and harmful consumption of articles, news feeds, radio, podcasts, talk shows and email newsletters. Those affected constantly check certain platforms, a behaviour also known as "doomscrolling" through social media feeds. As a subset of internet and technology addiction, news addiction can lead to changes in the brain over time that impair concentration, prioritisation, mood regulation and relationships with others.[27,38] News recommendation systems increase this risk through personalisation and maximising click-through rates.

Societal Level:

- **Click-Through Rates and Maximising Engagement:** News recommendation systems are not only tools for optimising platform services but also instruments of an attention economy. This means they are profit-driven tools designed to maximise user engagement in the form of clicks or time spent on the platform.[8] Research findings show that negative or emotionally charged news elicits the strongest reactions and is therefore recommended or shared more frequently.[14,16,17] This leads to the emergence of systematic content ***biases*** (see next point). Rather than ensuring balanced information, these systems promote the polarisation of content, which can lead to the fragmentation of society.

- **Reduction in the Diversity of Recommendations and *AI Bias*:** News recommendation systems often exhibit systematic ***biases*** (***AI bias***).[1,8,16,22,23,17] These ***biases*** reinforce users' beliefs and interests, leading to limited content presentation and the formation of ***echo chambers*** and ***filter bubbles***.[8,9,10,16] The term "echo chamber" describes an information bubble in which users are exposed only to articles that confirm their existing beliefs. The term "filter bubble" refers to intellectual isolation - the state of being cut off from differing viewpoints and new information. This arises from personalised search queries or algorithms and leads to information being selectively absorbed and restricted, creating a highly polarised information environment.[4,8,9,16] Furthermore, digital journalism is susceptible to a process known as "McDonaldization". In this process, editorial autonomy is often sacrificed for standardised content formulas whose strong performance is "metrically confirmed". This prioritises efficiency and predictability over the high costs and uncertain returns of investigative journalism, thereby further limiting the diversity and quality of news.[28,29]

- **Low Reliability, Disinformation and Fake News:** Due to their mathematical nature, AI systems are limited in their ability to correctly interpret context and assess the reliability of information and sources.[4,5,9] In practice, recommendation systems for news on social media have already been manipulated to direct readers towards fake news.[16] For example, YouTube was manipulated in coordination with the newspaper The Guardian to direct readers towards sensationalist and false news during the 2016 US elections.[5] A study across 35 countries also shows that using social media as a primary news source is associated with lower trust in news.[11]

Technical Level:

- **User Modeling:** : One of the greatest challenges for recommendation systems is the dynamic nature of user interests. In order to receive personalised recommendations for news articles, a comprehensive user profile must be created that takes into account preferences, likes and dislikes, previous interactions with the system, interests and even relationships with other users.[17] User modelling is used to identify these preferences, track changes continuously and update the profile accordingly. However, this can lead to additional ***privacy issues***.[5,17] EAnother problem is the lack of direct feedback, since many users do not rate or comment on articles. The system must therefore learn from indirect cues, such as clicks or reading time.[4,5]

Recommendations for Practical Use

For Platforms:

1. **Compliance with existing regulations:** All AI systems must be assessed to ensure compliance with the General Data Protection Regulation (GDPR) and the ***EU AI Act***. The implementation and application of the ***EU AI Act*** at Union level is overseen by bodies such as the European Artificial Intelligence Office (AI Office) and the European Artificial Intelligence Board (AI Board).[18] The Digital Services Act (DSA) introduces key obligations for social media platforms. These are intended to empower users and reduce the systemic risks associated with algorithmic curation. For instance, Article 27 (Transparency of Recommendation Systems) stipulates that platforms must provide clear explanations of the primary parameters of their recommendation systems, enabling users to comprehend the rationale behind the content displayed to them.[19] Article 38 (Non-profiled feeds) specifies that very large online platforms (VLOPs) must offer at least one recommendation system that does not use user profiles.[30] Article 40 (Data access for researchers) stipulates that verified researchers must be granted access to platform data in order to conduct studies that contribute to the identification of systemic risks (e.g. the dissemination of illegal content).[31]

2. **Democratic and "diversity-aware" systems:** The ability to diversify the news offered to users is key to democratic news representation. News recommendation systems should therefore actively employ diversification strategies. This enables them to recommend not only similar or confirmatory content, but also highlight divergent perspectives, diverse sources and a wide range of topics. This can help to reduce ***filter bubbles*** and ***echo chambers***.[5,8] Factors that must be considered in every recommendation system to enable diversification include news topics, writing styles, tags, perspectives, contexts and ideologies.[5,8,12] However, diversity-aware systems do not guarantee an effect on readers. Empirical studies disagree on the effectiveness of technological nudging, which steers user behaviour in predictable ways and displays diverse content, in news systems.[26]

3. **Data correction (data deing):** In order to generate high-quality news recommendations, it is important to develop effective methods of eliminating the influence of various types of ***bias*** on the results of recommendations.[1] Consistent, rebalanced and carefully selected data are the starting point for strategies to reduce ***bias***.[23]

For Users:

1. **Building and strengthening AI and media literacy:** It is important to learn about AI technologies, develop the right skills and understand one's rights.[20] In Austria, the Rundfunk- und Telekom Regulierungs-GmbH (RTR) serves as an information and contact point for the general public. The RTR AI Service Centre assists citizens with queries relating to ***transparency*** and their rights when interacting with AI systems or reviewing AI decisions.[21] Users can also learn about the specific methods employed by news recommendation systems. The algotransparency information group educates citizens on how they are steered towards increasingly biased information in each subsequent phase of the recommendation cycle, starting with a neutral search on YouTube.[13] The European Centre for Algorithmic Transparency (ECAT) assists the European Commission in its supervisory and enforcement duties concerning the systemic obligations of very large online platforms (VLOPs) and very large online search engines (VLOSEs) under the Digital Services Act (DSA). Furthermore, promoting media literacy among children and young people in the context of

social media is essential.[24] Furthermore, promoting media literacy among children and young people in the context of social media is essential.

2. **Fact-checking:** Although verifying the quality of information is a complex task, it can already be done. For instance, fact-checks on complex and controversial topics can be useful. The Austria Press Agency (APA), for instance, uses fact-checks to provide readers with insight into the research methods of the digital age. With the help of fact-checking, readers can form rational and fact-based opinions on complex and controversial topics.[25] Other media organisations that focus on investigative journalism, such as CORRECTIV. Faktencheck, also offer fact-checking services.

3. **Critical thinking:** Users should evaluate the recommendations provided by the news recommendation system critically and actively seek out alternative perspectives. To this end, it is recommended that they regularly read content from various media sources representing different political viewpoints and covering international contexts. Many platforms today offer customisation features that allow users to add or exclude certain sources based on their interests. Such settings can correct algorithmic ***bias*** and reduce the risk of ***filter bubbles***.[5,8,9]

4. **Time limits:** Setting time limits for social media use can generally help to reduce the overall risks associated with news recommendation systems. In particular, it can reduce the risk of news addiction and "doomscrolling".[35] Studies have shown a link between excessive social media use and depression.[33,35] Therefore, limiting social media use can improve overall well-being. It is particularly important not to give children and adolescents unrestricted access to social media. During this critical phase, behaviours such as forming online friendships, commenting, liking and reacting to specific content develop.[34] Most social media apps and smartphones currently offer settings that allow users to create daily schedules. These pause usage after preset time periods to promote more mindful consumption in line with personal goals.

Important Terms

AI Accuracy: Refers to an AI system's ability to make accurate predictions or decisions. It is an important measure of its performance and is crucial for determining its effectiveness and reliability.

AI Autonomy: The ability of an AI system to achieve a set of goals under a range of uncertainties in its environment, autonomously and without external intervention.

Data Privacy in AI: The totality of practices and concerns related to the ethical collection, storage, and use of personal data by artificial intelligence systems.

Echo Chamber: Refers to an information bubble surrounding a user in which only information that confirms the user's existing beliefs can be found.

European Union Law on Artificial Intelligence (EU AI Act): A European regulation on artificial intelligence (AI)—the first comprehensive regulation on AI ever issued by a major regulatory authority. It focuses in particular on high-risk AI systems.

Explainable AI (XAI): Refers to methods and techniques that make it possible to better understand and explain the decisions and results of AI systems.

Filter Bubble: Bezieht sich auf Methoden und Techniken, die es ermöglichen, die Entscheidungen und Ergebnisse von KI-Systemen besser zu verstehen und zu erklären.

Supervised Learning: A subfield of machine learning in which the training data is labeled in advance and the system learns the pattern between the content and the label. The task of such an AI system is to find a relationship that maps each input in the training set (the data) to an output (the label).

Systematic Bias (AI Bias): Bias is the systematic difference in the treatment of certain objects, individuals, or groups compared to others. Treatment refers to any type of action, including perception, observation, representation, prediction, or decision-making.

Transparency: This means that the functioning, decision-making processes, and areas of application of an AI system are transparent, explainable, and openly accessible—to developers, users, and other stakeholders.

Explanation of the ALAIT Risk Radar's Tiered Model

The ALAIT AI Risk Radar shows the relationship between application risk and autonomy of an AI system. The risk levels are based on the EU AI Act, in particular Article 6 and Annex III, which deal with high-risk areas of AI application. Lower system autonomy and application risks are represented by cooler colors (blue), while higher system autonomy and application risks are represented by warmer colors (red).

The change of color conveys the increased risk of AI applications. This color scale can be used to identify the overall risk: violet and dark red – very high, red and dark orange – high, light orange and yellow tones – medium, blue tones – low overall risk. Ideally, high application risks and system autonomy should be avoided or only be used after very careful consideration.

Degrees of Autonomy of the AI System

Level 1: No Autonomy

AI is a passive tool; humans make all decisions and initiate actions.

Example: Diagnostic systems that display raw medical data or analyze the data (without recommendations!)

Recommended use cases: Scenarios involving high risks or where ethical decisions are of crucial importance (e.g., medical diagnostics, judicial system).

Level 2: Low Degree of Autonomy (Human-in-the-Loop).

The AI provides recommendations or options, but users remain responsible for selecting and approving measures.

Example: AI suggests optimal routes for logistics or recommendation systems in e-commerce.

Recommended use cases: Tasks of medium complexity with moderate risks (e.g., supply chain optimization).

Level 3: Medium Degree of Autonomy (Human-on-the-Loop)

The AI performs certain tasks autonomously, with humans intervening only in exceptional cases.

Example: AI-supported manufacturing processes in which the system controls the machines, but users intervene in the event of anomalies.

Recommended use cases: Scenarios in which continuous human involvement is not required, but critical risks necessitate human oversight (e.g., industrial automation, monitoring of financial transactions).

Level 4: High degree of autonomy (Human in Control)

The AI system operates largely autonomously but allows users to override itself to avoid undesirable results.

Example: Autonomous Vehicles

Recommended use cases: Low to medium risk environments (e.g., logistics, simple traffic management).

Level 5: Full autonomy with minimal supervision

The AI system operates independently and requires minimal or no human intervention. Human involvement is limited to long-term oversight (audits).

Example: Autonomous agricultural machines, AI for power grid distribution, subways, airport trains.

Recommended use cases: Environments with low safety or ethical risks and high reliability of the AI system (e.g., repetitive tasks in controlled environments

Degrees of Application Risk

Level 1: Minimal Risk

The AI system has no significant impact on users or decision-making.

Examples: Filters, NPCs, recommendation algorithms without serious consequences (DeepL, other translation systems)

Criteria: No direct impact on the high-risk areas of the EU AI Act.

Level 2: Limited Risk

AI systems that interact with users but do not make high-risk decisions. The risk increases when there is a lack of transparency about the involvement of AI.

Examples: Chatbots and AI-generated content without disclosure, simple automation tasks.

Criteria: Areas not included in the “high risk” list of the EU AI Act.

Level 3: Medium Risk

AI systems do not have significant impact on a particular individual, but they do have an effect at the collective or societal level.

Examples: Generative AI such as ChatGPT and other systems that can indirectly influence the environment in which they are used.

Criteria: AI systems that are available for public use and have the potential to influence existing practices and change them in the long term.

Level 4: High Risk

Any algorithm that is used in “high-risk” areas as defined by the EU AI Act or that has a direct impact on individuals.

Examples: Medicine, biometrics, critical infrastructure, education and vocational training, employment, access to public sector services, law enforcement, migration

Criteria: Belongs to the “high-risk” area of the EU AI Act, only if the rules for transparency and data quality are complied with.

Level 5: Extreme Risik

Any algorithm used in “high-risk areas” as defined by the EU AI Act.

Examples: Medicine, biometrics, critical infrastructure, education and vocational training, employment, access to public sector services, law enforcement, migration.

Criteria: Belongs to the “high-risk” area of the EU AI Act and the rules for transparency and data quality are NOT complied with.

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About the ALAIT Project

The Austrian Lab for AI Trust (ALAIT) is a research and development project funded by the Austrian Federal Ministry for Innovation, Mobility and Infrastructure (BMIMI) aimed at building trust through knowledge in the field of artificial intelligence (AI). The ALAIT project aims to empower interested parties and key societal groups to use AI technologies responsibly and to establish ethical and high-quality standards for the use of AI.

The project is led by **winnovation** (Gertraud Leimüller and Lena Müller-Kress) and is being carried out in collaboration with **leiwand.ai** (Rania Wazir and Silvia Wasserbacher-Schwarzer), **TU Wien** (Sabine Köszegi and Ilya Faynleyb) and **Austria Presse Agentur – APA** (Verena Krawarik and Sophia Marecek)

The ALAIT dossiers are available on the project website: https://science.apa.at/project/alait/

The content of this dossier reflects the current state of the art and has been carefully compiled in accordance with scientific criteria. However, it is not intended to serve as legally binding information or advice.

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