

# **CHAPTER 13: AI/ML FOR QUALITY OF EXPERIENCE (QOE) ENHANCEMENT**

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Data-driven Quality of Experience (QoE) modeling through Machine Learning (ML) serves as a crucial facilitator for upcoming communication networks, enabling expedited and impartial QoE assessments that can autonomously adjust to evolving conditions. Conventional ML approaches typically yield black-box QoE models, which obscure the internal logic behind their predictions. This opacity complicates the extraction of meaningful insights from the data and understanding the factors influencing QoE, thereby hindering trust in the model's predictions. To overcome these issues and improve performance, we highlight four essential components for any data-driven QoE model: explainability, adaptability to context, quantification of uncertainty, and decentralization of data. Our focus is on eXplainable Artificial Intelligence (XAI), which presents a viable method to create interpretable models that address all these critical elements in data-driven QoE modeling.

This tutorial will introduce and elucidate pertinent concepts from XAI and associated fields. We will demonstrate the application of these techniques in two practical scenarios: video streaming QoE modeling and web QoE modeling, targeting classification and regression tasks respectively, while examining their significance within XAI-oriented data-driven QoE modeling. Furthermore, to enhance readers' comprehension, facilitate the application of the discussed techniques to their own cases, and encourage research in the realm of data-driven QoE modeling employing XAI, we provide access to Python Jupyter Notebooks.

### **13.1 QOE METRICS IN 6G SERVICES**

As wireless technology rapidly advances, sixth-generation (6G) networks are poised to deliver extremely high data transmission rates and minimal latency, which is essential for meeting the growing demands of digital twins (DTs). In this

context, quality-of-experience (QoE)—which encompasses users' overall satisfaction and perception of the DT service within 6G networks—plays a crucial role in optimizing services and enhancing user experience. Despite advancements in developing theories and systems for transmitting digital twins over 6G networks, the evaluation of QoE remains underdeveloped. To bridge this gap, presents the inaugural QoE evaluation database specifically for human digital twins (HDTs) operating in 6G network environments, aiming to systematically analyze and quantify relevant quality factors. We employ a mmWave network model to simulate channel capacity and use high-quality digital humans as source models, which are subsequently animated, encoded, and distorted for the final assessment of QoE. Subjective quality ratings are gathered from a rigorously controlled experiment involving 400 generated HDT sequences. Furthermore, we introduce an innovative QoE evaluation metric that incorporates both quality-of-service (QoS) and content-quality features. Experimental findings demonstrate that our model surpasses existing state-of-the-art QoE evaluation frameworks as well as other competitive quality assessment models, thereby making notable contributions to the field of 6G network applications for HDTs.

## **6G QoE Standards**

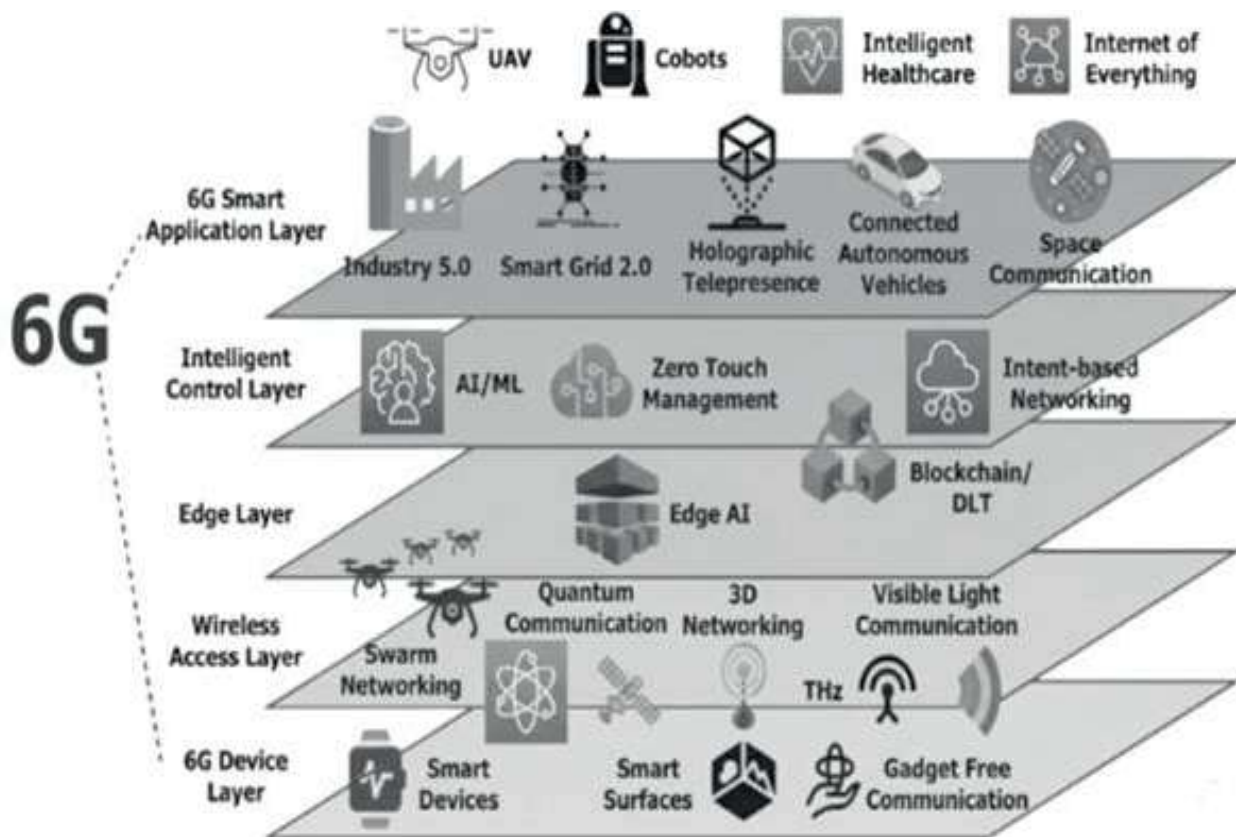
### **ITU-R M.2160-IMT-2030 Framework**

This recommendation establishes the groundwork for the development of 6G (IMT-2030), detailing various usage scenarios and functionalities, including immersive communication, extended reality (XR), multisensory interactions, and the convergence of sensing and communication technologies.

## ITU SG12 Activities

Group 12 is dedicated to creating standardized methods for evaluating quality of experience (QoE) in new services, such as virtual reality (VR). Their initiatives include the formulation of models that take into account human perception, system performance, and contextual variables.

## Industry Use Cases Highlighting QoE Enablers



*Figure 13.1 QoE Enablers*

To illustrate the significance and practical implications of QoE enablers, it is crucial to present real-world examples that underscore their importance in the industry and demonstrate how they enhance user experience across various applications. This discussion will center on key scenarios from adaptive bitrate streaming (ABR) and cloud gaming, areas where QoE-driven innovations have

been extensively utilized and validated. The selected cases exemplify tangible applications of QoE enablers in actual systems, showcasing their effectiveness across different service sectors.

In 2019, Netflix launched an innovative method called Hindsight to identify sessions with inadequate ABR performance, a task that had previously been unfeasible at scale due to its high computational requirements. By 2023, Netflix advanced this further by creating a specialized variant of the Video Multimethod Assessment Fusion (VMAF) metric tailored for high dynamic range (HDR) content, termed HDR-VMAF. This development facilitates Dynamically Optimized (DO) encoding that smartly modifies the bit rate according to perceived quality and content complexity. As a result, Netflix has significantly enhanced HDR streaming efficiency, achieving up to a 40% reduction in rebuffering incidents, lower initial bitrates, and decreased data consumption especially on mobile devices and tablets.

NVIDIA's GeForce NOW represents a cloud-based game streaming service that provides real-time gameplay directly from the cloud to users' devices. Utilizing optimized algorithms, GeForce NOW delivers superior cloud gaming performance compared to rival platforms such as Google Stadia and Sony's PS Now, resulting in reduced latency and fewer interruptions like buffering, frame drops, or resolution inconsistencies.

The leading video conferencing platforms—Microsoft Teams and Zoom utilize Adaptive Bitrate (ABR) algorithms to adjust audio and video quality dynamically in real time, ensuring optimal QoE under varying network conditions. These services continuously assess metrics such as available bandwidth, packet loss, jitter, and device capabilities to ascertain the best bitrate and resolution for each user session. When network conditions worsen, ABR algorithms automatically reduce video quality or frame rates to avoid buffering or audio disruptions;

conversely, when conditions improve, they increase the bitrate for higher-quality streams.

The ambitious vision of 6G fundamentally transforms the understanding and modeling of QoE by accommodating new use cases like holographic communication, tactile Internet experiences, and semantic communication. These emerging use cases go beyond traditional metrics such as throughput or latency by introducing novel dimensions of QoE based on human perception, semantic significance, and interactivity.

### **Modeling Mobile Video Streaming Quality of Experience (QoE)**

Video content constitutes the primary type of traffic within cellular networks, and its demand is expected to increase. Predictions indicate that by 2028, video will account for approximately 80 percent of all data traffic in these networks (refer to page 19). The trend in video consumption has progressively transitioned from traditional broadcasting to streaming formats, with mobile video quality advancing towards full-HD, 2K, and 4K resolutions. Nonetheless, the user experience associated with mobile video is influenced by various measurable factors, including intrinsic encoding quality—determined by aspects such as resolution, frame rate, and codec—as well as dynamic quality elements like time-to-content delays, instances of rebuffering, and adjustments in resolution based on channel capacity.

## **13.2 AI-BASED USER BEHAVIOR PREDICTION**

### **AI Agents' Predictions of User Behavior**

The prediction of user behavior by AI agents entails a comprehensive examination of the convergence of various sophisticated technologies and methodologies. These agents employ machine learning algorithms, data analytics, and pattern recognition to generate precise forecasts regarding user actions and preferences. The process

initiates with the accumulation and processing of extensive datasets that form the groundwork for developing predictive models.

### **Data Collection and Preprocessing**

The initial phase in forecasting user behavior involves the acquisition of diverse data types, which may include historical user interactions, demographic details, and contextual elements such as time or location. This data undergoes cleaning and preprocessing to guarantee its quality and relevance. Such preprocessing can involve addressing missing values, normalizing ranges, or encoding categorical variables. The objective is to convert raw data into a structured format that is conducive to analysis.

### **Feature Engineering**

Following data preparation, the subsequent stage is feature engineering. This step focuses on identifying and crafting pertinent features that can bolster the predictive capabilities of the models. For instance, within a retail scenario, relevant features might comprise purchase frequency, average transaction value, or elapsed time since the last purchase. Successfully implementing feature engineering is vital as it significantly influences both the accuracy and efficiency of predictive models.

### **Model Selection and Training**

Once data and features are set, AI agents choose suitable machine learning models tailored to their specific prediction objectives. Commonly used models include decision trees, neural networks, as well as ensemble methods like random forests or gradient boosting techniques. During training, these models detect patterns and relationships within the dataset while adjusting their parameters to reduce prediction errors.

## **Behavioral Segmentation and Analysis**

AI agents frequently categorize users into distinct groups based on shared behaviors or characteristics. This segmentation facilitates more personalized predictions and recommendations. For example, a streaming service might classify users according to their viewing habits, enabling the AI to propose content that resonates with each group's preferences.

## **Real-time Prediction and Adaptation**

After training is complete, AI agents are capable of making real-time predictions. They consistently evaluate new incoming data as it becomes accessible while updating their models to reflect shifting user behaviors and preferences. This adaptability proves essential in dynamic settings where user behavior can change rapidly due to external influences or evolving interests.

## **Use Cases and Applications**

The ability to predict user behavior holds immense value across multiple sectors. In e-commerce settings, AI agents can foresee future purchases or suggest products that enhance customer experiences while driving sales growth. Within healthcare contexts, anticipating patient behaviors can lead to improved treatment adherence and better health outcomes. In finance, AI systems can analyze transactional patterns to forecast market trends or identify fraudulent activities.

## **Ethical Considerations**

Despite the considerable advantages associated with predicting user behavior, ethical concerns also arise. Protecting user privacy and ensuring data security are critical priorities. Adopting transparent data practices along with obtaining consent for data collection are essential steps toward maintaining trust and adhering to regulatory standards.

In summary, AI agents predict user behavior through an intricate process involving data collection, model training, and continuous real-time analysis. By utilizing advanced machine learning techniques while prioritizing a user-centered approach, these agents yield valuable insights that inform decision-making processes and deliver tailored experiences.

## **Top 7 AI Techniques for Predicting User Behavior in Mobile Apps**

### **The Importance of User Behavior Prediction in Contemporary Applications**

Artificial intelligence-driven behavior prediction has become integral to application development, empowering companies to create distinctive experiences that resonate with users. Here are the reasons why predictive analytics is crucial:

**Enhanced Personalization:** Predictive analytics enables applications to customize content, recommendations, and interactions based on individual user preferences and historical behavior, resulting in a tailored experience for each user. This personalization fosters user loyalty, as individuals feel acknowledged when their preferences are recognized.

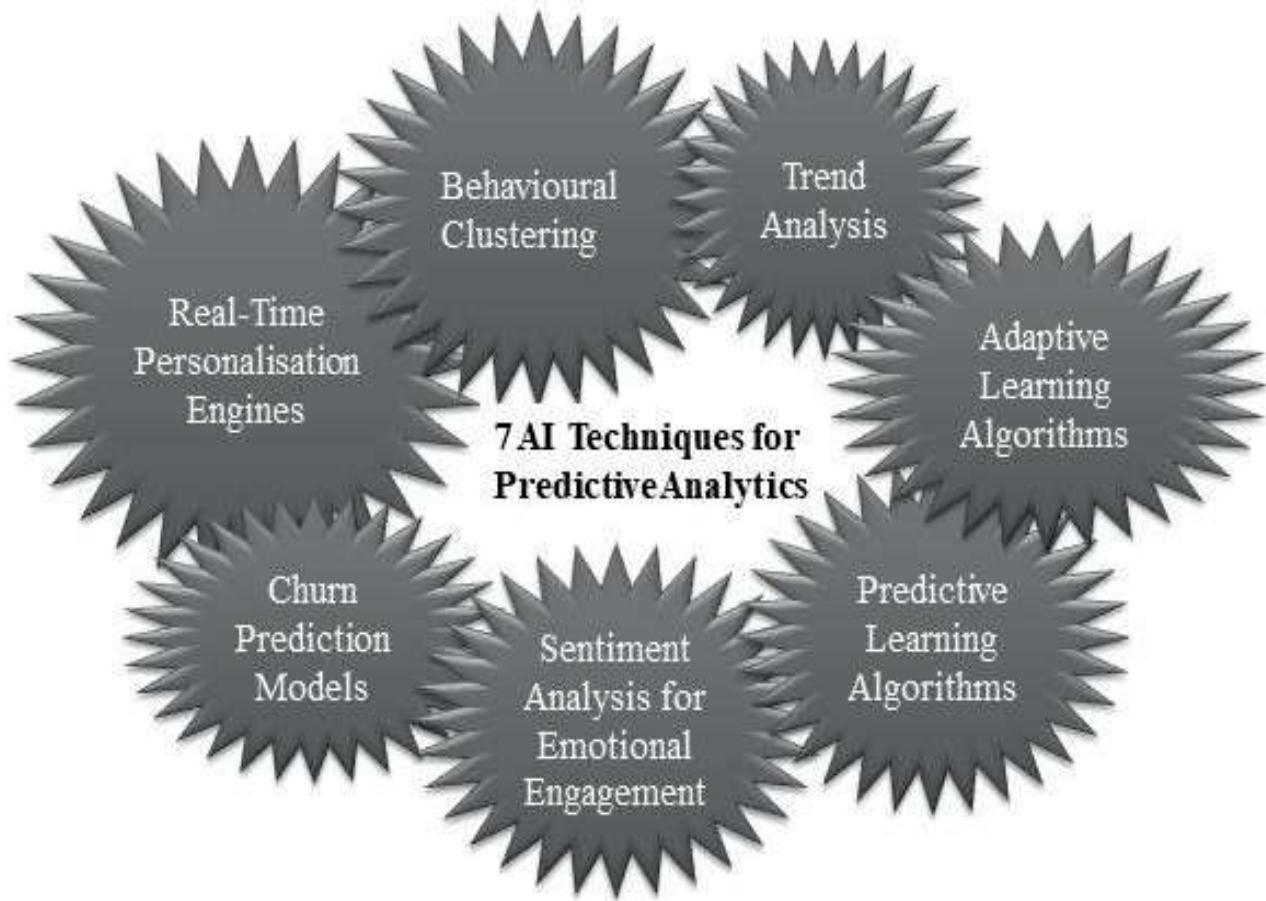
**Increased User Engagement:** Applications that respond to user needs in real-time maintain user interest for longer periods by providing relevant content and actions. By anticipating what users may find interesting, apps can present appropriate content at optimal moments, thereby extending session durations and encouraging repeat visits.

**Improved Retention and Reduced Churn:** Predictive analytics assists in detecting signs of disinterest, allowing applications to implement preventive measures such as sending personalized offers or re-engagement alerts. This proactive strategy helps minimize user churn and enhances long-term retention.

User behavior prediction empowers applications to transcend static interactions, delivering dynamic experiences that adapt alongside evolving user needs.

## 7 AI Techniques for Predictive Analytics

Here are seven efficient AI methods frequently employed to forecast user behavior and improve application performance:



*Figure 13.2 AI Techniques for Predictive Analytics*

### **Behavioural Clustering:**

**Overview:** Behavioural clustering classifies users according to shared behaviors, preferences, and interactions within the application.

**Application:** By segmenting users into distinct categories, applications can provide customized content, product suggestions, or feature recommendations that cater specifically to each group.

**Example:** In an e-commerce application, behavioural clustering can divide users based on their browsing patterns, frequency of purchases, and interests in specific products. This enables personalized product suggestions that can enhance purchase rates.

### **Trend Analysis:**

**Overview:** Trend analysis reveals patterns in user behavior over time, aiding in the anticipation of future preferences or actions.

**Application:** By recognizing changes in user behavior, applications can implement real-time modifications to enhance engagement, such as introducing seasonal promotions or popular content.

**Example:** Within a media streaming application, trend analysis can pinpoint times of maximum user activity, allowing for the optimization of content scheduling and an enhancement in user engagement.

### **Adaptive Learning Algorithms:**

**Overview:** Adaptive algorithms modify their predictions by learning from user interactions and adjusting to changes in behavior.

**Application:** This form of learning enables ongoing relevance in predictions, allowing applications to develop in line with the evolving needs and preferences of users.

**Example:** For instance, in a fitness application, adaptive algorithms can tailor workout suggestions according to a user's progress, thereby enhancing completion rates.

### **Predictive Modelling for Content Recommendations:**

**Overview:** Predictive modeling leverages historical data to suggest customized content that corresponds with individual user preferences and previous actions.

**Application:** Models for content recommendation prove to be particularly successful in applications related to media, education, and e-commerce, as pertinent content enhances user engagement.

**Example:** In a news application, predictive recommendations can match articles to the interests of users, leading to increased rates of article readership.

### **Sentiment Analysis for Emotional Engagement:**

**Overview:** Sentiment analysis employs natural language processing (NLP) techniques to assess the emotions expressed by users through textual data, including reviews, comments, or conversations in support chats.

**Application:** By comprehending user emotions, applications can tailor their responses or recommendations to enhance user satisfaction, especially within customer service and social media platforms.

**Example:** In a customer support application, sentiment analysis can identify negative feedback promptly, enabling proactive engagement and boosting satisfaction ratings.

### **Churn Prediction Models:**

**Overview:** Churn prediction models detect users who may disengage or exit the application by analyzing behavior patterns, including decreased activity levels or negative feelings.

**Application:** By forecasting potential churn, applications can reconnect with at-risk users through tailored incentives, such as special offers or customized content, thereby lowering churn rates.

**Example:** In a subscription-based application, a churn prediction model can minimize attrition by automatically dispatching re-engagement messages to users displaying indications of disengagement.

### **Real-Time Personalisation Engines:**

**Overview:** Real-time personalization modifies app content, features, or notifications in response to user activities during a session.

**Application:** This approach is particularly effective for applications that rely on immediate user engagement, such as social media platforms, gaming, and e-commerce. It enhances user involvement by delivering customized experiences aligned with ongoing interactions.

**Example:** For instance, within a social media application, a real-time personalization system can alter the content of the feed according to recent user engagements, thereby extending session durations.

### **How Predictive Models Enhance User Engagement**

Utilizing AI-driven predictive analytics enables app developers to improve user engagement, satisfaction, and retention. The following outlines the influence of these predictive models on app performance:

### **Minimizing Churn with Proactive Retention Strategies:**

By pinpointing users at risk of disengagement, AI-enhanced churn models empower apps to proactively connect with personalized offers or incentives, effectively lowering churn rates.

### **Improving User Satisfaction with Adaptive Experiences:**

Adaptive learning algorithms allow applications to adjust alongside users, ensuring that experiences stay relevant as preferences shift. Predictive analytics offers insights that help apps adapt to their users' evolving needs, resulting in more intuitive and personalized experiences that foster increased loyalty and lifetime value.

### **The Value of Predicting User Behavior for App Performance**

Predicting user behavior serves as a crucial strategy for optimizing app performance. Here's why it is essential in today's competitive landscape:

#### **Personalized Experiences Cultivate Loyalty:**

When users feel acknowledged and appreciated, they are more inclined to remain loyal. Customized content, recommendations, and notifications transform apps into tailored services that bolster user loyalty and retention.

#### **Data-Driven Product Development:**

Predictive analytics provides actionable insights regarding user preferences, enabling developers to focus on features that resonate most with their target audience, which enhances overall satisfaction. This data-centric approach ensures the app aligns closely with what users genuinely desire.

**Increased Conversion Rates and Revenue Growth:**

Employing predictive methods such as behavioral clustering and trend analysis allows apps to target users effectively with pertinent offers, thereby boosting conversions and revenue. Personalised promotions based on individual interests enhance the likelihood of sales across various avenues including in-app purchases, subscriptions, or e-commerce transactions.

By accurately forecasting user needs and behaviors, AI-driven applications can offer experiences that are both personalized and impactful—creating significant value for both users and businesses.

**Harnessing Predictive Analytics for Superior User Experiences**

In the current digital landscape, understanding user behavior is vital for developing mobile applications that engage and satisfy effectively. Advanced AI methodologies such as behavioral clustering, trend analysis, and adaptive learning equip app developers to create dynamic applications tailored to individual users. Predictive analytics ensures that apps not only function intelligently but also deliver consistently relevant and engaging experiences.

For businesses seeking to enhance engagement, retention, and customer loyalty through AI-based predictive analytics, these strategies lay the groundwork for developing high-performing mobile applications.

**13.3 ADAPTIVE CONTENT DELIVERY WITH ML**

Online machine learning, often referred to as incremental or streaming learning, is a form of machine learning where models are continuously updated with new data as it becomes available, in contrast to traditional batch training on fixed datasets. This methodology allows data to be processed sequentially, enabling the model to

learn from each incoming observation and gradually adjust its parameters to enhance predictive accuracy.

### **Applications of Online Machine Learning**

The advent of online machine learning has significantly impacted various sectors by facilitating real-time adaptation to continually changing data streams. Its speed and flexibility render it essential for applications involving ongoing data generation. Below are some key areas where online machine learning is applied:

#### **Online Recommendation Systems:**

**Dynamic Personalization:** Online learning underpins recommendation systems across e-commerce, media streaming, and content platforms by persistently refining user preferences based on immediate interactions.

**Adaptive Content Delivery:** These algorithms evaluate user behavior and preferences in real time to provide tailored recommendations, thereby boosting user engagement and satisfaction.

#### **Fraud Detection:**

**Real-Time Monitoring:** Algorithms leveraging online learning identify fraudulent activities in financial transactions, online payments, and cybersecurity by scrutinizing streaming data for unusual patterns.

**Immediate Response:** By adjusting to evolving fraud patterns instantaneously, these systems can swiftly detect and counteract fraudulent actions, thus reducing financial losses while preserving trust.

**Predictive Maintenance:**

**Equipment Health Monitoring:** Online learning models assess sensor data and telemetry streams to forecast equipment failures and maintenance requirements within manufacturing, energy, and transportation sectors.

**Proactive Intervention:** This approach supports proactive maintenance strategies that minimize downtime and enhance asset performance by pinpointing potential failures before they arise.

**Dynamic Pricing:**

**Real-Time Pricing Optimization:** Online learning algorithms refine pricing strategies in retail, hospitality, and transportation industries through real-time analysis of market trends, competitive pricing, and consumer behavior.

**Demand-Sensitive Pricing:** By modifying prices dynamically according to fluctuations in demand and supply, these systems optimize revenue while ensuring competitiveness.

**Sentiment Analysis and Opinion Mining:**

**Social Media Monitoring:** Algorithms utilize online learning techniques to analyze social media feeds, customer reviews, and online discussions instantaneously for sentiment analysis.

**Brand Reputation Management:** Such systems assist businesses in effectively overseeing their brand reputation by tracking public sentiment and spotting emerging trends or concerns.

**Adaptive User Interfaces:**

**Personalized User Experience:** Online learning algorithms drive adaptive user interfaces across web applications, mobile apps, and smart devices by tailoring user interactions based on current usage patterns.

**Context-Aware Interaction:** These systems enhance user engagement by responding adaptively to contextual factors like location, device type, and individual behavior.

**Healthcare Monitoring and Diagnostics:**

**Continuous Health Monitoring:** Streaming data from wearable devices, medical sensors, and electronic health records are analyzed using online learning models for real-time patient health monitoring.

**Early Disease Detection:** By identifying initial signs of health issues or disease progression early on, these systems facilitate timely interventions alongside personalized healthcare delivery.

**Autonomous Vehicles:**

**Real-Time Decision Making:** Online learning algorithms enable autonomous vehicles by constantly evaluating sensor inputs along with traffic conditions to make instantaneous navigation decisions.

**Adaptive Driving Behavior:** Through real-world interaction analysis that adapts to varying road conditions over time, these systems improve both safety levels and efficiency in autonomous driving.

From dynamic recommendations to fraud detection mechanisms as well as predictive maintenance strategies and self-driving technologies—online machine learning transforms numerous fields by promoting adaptive AI solutions capable of

thriving in ever-changing settings. These applications highlight the transformative power of this technology in fostering innovation while enhancing efficiency across diverse industries.

### **What Can We Anticipate for the Future?**

The future landscape of online machine learning is set to be revolutionary, influenced by continuous improvements in algorithms, technologies, and applications that are driving the advancement of adaptive AI systems. As we move forward, several significant trends and developments are likely to shape the future trajectory of online machine learning:

#### **Ongoing Progress in Algorithms**

**Deep Learning in Online Contexts:** The persistent exploration and enhancement of online deep learning algorithms will facilitate the incorporation of deep neural networks into online learning structures, opening up new avenues for processing high-dimensional data streams.

**Adaptive Learning Methods:** The rise of innovative adaptive learning methodologies, such as meta-learning and lifelong learning, will empower online systems to consistently adjust and progress in response to evolving environments and tasks.

#### **Integration with Edge Computing and IoT**

**Decentralized Learning:** Merging online learning with edge computing and Internet of Things (IoT) devices will support decentralized training processes at the edge, allowing for model training and updates directly on edge devices utilizing streaming data.

**Immediate Decision-Making:** Online learning systems based at the edge will promote real-time decision-making and autonomous control within IoT applications, leading to intelligent and responsive edge devices.

## **Distinctions Between Traditional ML and Adaptive ML**

### **Understanding Adaptive Machine Learning**

Adaptive machine learning is characterized by its ability to modify and enhance algorithmic behavior in relation to changes in incoming data. Unlike traditional ML models that operate on a static dataset, adaptive ML algorithms can refine their performance based on newly encountered data. These models continuously refresh themselves with recent information, adjust internal parameters according to new input points, optimize their learning rates, and improve their decision-making processes. Below is an overview of how adaptive machine learning has progressed within eLearning technologies over time:

**Online Learning:** As fresh data becomes available, the parameters of the ML model undergo continual updates. This iterative process allows models to adapt dynamically as they learn from incoming data points.

**Incremental Learning:** This approach involves enhancing the model with additional information without necessitating a complete retraining process. Techniques like online gradient descent are employed for parameter updates during incremental learning.

**Adaptive Algorithms:** These algorithms modify their behavior based on specific characteristics observed in incoming data. For instance, when utilizing adaptive methods like Adam, RMSProp, or AdaGrad, adjustments are made to the learning rate depending on certain parameters. Such modifications lead to improved performance even amid ongoing changes in data.

**Reinforcement Learning:** In reinforcement learning contexts, algorithms develop through feedback received from their environment—akin to a trial-and-error approach which enhances their decision-making capabilities.

**Adaptability is essential in contemporary AI applications for several reasons.**

### **Navigating Changing Environments**

As real-world contexts evolve over time, adaptive AI systems can modify their decision-making capabilities to align with these changes. This adaptability ensures that the systems remain relevant and effective as circumstances shift.

### **Customization**

Adaptive AI technologies have the ability to personalize their predictions and recommendations according to individual user preferences. This personalization not only enhances user engagement but also contributes to greater overall satisfaction.

### **Ongoing Learning**

In fields where new data is consistently generated, continual learning becomes crucial for AI systems to maintain relevance. Adaptive models are designed to assimilate new information without losing previously acquired knowledge, enabling them to adjust to evolving preferences and trends over time.

### **Efficient Resource Management**

By dynamically adjusting resources in accordance with the current context or specific tasks, adaptive AI systems can optimize resource use. For example, these models can scale their operations up or down based on the complexity of incoming data, resulting in notable gains in efficiency and scalability.

## Key Differences between Traditional ML and Adaptive ML

There are numerous distinctions between traditional machine learning and adaptive machine learning.

*Table 13.1 Traditional ML vs Adaptive ML*

<b>Parameter</b>	<b>Traditional ML</b>	<b>Adaptive ML</b>
Data Management & Processing	Functions with unchanging datasets and performs processing in an offline manner.	Manages changing data distributions and performs processing in real-time.
Educational Strategies & Model Enhancements	Acquires knowledge from established datasets, requiring model retraining for any updates.	Continuously learns by refining the model with new information.
Expandability & Adaptability	Limited in scalability and may exhibit inflexibility.	Capable of efficient scaling and offers greater flexibility.
Areas of Application	Applicable in areas such as email spam identification, medical diagnostics, predictive maintenance, and fraud detection.	Applied in adaptive user interfaces, dynamic e-commerce pricing, autonomous vehicles, and financial trading.

## **Benefits of Adaptive Machine Learning Over Traditional Approaches**

### **Dynamic Learning**

Adaptive algorithms possess the capability to learn from new data autonomously. This enables them to adjust to shifts in learner behavior and data trends, allowing them to effectively manage real-time situations.

### **Enhanced Accuracy**

By modifying parameters according to new information, adaptive models achieve high levels of accuracy, resulting in better learning outcomes through continuous refinement of their predictions.

### **Flexibility**

Adaptive algorithms can process a variety of data types, which enhances their versatility and allows for implementation across numerous eLearning platforms.

### **Rapid Adaptation**

These algorithms can incrementally update their parameters based on incoming data, enabling quicker adaptation and timely responses to changes in user behavior and educational requirements.

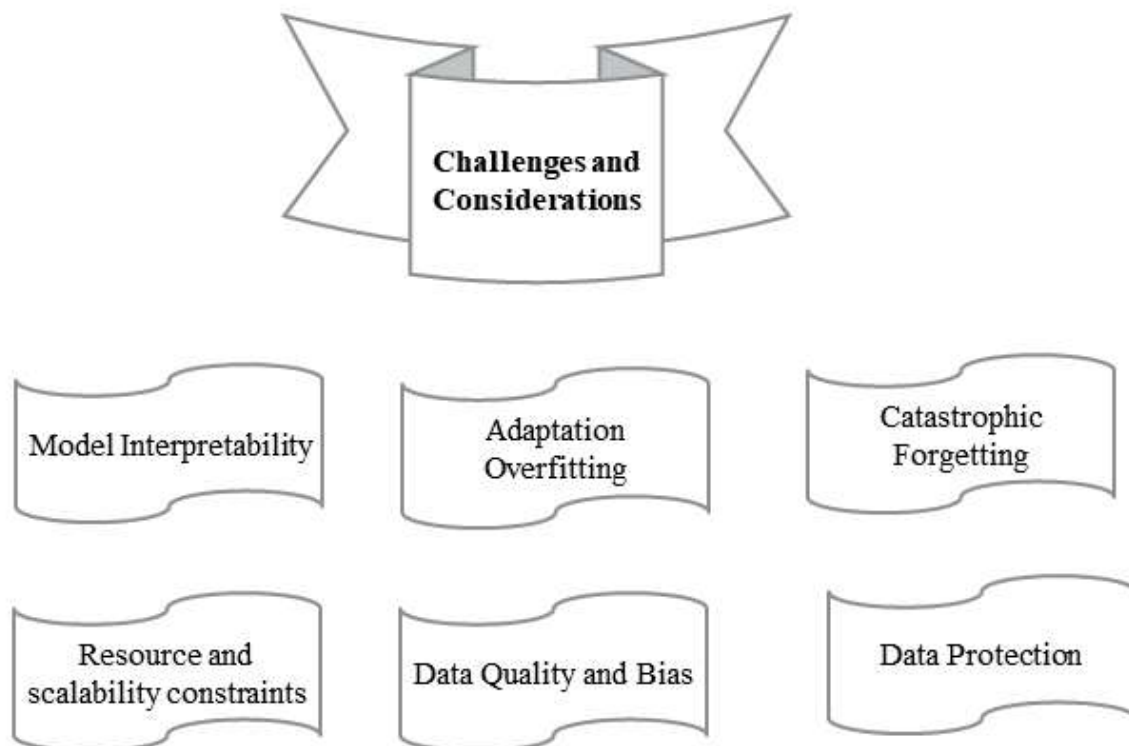
Ultimately, adaptive learning methodologies are capable of addressing "non-stationarity" by revising models to incorporate the most recent data. This ensures optimal performance even as conditions evolve over time.

## **Challenges and Considerations in Implementing Adaptive ML**

Course and platform developers face various obstacles in the integration of Adaptive Machine Learning within eLearning environments. Nonetheless, it is crucial to tackle these issues, as adaptive ML provides a wide range of advantages.

**Model Interpretability:** Due to the intricate characteristics of Adaptive ML models, comprehending their decision-making processes can be difficult. Developers might struggle to identify the rationale behind specific recommendations for adaptations. However, the burgeoning discipline of Explainable AI has the potential to improve model interpretability, aiding both trainers and learners in grasping the reasoning behind these suggestions.

**Adaptation Overfitting:** When adaptive machine learning models overly customize the educational experience according to a learner's preferences, it results in limited exposure to varied content throughout the eLearning course. To provide a well-rounded education, developers must broaden and enhance the training dataset to avoid “overfitting.”



*Figure 13.3 Challenges and Considerations in Implementing Adaptive ML*

**Catastrophic Forgetting:** As an adaptive model assimilates new data, it may occasionally erase or lose previously learned information, a phenomenon referred to as "catastrophic forgetting." To address this issue, it is essential to create a well-structured model architecture and corresponding algorithms. This approach aims to achieve a delicate equilibrium between the capacity to absorb new information and the capability to preserve established knowledge.

**Resource and scalability constraints:** When planning to implement adaptive machine learning, it is essential to have substantial computational resources and a flexible infrastructure. Additionally, enlisting the help of an expert to train and manage the adaptive model is necessary. Furthermore, ensuring scalability while adhering to resource limitations is crucial for the effective adoption of adaptive eLearning solutions.

**Data Quality and Bias:** To effectively meet learner preferences, adaptive AI relies on high-quality and representative user data. However, the presence of incomplete or biased data can result in unfair practices. Therefore, it is crucial to tackle concerns related to data quality and promote equitable practices.

**Data Protection:** While Adaptive ML systems collect user data for analysis, including behavioral patterns and individual preferences to enhance the learning experience, it is crucial to prioritize data privacy. This is vital in reducing the risk of data breaches or misuse.

### **Uses of Traditional and Adaptive Machine Learning in eLearning**

Adaptive and traditional machine learning techniques have a wide range of applications within the eLearning sector.

**Personalized Learning Paths:** By utilizing Adaptive Machine Learning, algorithms can adjust dynamically to the learner's pace and level of difficulty based

on their existing knowledge and skills. For instance, if a student is performing well in math, the system will suggest more advanced materials. This approach not only increases engagement but also improves the effectiveness of eLearning content.

**Predictive Analysis:** Conventional Machine Learning algorithms can forecast a student's performance and the likelihood of course completion by analyzing specific performance indicators and historical data. This capability allows for proactive intervention and support for those who may have disengaged from learning.

**Dynamic Assessment:** Adaptive assessment tools allow for modifications in both the difficulty level and format of evaluations. These applications can also provide insights into a learner's proficiency and progression throughout the eLearning course.

**Content Suggestion:** Through an analysis of the learner's behavior, preferences, and performance metrics, traditional ML algorithms can offer recommendations regarding suitable training materials. For example, the system might propose additional practice exercises for students encountering challenges with particular concepts.

**Enhancing Engagement Through Interactive Content:** As AI and ML techniques assess how learners interact with eLearning content, this information can empower course developers to enhance engagement through various interactive elements.

**Assessment and Feedback Automation:** By evaluating learners' responses across different assessments, ML models can streamline the evaluation process. Learners can anticipate receiving immediate feedback upon completing an assessment.

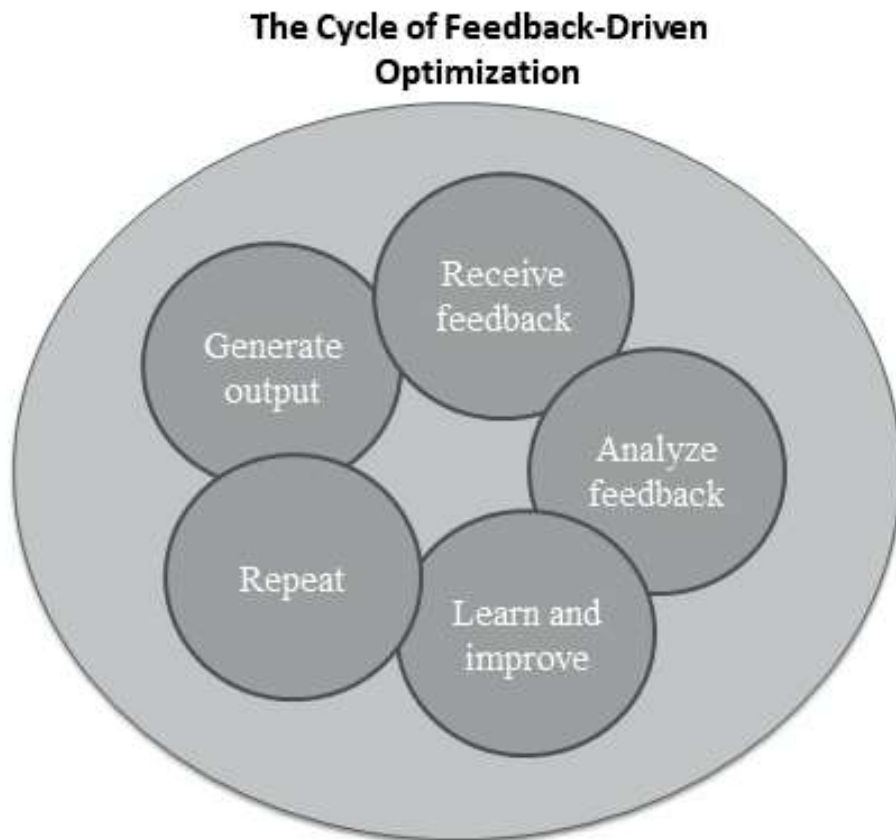
## 13.4 FEEDBACK-DRIVEN SERVICE OPTIMIZATION

### What is Feedback-Driven Optimization?

We are continuing to develop a framework for human-artificial intelligence (AI) collaboration. Our focus this week is on feedback-driven optimization. Feedback-driven optimization in artificial intelligence refers to the process by which AI systems continuously adapt and enhance their behaviors, models, and parameters based on feedback received from their environment, users, or automated evaluation mechanisms.

### The Cycle of Feedback-Driven Optimization

The process for creating optimization based on feedback involves multiple stages:



*Figure 13.4 The Cycle of Feedback-Driven Optimization*

**Generate output** - The system is required to generate outputs that rely on its current knowledge base. This includes outputs such as decision-making, text generation, and image categorization.

**Receive feedback-** The system is required to generate outputs that rely on its current knowledge base. This includes outputs such as decision-making, text generation, and image categorization.

**Analyze feedback** – AI employs machine learning techniques to derive insights, recognize patterns, and ascertain effective strategies as well as areas for enhancement via algorithms. Additionally, human evaluation is essential to assess the results produced by AI.

**Learn and improve** – Using the feedback received, AI modifies its algorithms, internal parameters, and knowledge base through a learning process aimed at boosting overall performance by reducing errors and streamlining processes. This enhancement is further supported by the incorporation of human insights.

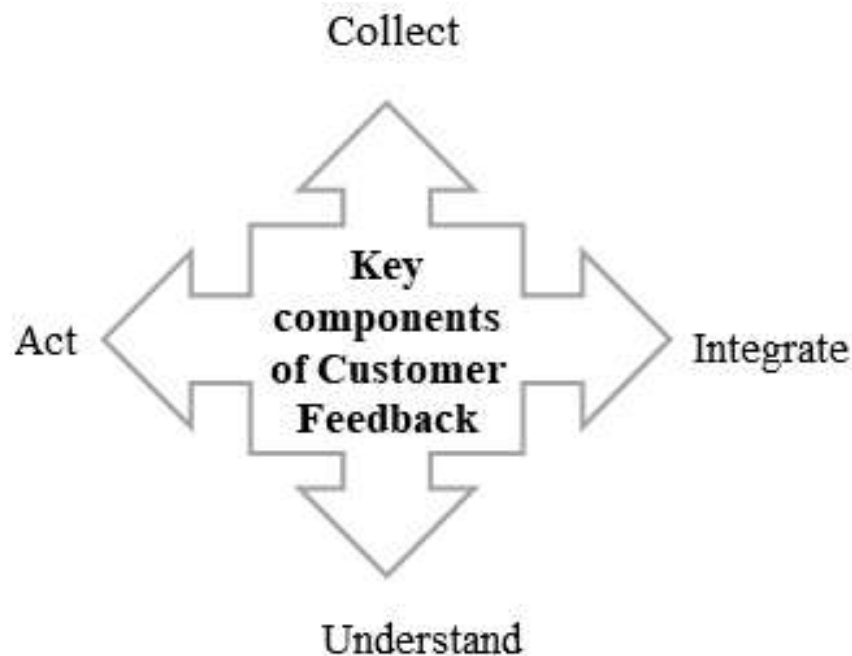
**Repeat** – Utilizing continuous feedback allows AI to gain supplementary insights, leading to an ongoing enhancement of its overall performance.

Adopting an approach that emphasizes human involvement in feedback-driven optimization is essential for correcting biases, facilitating ongoing adaptation and learning, improving accuracy and efficiency, and enhancing overall robustness and reliability. Feedback-driven optimization acts as the driving force behind AI development, allowing systems to progress and become more intelligent and effective over time.

Customer Feedback Management entails a systematic method for gathering and utilizing customer insights throughout the entire lifespan of the customer relationship. This process includes collecting feedback from diverse channels,

analyzing it to uncover trends and identify areas needing improvement, and making necessary adjustments based on these findings. By efficiently managing customer feedback throughout this lifecycle, organizations can refine their products, enhance the customer experience, and improve service operations, ultimately resulting in higher levels of customer satisfaction.

**Key components of Customer Feedback Management include:**



*Figure 13.5 Key components of Customer Feedback*

**Collect:** Collecting input via surveys, evaluations, personal engagements, and spontaneous remarks on social media platforms and review websites.

**Integrate:** Incorporating this feedback into your CRM links it to customer profiles, providing a comprehensive perspective on each interaction.

**Understand:** Analyzing feedback to recognize patterns and opportunities for enhancement. Utilizing integrated CRM data improves analysis by enabling

companies to categorize insights based on customer type, account size, lifecycle stage, and additional factors.

**Act:** Implementing modifications and enhancements based on feedback. Through CRM integration, actions informed by feedback—like follow-ups, escalations of cases, or success evaluations—can be automatically initiated using up-to-date customer insights.

### **Benefits of Customer Feedback Management**

Implementing a thorough system for managing customer feedback provides a variety of benefits:

**Higher Customer Satisfaction:** Seventy percent of customers indicate that a company's comprehension of their requirements impacts their loyalty [PwC].

**Higher Customer Retention:** Responding to feedback exemplifies superior customer service, increasing the likelihood of customers returning for additional purchases.

**Lower Customer Churn:** Engaging with customers and responding to their feedback is essential for keeping those who might otherwise depart.

**Better Products and Services:** Customer feedback enables companies to recognize areas of improvement and enhance their product offerings.

**Enhanced Brand Reputation:** Listening to customer feedback demonstrates that their views are significant, which encourages positive recommendations and improves the brand's reputation. Additionally, addressing feedback increases trust; according to HubSpot, 93% of customers are more inclined to return to a company that delivers outstanding service.

## **Best Practices for Customer Feedback Management**

**Be Prompt:** Gather customer feedback soon after a service interaction to maintain its relevance and precision.

**Leverage Automation and AI:** Use automated surveys powered by AI to simplify the data collection process.

**Conduct Surveys Across Multiple Channels:** Implement surveys on all service channels to capture insights from every customer interaction.

**Activity:** Pick a digital service (like streaming or e-learning) and explain how AI/ML can predict user behavior or adapt content in real time to improve user satisfaction. Show one example of feedback-driven improvement or personalization.

## EXERCISE

### 10 SHORT QUESTIONS

1. Define Quality of Experience (QoE) in 6G networks.
2. List four essential components for data-driven QoE models.
3. Identify two practical scenarios used to demonstrate XAI in QoE modeling.
4. Name three AI techniques for predicting user behavior in mobile applications.
5. Mention two industries where QoE enablers like ABR algorithms are applied.
6. Define online machine learning and its key characteristic.
7. List three applications of adaptive content delivery using ML.
8. Mention two differences between traditional ML and adaptive ML.
9. Identify two challenges in implementing adaptive ML in eLearning.
10. Name the key stages in the cycle of feedback-driven optimization.

### 10 LONG QUESTIONS

1. Describe the process of AI-based user behavior prediction from data collection to real-time adaptation.
2. Collect the benefits of predictive analytics for mobile apps in enhancing engagement and retention.
3. Record the key QoE metrics used in evaluating human digital twins over

6G networks.

4. Translate the impact of adaptive bitrate streaming and cloud gaming on user QoE improvements.
5. Practice applying explainable AI techniques for modeling video streaming QoE using regression and classification tasks.
6. Describe the process of adaptive machine learning from online learning to reinforcement learning.
7. Collect benefits of adaptive ML over traditional approaches in eLearning and other applications.
8. Record methods of managing customer feedback for service optimization.
9. Plan the integration of online learning algorithms into real-time recommendation systems.
10. Practice applying feedback-driven optimization to improve AI system performance and customer satisfaction.