

Data-Driven Curriculum Design in Creative Tech Education Using Student Interaction Analysis

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Abstract: Creative technology domains such as animation, UI/UX design, and visual effects (VFX) are evolving at a rapid pace, often outstripping the adaptability of conventional academic curricula. This research explores a data-centric strategy for designing curricula by analyzing how students interact with digital learning environments. Through the systematic collection and evaluation of metrics—such as participation levels, project completion rates, attendance records, learner feedback, and performance assessments—we uncover patterns that reveal students’ strengths, challenges, and areas of interest. The goal is to reduce the disconnect between academic content and real-world industry needs by leveraging these behavioral insights to refine instructional material, sequencing, and delivery approaches. This model supports greater student involvement and success, while ensuring that educational programs remain current, flexible, and closely aligned with professional standards. The study highlights how educational data analytics can play a transformative role in continuously evolving creative technology education.

Key Words: Data-Driven Curriculum, Creative Tech Pedagogy, Student Behavioral Insights, Learning Analytics, Educational Data Mining, UI/UX Instruction, Animation and VFX Training, Personalized Education, Curriculum Innovation, Adaptive Learning Design

1. INTRODUCTION

In today's digitally driven world, the need for proficient professionals in creative technology sectors—such as animation, UI/UX design, and visual effects (VFX)—continues to rise. To meet this growing demand, academic institutions offering courses in these disciplines must ensure their curricula are agile and responsive to changing industry landscapes and evolving learner needs. Traditional methods of curriculum development, which depend largely on infrequent updates and manual revisions, fall short in maintaining the relevance and impact of instructional content.

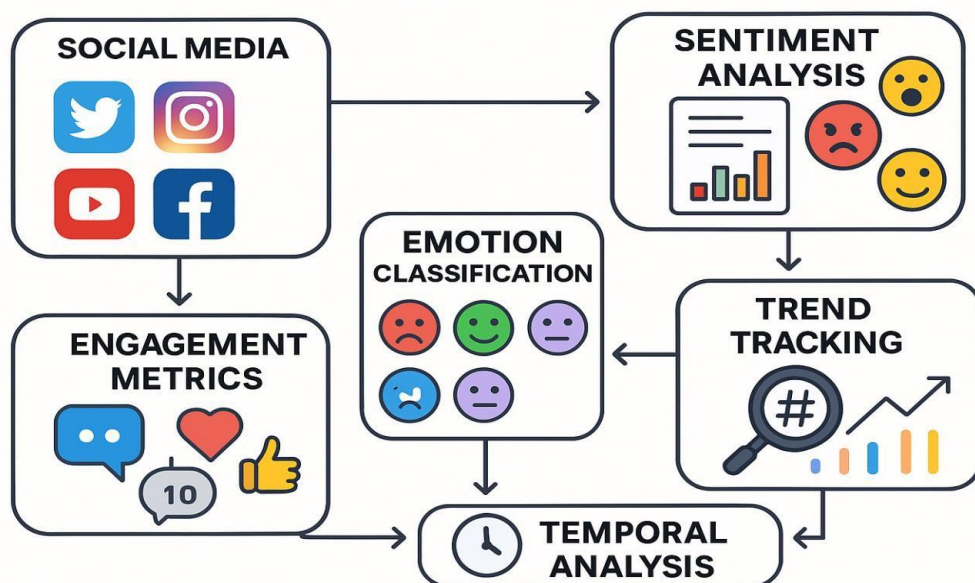


Fig 1: Social Media and Sentiment Analysis Visualization

This study proposes a data-informed curriculum development model that draws insights from real-time student interaction data, obtained through tools such as learning management systems (LMS), project tracking software, and structured feedback channels. By examining how students interact with learning materials—through engagement metrics, performance indicators, and behavioral trends—educators can uncover critical insights into where the curriculum excels and where it requires refinement.

Additionally, this research delves into the broader relevance of behavioral data in content evaluation systems. Traditional popularity-based ranking models often fail to reflect the true value of content, especially in interactive environments like Q&A forums. Behavioral cues—such as time spent on content, scroll activity, link engagement, depth of commentary, and frequency of content sharing—offer deeper context into user interest and content quality. For example, an answer that stimulates in-depth discussion or sustains user attention may hold more educational value than one that garners superficial likes or brief views.

By integrating these behavioral indicators into content ranking and curriculum design frameworks, educational platforms and learning environments can achieve greater transparency, relevance, and user satisfaction. This research aims to explore how such behavior-driven analytics can inform a more adaptive, learner-focused curriculum model in creative tech education, aligning academic programs more closely with both learner engagement patterns and professional competencies.

II.SOCIAL MEDIA AND SENTIMENT ANALYSIS

Social media platforms serve as dynamic environments where users express opinions, share experiences, and react to events in real-time. These platforms generate massive volumes of unstructured data, which, when analyzed properly, can reveal public sentiment, emerging trends, and behavioral insights. Sentiment analysis, when applied to social media data, goes beyond merely classifying posts as positive or negative—it uncovers deeper emotional tones, contextual relationships, and societal implications.

Textual Emotion Detection: At the core of sentiment analysis lies the task of interpreting textual data. Unlike traditional review-based sentiment tasks, social media language is informal, filled with emojis, slang, abbreviations, and sarcasm. Advanced NLP techniques, such as transformer-based models like BERT, are used to extract contextual sentiment, enabling accurate emotion classification even in complex linguistic environments. For instance, a sarcastic tweet that says “Great service, as always 😊” may seem positive superficially but actually carries negative sentiment.

Hashtag and Trend Tracking: Hashtags play a key role in categorizing content and rallying users around specific topics. By analyzing the frequency, context, and sentiment associated with trending hashtags, researchers can gauge public response to events, marketing campaigns, or political movements. For example, spikes in negative sentiment around a brand’s hashtag can indicate a crisis, prompting immediate response strategies.

Engagement-Based Sentiment Weighting: Not all posts carry equal influence. Sentiment derived from high engagement content—such as tweets with thousands of retweets or posts shared across multiple platforms—often reflects more impactful public opinions. Incorporating metrics like likes, shares, and comments helps weigh sentiment strength and determine which opinions have the most social resonance.

Visual Sentiment Cues:

Contemporary sentiment analysis on social media goes far beyond just textual data. Visual elements such as emojis, GIFs, and shared images play a crucial role in conveying emotional tone. Platforms like Instagram and TikTok, where visual content is predominant, benefit from multimodal sentiment analysis—combining computer vision with natural language processing to extract richer emotional context from both images and accompanying text.

Temporal Dynamics of Sentiment:

Emotional responses on social platforms are fluid, shifting with time and events. Time-based sentiment tracking allows analysts to monitor how public opinion changes across different stages—before, during, and after significant events. This method is particularly valuable in contexts like political campaigns, health awareness drives, or managing brand reputation during a crisis. Recognizing these evolving sentiment patterns enables timely and informed decision-making.

Individual Sentiment Profiling:

Examining sentiment on a per-user basis helps classify individuals according to their emotional tendencies and their potential influence. Different types of users—such as influencers, detractors, loyal followers, and automated bots—display unique emotional behavior. Profiling these groups allows for personalized engagement strategies and assists in filtering inauthentic or disruptive content from meaningful public dialogue.

Emotional Triggers and Misinformation:

Research reveals that content infused with intense emotional charge—whether positive or negative—is more likely to go viral, often irrespective of its factual correctness. This emotional virality is especially relevant in the spread of misinformation. By identifying the sentiment characteristics of misleading or manipulative content, more effective detection and intervention systems can be developed to limit its impact.

By applying machine learning and real-time data analysis across these dimensions—visual sentiment, temporal trends, user-specific behavior, and misinformation dynamics—researchers and practitioners can gain deeper insights into public discourse. These insights support smarter marketing, more effective communication strategies, better crisis responses, and even the prediction of societal shifts. In this way, sentiment analysis turns chaotic digital chatter into structured, actionable intelligence about human behavior online.

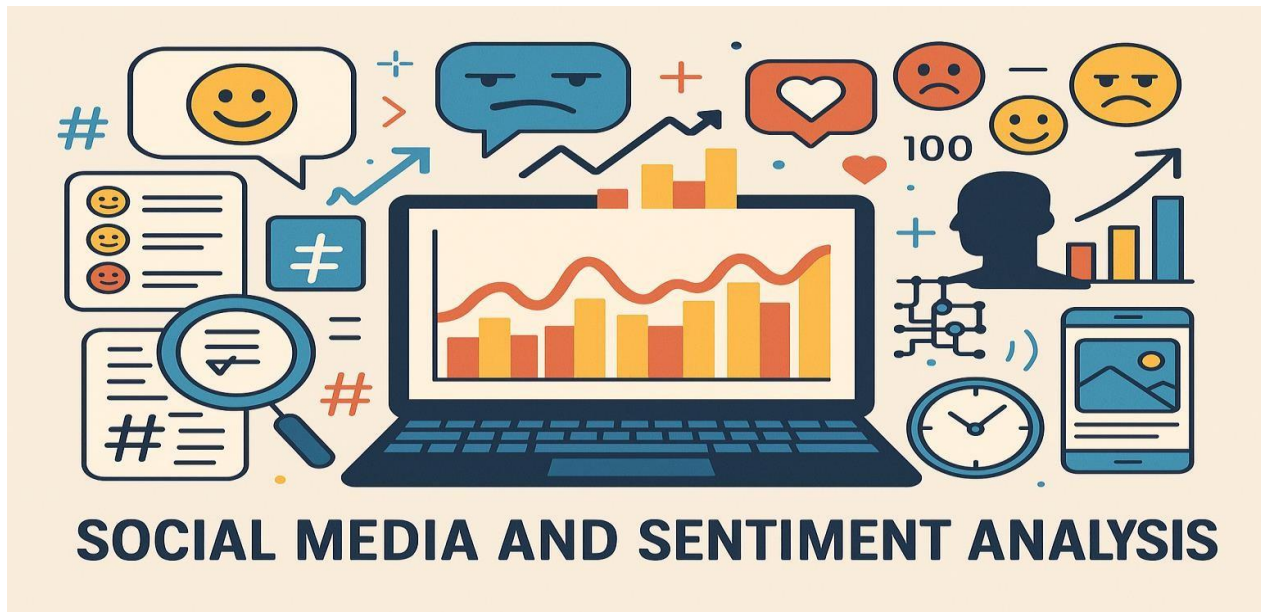


Fig. 2. Social Media and Sentiment Analysis Visualization

III. LITERATURE REVIEW

The evolution of sentiment analysis, especially in the context of social media, has been widely studied over the last two decades. Early research primarily focused on analyzing sentiment from structured sources such as reviews and surveys using lexicon-based approaches. However, with the rise of platforms like Twitter, Facebook, and Instagram, researchers began exploring unstructured, real-time data to understand public mood and opinion at scale.

Pang and Lee (2002) were among the earliest researchers to apply machine learning techniques to sentiment classification, exploring algorithms like Naïve Bayes, Maximum Entropy, and Support Vector Machines to evaluate movie reviews. Their foundational work set the stage for future studies to employ similar approaches across diverse domains. Building on this, Turney (2002) introduced an unsupervised methodology utilizing pointwise mutual information (PMI) to determine sentiment polarity in reviews, representing a transition from traditional rule-based systems to data-driven statistical models.

As user-generated content began to surge, sentiment analysis naturally extended to social media platforms. Go et al. (2009) introduced a novel method known as distant supervision for classifying sentiment on Twitter, leveraging emoticons as surrogate sentiment labels. This technique was significant because it facilitated the generation of extensive training datasets without the need for manual labeling. Shortly after, Pak and Paroubek (2010) contributed to the field by constructing a sentiment dataset specifically for Twitter and experimenting with a range of linguistic features. Their work played a key role in advancing preprocessing strategies and dataset creation tailored to the unique nature of social media data.

Recent advances have shifted towards deep learning models. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have shown superior performance in capturing sequential dependencies and contextual sentiment. Moreover, transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) have set new benchmarks in sentiment classification tasks. Devlin et al. (2018) demonstrated BERT's effectiveness across several NLP tasks, including sentiment analysis, due to its deep bidirectional architecture.

In terms of applications, sentiment analysis has been used extensively in political science, marketing, and disaster management. Tumasjan et al. (2010) demonstrated how Twitter sentiment could predict election outcomes, while researchers like Mostafa (2013) explored brand sentiment analysis to understand consumer perceptions. The use of sentiment analysis during the COVID-19 pandemic also highlighted its relevance in tracking public health concerns and misinformation.

Overall, the literature indicates a consistent evolution from simple lexicon-based methods to complex deep learning models. It also highlights the challenges of dealing with the informal, multilingual, and rapidly evolving nature of social media content. Despite these challenges, sentiment analysis remains a powerful tool for extracting insights from digital communication, and continues to be a vital area of interdisciplinary research.

IV. ROLE OF SOCIAL MEDIA IN SENTIMENT ANALYSIS

Social media has revolutionized the way individuals express opinions, emotions, and thoughts about various events, brands, policies, and social issues. Platforms like Twitter, Facebook, Instagram, Reddit, and YouTube generate massive volumes of real-time data that reflect public sentiment on a global scale. Sentiment analysis, when applied to this social media data, serves as a powerful tool to capture the voice of the people and understand collective behavior and reactions.

Instantaneous Public Feedback:

Social media platforms offer a continuous, real-time stream of public sentiment that can be analyzed as events unfold. This immediacy is especially useful for tracking public perception related to brand image, political developments, or societal reactions to major happenings such as product unveilings, elections, or emerging crises.

Variety and Richness of Content:

Unlike traditional feedback channels, social media hosts a wide spectrum of content types—ranging from text and comments to hashtags, emojis, images, and even memes. This diverse and often unstructured data presents sentiment analysis tools with an opportunity to extract nuanced emotional signals and context-rich insights.

Shaping and Amplifying Public Narratives:

The viral nature of social media means that a single post or trending topic can rapidly influence collective sentiment. Sentiment tracking allows for the observation of how opinions emerge, shift, and circulate within and across online communities, helping analysts understand the dynamics of public influence.

Crisis Identification and Response:

A sudden increase in negative sentiment can signal the onset of a crisis—be it a defective product, a scandal, or misinformation going viral. Timely sentiment analysis enables organizations to intervene early, mitigate risks, and maintain trust by communicating effectively with their audience.

Cross-Industry Relevance:

- **Marketing & Business:** Brands use sentiment insights to evaluate customer satisfaction, discover areas for improvement, and fine-tune advertising campaigns.
- **Politics:** Political strategists monitor public opinion on issues, policies, and figures to forecast election results or understand voter sentiment.
- **Healthcare:** Insights from public discourse on topics like vaccines, outbreaks, or health advisories help shape effective awareness and education strategies.
- **Finance:** Investor sentiment, drawn from platforms like Twitter and financial news, often impacts stock trends and trading behaviors.

V.CHALLENGES IN SOCIAL MEDIA SENTIMENT ANALYSIS

While social media offers an abundant source of real-time data for sentiment analysis, extracting meaningful insights from this data comes with several unique challenges. These obstacles stem from the informal nature of communication on social platforms, the diversity of users, and the limitations of current natural language processing (NLP) techniques.

Informal Language and Slang: Social media users often use informal language, abbreviations, slang, and creative spellings that deviate from standard grammar. Phrases like “LOL,” “lit,” or sarcastic comments are difficult for traditional sentiment analysis tools to interpret accurately, leading to potential misclassification of sentiment.

Sarcasm and Irony: Detecting sarcasm or irony is one of the most difficult tasks in sentiment analysis. A sentence like “Oh great, my phone just died again!” may appear positive if analyzed literally but is actually expressing frustration. Current models often struggle to capture such nuanced emotions without additional context.

Short Text Length: Platforms like Twitter restrict the length of posts, which means that many social media messages are short and lack detailed context. This brevity makes it harder to determine the sentiment, especially when combined with hashtags, emojis, or abbreviations.

Multilingual and Mixed-Language Posts:

On social media, it's common for users to express themselves using multiple languages or mix languages within a single message—for example, “This movie is super mast!” Such linguistic blending, known as code-mixing, is especially prevalent in multilingual societies and poses challenges for sentiment analysis tools that are designed for single-language input or lack exposure to hybrid language datasets.

Irrelevant and Noisy Data:

The open nature of social platforms results in a high volume of noise, including promotional content, bot-generated posts, spam, and off-topic messages. Identifying and removing this noise is a critical but difficult step, as malicious or irrelevant sources are constantly evolving to bypass detection mechanisms.

Interpreting Emojis and Hashtags:

While emojis and hashtags enrich online communication by conveying tone and sentiment, interpreting them accurately is complex. For instance, a simple smiley 😊 often suggests positivity but can carry sarcasm or irony depending on the surrounding text. Similarly, hashtags like #blessed or #fail can completely alter the emotional meaning of a post depending on usage.

Demand for Real-Time Sentiment Processing:

Certain applications—such as event tracking, brand monitoring, or crisis detection—require the sentiment engine to analyze massive volumes of social media content in real time. Meeting these demands necessitates highly optimized algorithms and robust computational infrastructure, which can be difficult to maintain at scale.

Contextual Ambiguity:

Language on social media is often informal and context-dependent. Words like “sick” may imply illness in one context or excitement in another (“That game was sick!”). Without a deep understanding of context, sentiment analysis systems may inaccurately label posts, leading to misinterpretations.

Inconsistent Datasets and Evaluation Standards:

There is no universally recognized benchmark dataset for conducting sentiment analysis on social media. Researchers often build and use custom datasets tailored to specific platforms or use cases, resulting in inconsistent model performance and limited comparability across different implementations.

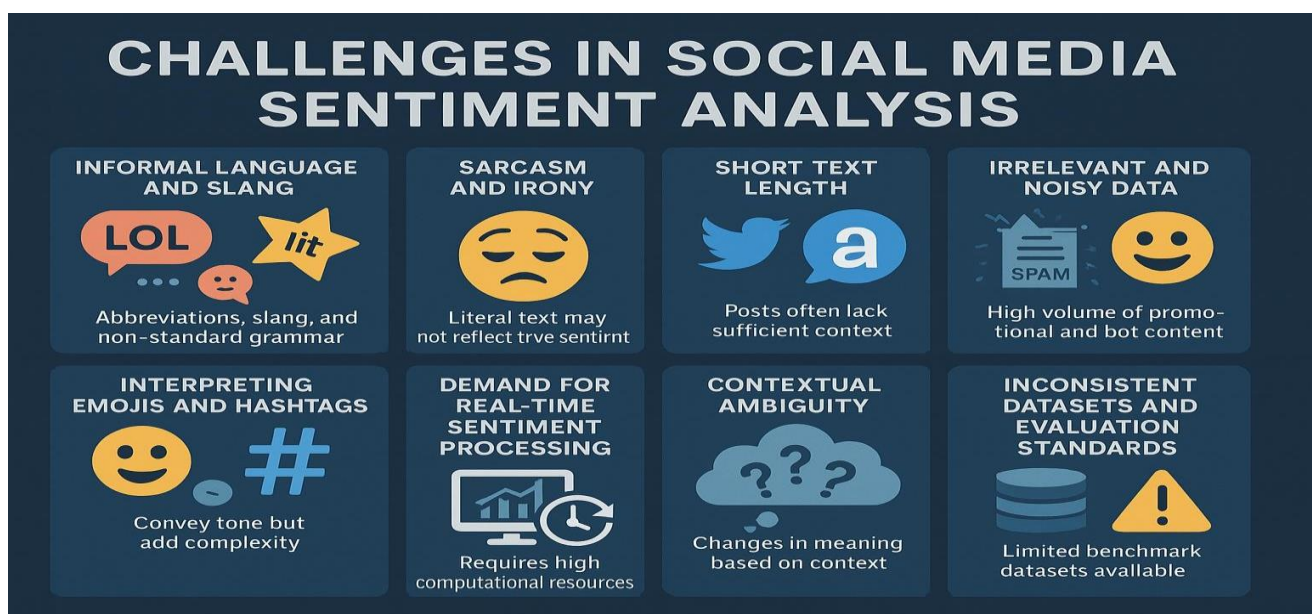


Fig 3: Challenges in Social Media Sentiment Analysis

VI. CHALLENGES AND ETHICAL CONSIDERATIONS

Integrating student interaction data into curriculum planning within creative technology education brings significant potential, but it also introduces complex challenges and ethical concerns. Addressing these issues responsibly is essential to ensure the fair, effective, and respectful use of data in educational settings.

1. Privacy and Informed Consent

The collection and use of student interaction data raise critical questions about privacy and consent. Educational institutions must adhere to legal standards such as the General Data Protection Regulation (GDPR) or the Family Educational Rights and Privacy Act (FERPA). Transparent policies, informed consent procedures, and data anonymization techniques are vital to protect student identities and maintain trust.

2. Bias and Data Misinterpretation

Interpreting interaction data is inherently complex, as behavior is often context-sensitive. Misreading trends can result in misguided conclusions about learners' needs. Additionally, analytical algorithms may carry embedded biases that unfairly impact certain student demographics, leading to inequitable educational experiences.

3. Infrastructure and Technical Constraints

Effective data analysis relies on high-quality, standardized data and robust technological support. Variations in data logging, fragmented datasets, and lack of integration across platforms can compromise the reliability of insights, limiting their utility for curriculum design.

4. Limitations of Quantitative Analysis

Creative disciplines often produce learning outcomes that are subjective and difficult to quantify. An excessive focus on measurable data could marginalize important aspects of education—such as creativity, emotional intelligence, and critical thinking—that are not easily captured through metrics alone.

5. Responsible Application of Insights

Data should be used to empower students, not to restrict them. Insights must drive supportive strategies such as personalized learning interventions rather than punitive measures. Establishing ethical guidelines for how data-driven decisions influence curriculum design is imperative to avoid unintended harm.

6. Cultural and Institutional Resistance

Resistance from faculty and students may stem from concerns over surveillance, erosion of academic autonomy, or distrust in algorithmic processes. Building acceptance requires transparent communication, ongoing training, and meaningful inclusion of stakeholders in the development and implementation of data-driven strategies.

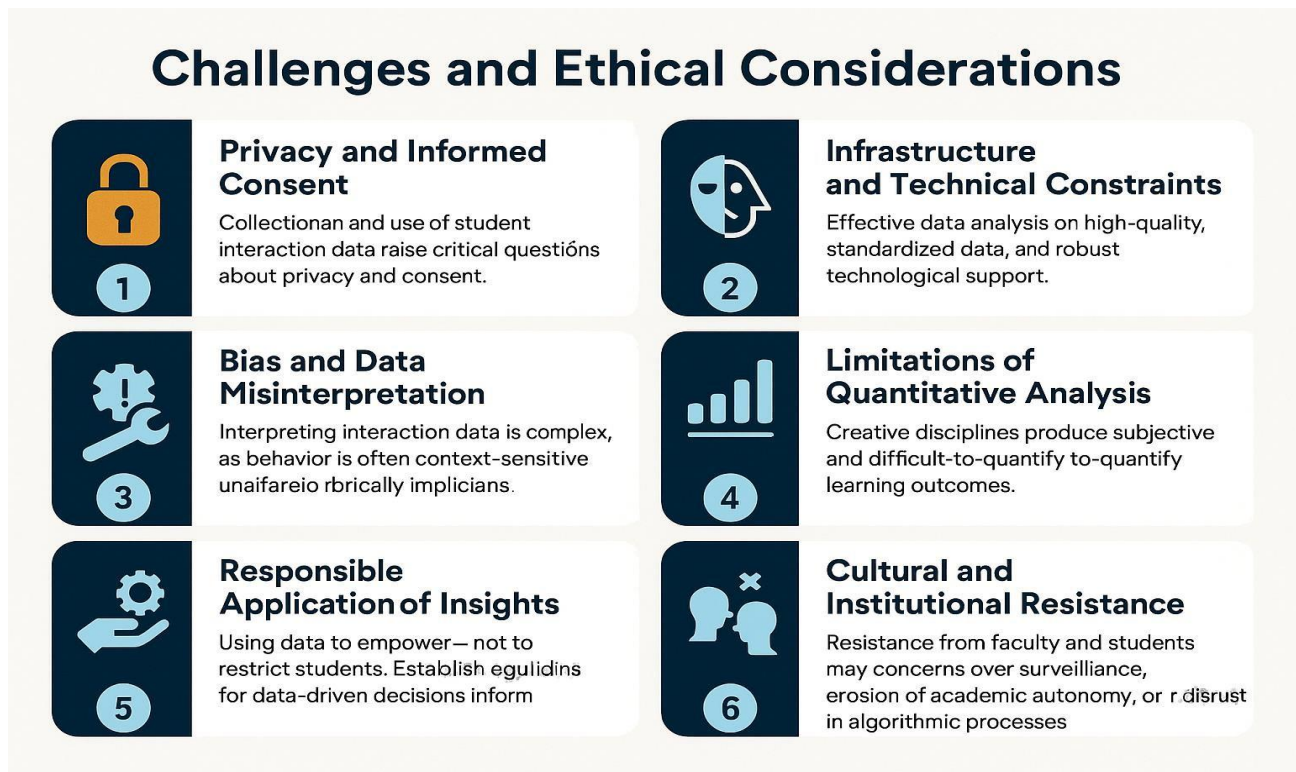


Fig 4: Challenges and Ethical Considerations

VII. FUTURE SCOPES

The application of data-driven strategies in curriculum development—particularly in creative technology education—presents vast opportunities for innovation, personalization, and enhanced learner engagement. As digital technologies continue to advance, the potential to tailor and enrich educational experiences becomes increasingly attainable.

- **Personalized Adaptive Learning:** Future educational platforms may leverage real-time student interaction data to dynamically adjust content according to individual learning speeds, styles, and creative inclinations.
- **Intelligent Feedback Mechanisms:** Artificial Intelligence can deliver personalized, context-sensitive feedback, allowing students to refine their work more effectively while providing educators with insights to continuously improve course content.
- **Integrated Cross-Tool Analytics:** Merging data from learning management systems, design tools, and collaborative platforms can offer educators a comprehensive understanding of student participation, creativity, and learning progress.
- **Gamification Strategies and Motivation Tracking:** Behavioral data can inform the design of gamified learning modules, which encourage student motivation, increase engagement, and stimulate creative problem-solving abilities.
- **Immersive Learning through AR/VR:** Interaction and sentiment data could help shape customized augmented or virtual reality learning spaces, delivering experiences tailored to individual engagement patterns.
- **Ethical and Responsible Data Use:** As reliance on data grows, developing transparent governance models that prioritize informed consent, data protection, and ethical usage will be critical for maintaining trust and integrity in education.
- **Global Curriculum Innovation:** Data-informed curriculum models can be adapted and shared across institutions worldwide, fostering collaboration and enabling scalable improvements in educational design on a global scale.
- **Predictive Student Support Systems:** Advanced analytics can help anticipate academic performance trends and potential dropout risks, enabling timely and targeted interventions to support learner success.

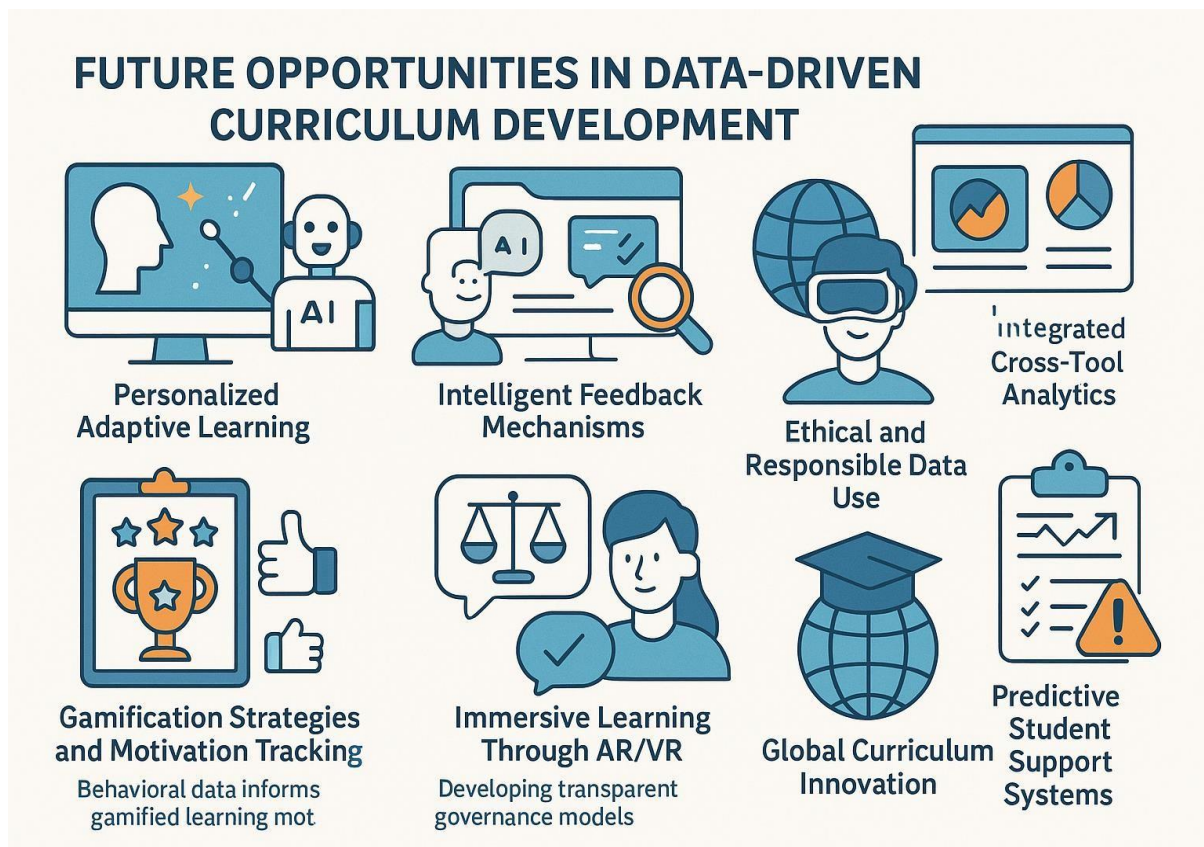


Fig 5: Future Opportunities in Data-Driven Curriculum Development

VIII.CONCLUSION

Data-driven curriculum design marks a transformative shift in creative technology education, where traditional The integration of data-driven methodologies into curriculum development signifies a major evolution in creative technology education. Traditional instructional approaches are being reimaged through the use of real-time analytics, behavioral insights, and student feedback. By utilizing social media sentiment, engagement metrics, and machine learning, educators can deliver more personalized, relevant, and impactful learning experiences. This data-informed shift moves away from outdated evaluation models and embraces adaptive, student-centered learning.

Beyond improving how content is delivered, this approach ensures alignment with current industry expectations and the evolving interests of students. While challenges such as data security, ethical use, and interpretive accuracy remain, these innovations open up new opportunities for predictive learning support, early interventions, and instructional creativity.

By merging data science with education, institutions can cultivate a more inclusive, responsive, and forward- thinking learning environment. This empowers both instructors and students, promoting ongoing enhancement, informed choices, and better educational outcomes. As institutions adopt these approaches, they are better equipped to produce graduates who are both creatively proficient and industry-ready.

In the broader digital context, sentiment analysis has become a crucial method for interpreting emotional trends, public discourse, and feedback in real time. As illustrated in this study, such analysis equips educators, policymakers, businesses, and institutions with the tools to make more nuanced and timely decisions based on public sentiment and engagement data.

When applied to the context of curriculum design in creative tech education, sentiment analysis offers unique advantages. By analyzing student reactions, emotional tone, and interaction trends across platforms like forums, learning systems, and social media, educators can fine-tune content and assessment strategies that resonate more deeply with learners. This supports a more holistic, learner-focused approach that values emotional engagement alongside intellectual growth.

Despite advancements, sentiment analysis still faces limitations, including difficulties with sarcasm detection, multilingual content, bias in algorithms, and concerns over privacy and consent. Addressing these limitations will be key to advancing fairness and contextual awareness in machine learning models.

Looking ahead, the fusion of sentiment analysis with AI, big data, and adaptive learning technologies presents enormous potential. It can enhance personalization, boost student engagement, and raise academic success rates. Ultimately, sentiment analysis is not just a passive monitoring tool—it is a transformative force for building emotionally intelligent, responsive, and equitable systems in education and beyond.

As our digital ecosystems continue to evolve, understanding the emotions and opinions conveyed within them will be essential for informed and empathetic decision-making across all sectors.

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