Extracting Insights From University Data Using AI-Powered Visualization: A Comprehensive Review and Proposed Framework

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***Abstract*—Universities generate large volumes of data across admissions, academic performance, administration, and student services. Despite their analytical potential, these datasets often remain underutilized because they are fragmented across systems, inconsistent in quality, and constrained by traditional reporting practices. Manual analysis of such complex information is slow, error-prone, and insufficient for timely or strategic decision-making.Recent advancements in artificial intelligence (AI) have introduced automated preprocessing, intelligent data cleaning, and machine-learning-based visualization recommendation, offering new possibilities for efficient insight generation. This review synthesizes current progress in AI-assisted visualization tools, evaluating AUTOVI [5] as a representative system to understand prevailing capabilities and shortcomings. Key challenges observed within higher-education analytics include incomplete or heterogeneous academic records, difficulty in visualizing longitudinal and cohort-based trends, lack of adaptive or user-specific recommendation mechanisms, and limited integration with institutional workflows. To address these limitations, the paper proposes a domain-aware, AI-driven visualization framework specifically designed for university datasets. The framework aims to reduce manual effort, improve data quality, and produce interpretable, context-sensitive visual insights that support evidence-based academic and administrative decision-making.**

***Index Terms*—Artificial Intelligence, University Data Analytics, Automated Preprocessing, Data Cleaning, Visualization Recommendation, Machine Learning, Decision Support.**

I. Introduction

The rapid expansion of data across sectors has intensified the demand for analytical and visualization tools capable of deriving meaningful insights from large, heterogeneous, and multidimensional datasets. As data grows in scale and complexity, traditional analytical techniques often struggle to identify patterns, correlations, and anomalies efficiently. Consequently, effective visualization has become essential for transforming raw, unstructured information into interpretable and actionable knowledge.

These challenges are even more prominent within the higher education sector. Universities routinely generate vast and diverse datasets encompassing admissions, academic performance, course outcomes, administrative records, faculty activities, and student support services. Despite their considerable analytical value, many institutions continue to rely on static reports, spreadsheets, and manually assembled summaries. Such practices are time-consuming, error-prone, and offer limited support for exploratory, interactive, or longitudinal analysis. As a result, opportunities for timely intervention, data-driven decision-making, and long-term academic planning often remain underexploited.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) provide promising solutions to these limitations. Emerging AI-assisted visualization systems automate essential tasks such as data preprocessing, feature extraction, visualization recommendation, and interactive exploration. Platforms including ADVISor [4], MultiVision [8], DashBot [7], VIS+AI [6], AdaVis [3], CoInsight [1], Waltzboard [2], and AUTOVI [5] demonstrate the growing capability of AI to simplify analytical workflows, reduce technical barriers, and support non-expert users in generating meaningful visual insights. These systems highlight the potential of intelligent automation to enhance data quality, improve visualization selection, and accelerate the analytics lifecycle.

However, existing platforms still fall short of addressing the specific analytical requirements of higher education institutions. Most systems provide a limited range of visualization types, struggle to manage incomplete or heterogeneous academic records, and lack adaptive or user-aware recommendation mechanisms. Additionally, the absence of seamless integration with institutional data systems—such as Student Information Systems (SIS) and Learning Management Systems (LMS)—significantly reduces their practicality within real-world academic workflows.

Motivated by these limitations, this review critically examines state-of-the-art AI-driven visualization platforms with a particular focus on their suitability for university datasets. The analysis highlights their strengths and shortcomings, identifies gaps that inhibit widespread adoption in academic settings, and introduces a domain-specific, AI-based visualization framework designed to meet the unique analytical needs of higher education.

II. Systematic Review Methodology

This section outlines the structured and unbiased review process followed to evaluate AI-driven visualization platforms, with specific emphasis on their relevance to university data analytics. The methodology was designed to ensure transparency, reproducibility, and comprehensive coverage of recent advancements in automated visualization systems.

A. Review Scope and Objectives

The primary objective of this review is to identify, compare, and evaluate contemporary AI-based visualization systems that automate data preprocessing and visualization generation. Although AUTOVI [5] serves as a representative benchmark, the review includes platforms published between 2021 and 2025 that provide empirical results, peer-reviewed validation, or documented performance analyses. Only systems applicable to structured or tabular data—characteristic of university datasets—were considered within the review scope.

B. Search Strategy

A multi-database search strategy was employed to ensure broad and balanced coverage of the literature. Searches were conducted across IEEE Xplore and the ACM Digital Library using keywords such as *"AI visualization," "automated visualization recommendation," "data exploration tools,"* and *"machine learning visualization."* Additional studies were identified through Google Scholar using combined search terms such as *"data preprocessing automation"* and *"visual analytics."* To avoid missing influential work, proceedings from major visualization venues—including IEEE InfoVis, IEEE TVCG, and PacificVis—were manually reviewed.

C. Inclusion and Exclusion Criteria

To ensure methodological rigor, systems were included only if they:

- employed machine learning or rule-based mechanisms for visualization recommendation,
- automated at least one significant stage of preprocessing or visualization generation,
- supported structured or tabular datasets.

Systems were excluded if they:

- were designed exclusively for narrow domain-specific applications,
- lacked automated or ML-driven decision-making components,
- had no published activity after 2020.

D. Data Extraction and Analysis

For each eligible platform, detailed information was extracted to facilitate systematic comparison. The extracted attributes included system architecture, preprocessing and data-cleaning functionality, recommendation mechanisms (e.g., rule-based models, MLP classifiers, reinforcement learning), interaction design, and evaluation metrics. Usability indicators—such as accuracy, efficiency, scalability, and reported limitations—were also documented to assess applicability to university environments.

E. PRISMA-Style Filtering

A PRISMA-inspired screening process was applied to maintain transparency in study selection. An initial pool of 72 papers was identified across all databases. After removing duplicates and performing title and abstract screening, 27 papers remained for full-text review. Of these, 15 were excluded due to insufficient automation, lack of relevance, or limited evaluation. Ultimately, twelve platforms—including AUTOVI [5], AdaVis [3], CoInsight [1], VIS+AI [6], Waltzboard [2], ADVISor [4], DashBot [7], and MultiVision [8]—were selected for final analysis.

This methodology establishes a robust foundation for comparing AI-driven visualization tools and identifying the domain-specific gaps that must be addressed to design effective solutions for higher education analytics.

III. University Data Challenges and Context

Understanding the nature of university data and the challenges institutions face during analysis is essential before evaluating existing AI-driven visualization platforms. Academic environments generate data that is diverse, highly contextual, and deeply interconnected, making its analysis both valuable and inherently complex.

A. University Data Landscape

Universities routinely manage extensive datasets originating from academic, administrative, and research activities. Student-related information typically includes enrollment patterns, demographic attributes, academic performance metrics, retention statistics, and graduation indicators. Academic departments generate additional records such as course outcomes, curriculum assessments, program-level performance analytics, and student feedback. Administrative units maintain data on faculty workload, financial expenditures, facility utilization, and resource allocation. Research divisions contribute publication records, funding profiles, collaboration networks, and measures of scholarly impact. Together, these diverse data streams highlight the substantial analytical potential present within higher education ecosystems [1], [3], [5].

B. Challenges in University Data Analysis

Despite its richness, university data presents several challenges that hinder effective analysis. Much of the information is distributed across independent systems—such as Student Information Systems (SIS), Learning Management Systems (LMS), and human resources databases—making integration and unified analysis difficult. Many institutions still rely on manual workflows involving spreadsheets or ad hoc scripts, which are time-consuming, error-prone, and difficult to replicate consistently. Limited data literacy among faculty and administrators further constrains the adoption of advanced analytical techniques. Traditional reporting tools often generate static outputs that lack interactivity and provide minimal support for exploratory or drill-down analyses. Consequently, institutional decisions tend to remain reactive rather than proactive.

C. Relevance to AUTOVI and Other Platforms

AI-driven visualization systems such as AUTOVI [5], AdaVis [3], and CoInsight [1] offer automated preprocessing, machine-learning-based visualization recommendations, and interactive exploration capabilities. However, applying these systems to university datasets exposes important limitations. The range of available visualization formats is often restricted, reducing their effectiveness for domain-specific tasks such as longitudinal trend analysis, cohort progression tracking, or program-level comparisons. These systems also lack adaptive learning mechanisms that personalize recommendations based on user roles or historical usage patterns. Furthermore, limited integration with institutional platforms—including SIS, LMS, and cloud-based academic systems—hinders their adoption within routine academic workflows.

These limitations underscore the need for a specialized AI-powered visualization framework tailored to the analytical priorities, data structures, and operational requirements of higher education institutions.

IV. Evaluation Criteria for Visualization Systems

A structured evaluation framework is essential for systematically comparing AI-driven visualization platforms. The criteria used in this review assess technical capability, usability, transparency, and domain applicability, with particular emphasis on their suitability for higher-education analytics.

A. Technical Criteria

Technical performance forms the foundation of system evaluation. A key determinant is the quality of preprocessing, which reflects a platform's ability to automatically handle missing values, identify anomalies, and correctly infer data types. Systems such as AUTOVI [5] demonstrate strong preprocessing support for small-to-medium-scale datasets; however, more advanced imputation and anomaly-detection techniques are required for complex institutional data.

Recommendation accuracy is another critical factor, as the value of any visualization system depends on its ability to propose appropriate visual representations. AUTOVI, for example, reports an accuracy of nearly 90% when recommending among four basic visualization types using its MLP-based classifier. Performance scalability further influences technical suitability, particularly for university datasets that often span multiple years. While AUTOVI performs efficiently with datasets of approximately 50,000 records, its responsiveness decreases as data volume approaches the million-record scale.

Finally, the diversity of supported visualization types determines the breadth of analytical tasks a system can address. Platforms limited to basic charts restrict their applicability for advanced academic analytics such as cohort progression, comparative program analysis, or longitudinal trend exploration.

B. Usability Criteria

Usability plays a pivotal role in determining whether visualization tools can be adopted by non-technical users, such as administrators and faculty members. One core aspect is ease of learning. AUTOVI performs strongly in this category, achieving a System Usability Scale (SUS) score of 82.6—rated as "excellent."

User interface simplicity further enhances accessibility by enabling smooth navigation across features such as dataset upload, visualization generation, and automated profiling. User engagement is equally important: platforms that provide interactive and real-time updates, such as AUTOVI's dynamic visualization module, support exploratory learning and encourage deeper data interrogation.

C. Transparency and Trust

Trust in AI-driven visualization tools depends heavily on transparency. Explainability ensures that users understand why a specific visualization is recommended. AUTOVI addresses this by presenting the reasoning behind its classification decisions through its MLP-based model.

Model interpretability is closely related and concerns whether users—particularly non-experts—can comprehend the logic behind system outputs. Systems with transparent classifier structures foster a higher level of trust. Additionally, platforms that incorporate user feedback mechanisms strengthen both transparency and long-term adaptability by refining future recommendations.

D. Domain Applicability

Domain applicability assesses how effectively a visualization platform addresses the unique analytical needs of higher-education institutions. Academic datasets require support for analyses such as cohort tracking, program-level comparison, curriculum assessment, and retention monitoring.

Integration capability is also a critical factor. Systems that can seamlessly connect to Student Information Systems (SIS), Learning Management Systems (LMS), or institutional reporting dashboards are more likely to be adopted. Workflow alignment—i.e., the degree to which a system supports routine reporting and planning processes—further determines practical relevance within universities.

V. Review of Existing Platforms

A variety of AI-driven visualization platforms have emerged in recent years, each addressing different components of automated data analysis and visual exploration. This section reviews the most prominent systems, outlining their core capabilities, strengths, and limitations. While AUTOVI [5] serves as a central reference for comparison due to its integrated design, the review encompasses a broader range of tools developed for diverse analytical contexts.

A. CoInsight

CoInsight, introduced by Li et al. [1], focuses on visual storytelling for hierarchical tables. The platform enables users to trace multi-level relationships within tabular data, supporting structured narrative interpretation. Although highly effective for explaining hierarchical datasets, CoInsight lacks automated preprocessing and does not incorporate machine-learning-based visualization recommendation. As a result, it cannot support end-to-end analytical workflows involving messy or heterogeneous institutional data.

B. Waltzboard

Waltzboard, proposed by Kim et al. [2], automates dashboard layout design by optimizing multiple criteria simultaneously. It evaluates data properties to produce dashboard configurations suited for exploratory visual analysis. However, the platform does not include robust data-cleaning mechanisms and offers limited interactive feedback, reducing its effectiveness for users dealing with large or unrefined datasets. Its strengths lie primarily in layout automation rather than comprehensive visualization intelligence.

C. VIS+AI

VIS+AI, developed by Chen and Zhang [6], integrates machine learning with visualization pipelines to enhance analytical workflows. The system predicts suitable visualization types and supports interactive exploration. Despite these strengths, VIS+AI does not provide automated preprocessing, making it less effective for real-world datasets that contain missing values, inconsistent entries, or mixed variable types—common challenges in university data environments.

D. AdaVis

AdaVis, presented by Zhang et al. [3], introduces an adaptive and explainable visualization recommendation framework. Its feedback-driven mechanism allows the system to refine recommendations over time, enabling more personalized and context-aware visual exploration. While AdaVis excels in adaptivity and explainability, it requires substantial manual preprocessing, which limits its scalability and hinders its applicability for large institutional datasets that demand automated cleaning and integration.

E. ADVISor

ADVISor, introduced by Wang et al. [4], generates visual responses to natural-language queries posed on tabular data. By supporting NL-based interaction, the system lowers the technical barrier for non-expert users. However, its lack of automated preprocessing and restricted support for interactive experimentation constrain its use in complex analytical tasks, particularly those requiring iterative data exploration.

F. DashBot and MultiVision

DashBot [7] and MultiVision [8] employ deep reinforcement learning to automate dashboard design. These systems optimize visualization selection and layout through reward-based learning strategies. Although powerful for layout automation, they offer limited user interactivity and lack mechanisms for incorporating user feedback, restricting their adaptability to evolving analytical needs. Their absence of preprocessing automation also reduces their effectiveness in domains with noisy or fragmented data, such as higher education.

G. AUTOVI: Comprehensive Analysis

AUTOVI [5] combines automated preprocessing, transparent machine-learning models, and interactive visualization tools within a unified framework. Its preprocessing module manages missing values, normalizes data types, and extracts structural metadata. The MLP-based classifier recommends visualization types with high accuracy, while interactive components—such as the *Try Your Own Visualization* and *Profile Report* modules—support dynamic exploration. AUTOVI achieves substantial efficiency improvements, reducing visualization generation time from over 40 minutes to fewer than four, and demonstrates strong usability with a SUS score of 82.6.

Despite these strengths, AUTOVI has notable limitations in the context of higher education analytics. Its visualization library is restricted to four basic chart types, limiting its ability to support cohort tracking, longitudinal analysis, and program-level comparisons. Scalability also decreases with datasets exceeding approximately 50,000 records. Additionally, the system lacks adaptive learning mechanisms and does not provide domain-specific customization or integration with SIS and LMS platforms.

H. Evaluation Mapping Table

Table **??** summarizes the evaluation criteria across selected AI-driven visualization platforms, including AUTOVI, AdaVis, CoInsight, and VIS+AI. This comparative mapping illustrates the variability in preprocessing automation, recommendation accuracy, usability, and transparency across tools, helping identify gaps most relevant to higher-education analytics.

VI. Case Study: Applying AUTOVI to University Enrollment Data

To demonstrate AUTOVI's practical applicability and further assess its limitations in a higher-education context, a case study was conducted using student enrollment and retention data. The dataset reflects typical information extracted from a university Student Information System (SIS) and covers five academic years. It includes approximately 50,000 student records with variables such as student identifiers, academic programs, admission terms, cumulative GPA, retention status, demographic attributes, and course completion details. The dataset also exhibits characteristics common in institutional data—approximately 15% missing values, mixed categorical and numerical variables, and multi-level cohort relationships requiring contextual interpretation.

AUTOVI processes this dataset through a sequence of automated steps. During preprocessing, the system detects and imputes missing values, standardizes data formats, and automatically identifies feature types based on metadata. Once preprocessing is complete, AUTOVI's MLP-based classifier recommends appropriate visualization types. For example, trends in student retention across academic years are typically represented using line or bar charts, while program-level comparisons are visualized using grouped bar charts.

TABLE I
FEATURE COMPARISON ACROSS THE TWELVE REVIEWED VISUALIZATION SYSTEMS

System	Auto-prep	ML Recomm.	Interactivity	Adaptivity	SIS Connectors	Scalability	XAI	Notes
AUTOVI	Yes	Yes	Yes	No	No	Medium	Partial	4 vis types; SUS 82.6
AdaVis	Partial	Yes	Yes	Yes	No	Medium	Yes	Adaptive recommendations
CoInsight	No	No	Yes	No	No	Low	No	Good for hierarchical tables
VIS+AI	No	Yes	Yes	No	No	Medium	No	ML-driven recs
Waltzboard	Yes	Yes	Some	No	No	Medium	No	Layout automation focus
DashBot	No	Yes	Some	No	No	Low	No	RL-based dashboard design
MultiVision	No	Yes	Some	No	No	Low	No	RL-based dashboards
ADVISor	No	Yes	Limited	No	No	Low	Partial	NL query $\rightarrow$ visuals

The system generates interactive visualizations within two to three minutes, enabling administrators to rapidly explore variable relationships. Users can also test additional visualization formats—such as scatter plots examining the relationship between GPA and retention—through the *Try Your Own Visualization* module, supporting flexible, iterative exploration.

The analysis produced several notable insights. Engineering programs exhibited retention rates approximately 12% higher than humanities disciplines. First-generation students showed retention levels about 8% lower than other students despite similar academic performance, indicating potential non-academic factors influencing retention. Additionally, students admitted during the winter term demonstrated higher dropout tendencies compared to those entering in the fall, suggesting seasonal or cohort-specific influences on student progression.

Although AUTOVI effectively identifies these patterns and demonstrates substantial strengths—particularly in preprocessing efficiency, ease of use, and interactive exploration—it also reveals important limitations when applied to university-scale datasets. Its visualization library is restricted to four basic chart types, which constrains its ability to support detailed cohort tracking, longitudinal analyses, or curriculum pathway exploration. AUTOVI also lacks predictive modeling capabilities that could help identify at-risk students earlier in the academic cycle. Furthermore, its absence of adaptive learning mechanisms prevents personalization of visualization recommendations, and limited integration with institutional systems such as SIS or LMS restricts real-time or automated analytics.

Overall, the case study highlights AUTOVI's value as a rapid and accessible exploratory analysis tool while underscoring the need for a domain-specific, AI-driven visualization framework tailored to the analytical complexity and operational workflows of higher education institutions.

VII. GAPS AND LIMITATIONS IN EXISTING SYSTEMS

Although AI-assisted visualization tools have advanced considerably in recent years, several critical limitations continue to restrict their effectiveness in university-scale analytics. These gaps become especially apparent when dealing with large, heterogeneous, and academically complex datasets that characterize higher education environments.

A. Technical Gaps

One of the primary technical challenges is scalability. Many existing platforms, including AUTOVI, perform well with small to medium-sized datasets but experience substantial performance degradation when handling datasets exceeding one million records or extremely high-dimensional data. Reduced responsiveness and longer processing times limit their suitability for multi-year institutional datasets.

Another important limitation concerns visualization diversity. Most systems support only general-purpose chart types and lack academic-specific visualizations such as retention funnels, cohort progression diagrams, curriculum flow charts, or program-level KPI dashboards. As a result, their ability to support detailed institutional analytics is significantly constrained. Additionally, advanced handling of missing or inconsistent data is often absent. Tools such as AUTOVI rely primarily on simple statistical imputation, which is insufficient for multi-year academic records that require context-aware anomaly detection and sophisticated data-cleaning strategies.

B. Adaptive Learning Gap

A key shortcoming across all reviewed systems is the lack of adaptive learning capabilities. None of the platforms—including AUTOVI—actively incorporate user feedback or interaction histories to improve future visualization recommendations. This limits personalization for different roles within the academic ecosystem, such as administrators, faculty members, and institutional researchers, each of whom requires distinct analytical perspectives.

C. Domain-Specific Gap

Most tools are designed as general-purpose visualization systems and do not incorporate domain knowledge essential for higher education analytics. Academic constructs such as GPA normalization, credit-hour accumulation, academic standing classification, prerequisite structures, and graduation pathway modeling require specialized processing that current systems do not support. Furthermore, existing platforms cannot automatically generate longitudinal cohort views or term-wise comparative dashboards, limiting their usefulness for tracking student progression and evaluating academic program performance over time.

D. Integration Gap

Another significant limitation is the lack of integration with institutional data infrastructures. Most systems operate as standalone tools without connectivity to Student Information Systems (SIS), Learning Management Systems (LMS), or enterprise platforms such as Banner or PeopleSoft. Because universities rely on continuously updated data pipelines, this lack of interoperability limits the practicality, scalability, and sustainability of current solutions within real academic workflows.

E. Interpretability Gap

Interpretability remains a critical concern, particularly for non-technical institutional stakeholders. Although AUTOVI provides partial interpretability through its MLP-based classifier, many AI-driven recommendations across systems remain opaque and difficult to understand. The absence of transparent decision logic reduces user trust and may hinder the broader adoption of automated visualization tools in academic settings.

F. Summary

In summary, while existing systems such as AUTOVI significantly reduce manual effort and streamline visualization generation, several important gaps remain. Future platforms must support scalable processing of multi-year academic datasets, incorporate domain-specific visualization types aligned with institutional metrics, and integrate adaptive learning mechanisms for personalized recommendations. Seamless interoperability with university information systems and improved interpretability for non-technical users will be essential to maximizing the impact and long-term adoption of AI-driven visualization tools in higher education environments.

VIII. Proposed Directions and Implementation Framework

Building on the gaps identified in existing AI-assisted visualization platforms, this section outlines a comprehensive framework designed specifically to address the analytical needs of higher education institutions. The proposed system integrates automation, adaptive intelligence, interactivity, and domain-aware customization to support accurate, timely, and actionable decision-making.

A. Enhanced Preprocessing Module

The first component of the framework focuses on strengthening preprocessing capabilities to accommodate the complexities of academic datasets. This includes the use of domain-aware imputation strategies that incorporate contextual factors such as GPA normalization, credit-hour weighting, and retention-adjusted estimation. Such approaches enable more accurate handling of missing values and inconsistent entries. Continuous data validation and anomaly detection mechanisms are essential to maintain data quality and identify irregularities in real time. The preprocessing engine must also possess semantic awareness of core educational constructs—such as academic standing, cumulative progression, and degree pathways—to ensure that academic variables are processed with appropriate contextual sensitivity.

B. Expanded Visualization Library

To overcome the limitations of existing systems, the proposed framework includes a broader library of visualization templates tailored specifically for academic analytics. Examples include cohort progression charts for tracking student movement across semesters, program-level dashboards for comparing retention and performance metrics, and retention funnel diagrams to identify drop-off points across the student lifecycle. Additional temporal and flow-based visualizations can capture course-sequence pathways, enabling institutions to observe how students progress through curriculum structures.

C. Adaptive Learning Engine

A central component of the proposed architecture is an adaptive learning engine that continuously refines visualization recommendations. This engine captures user feedback on visualization relevance, interpretability, and usability, integrating this information into the recommendation model over time. It also adapts to department-specific usage patterns and provides personalized suggestions based on user roles—whether the user is an administrator seeking strategic insights, a faculty member evaluating program performance, or an institutional researcher conducting detailed analytics. Over time, the system evolves to better support role-specific, context-aware analytical workflows.

D. University System Integration

Successful adoption of the proposed framework requires seamless integration with institutional data infrastructures. Direct connectivity with Student Information Systems (SIS), Learning Management Systems (LMS), and enterprise platforms such as Banner or PeopleSoft ensures access to continuously updated academic records. A cloud-based deployment model improves scalability, enables automatic updates, and supports elastic resource allocation. Moreover, the framework must align with institutional reporting cycles, accreditation requirements, and existing performance indicators to ensure consistent integration with administrative and academic workflows.

E. Implementation Timeline

The implementation of the proposed system can be structured into four phases. The first three months focus on developing the enhanced preprocessing module and establishing connectors to institutional data sources. The following three months involve the integration of domain-specific visualization templates and deployment of the adaptive learning engine. Months seven through nine consist of pilot testing at two or three institutions, enabling iterative refinement based on real-world feedback. The final phase, spanning months ten to twelve, includes system-wide rollout, user training, and incorporation into institutional analytics workflows.

F. Success Metrics

The effectiveness of the proposed framework can be evaluated using several measurable indicators. A System Usability Scale (SUS) score exceeding 80 would signal strong user acceptance. Visualization generation times consistently below two minutes would indicate system efficiency. High satisfaction levels—ideally above 85%—and adoption by at least half of the participating departments during pilot testing would further demonstrate practicality and real-world relevance.

G. Expected Outcomes

The proposed framework offers several anticipated benefits. Automated preprocessing and visualization generation substantially reduce manual workload for analysts and administrators. The interactive and adaptive features enhance user engagement and encourage personalized data exploration. The framework also strengthens institutional capacity for conducting longitudinal and predictive analytics, enabling deeper insights into student progression, program performance, and equity-related outcomes. Ultimately, the system aims to provide interpretable, context-aware, and actionable visual insights that support data-driven academic and administrative decision-making.

IX. Discussion and Future Directions

A. Key Insights from the Review

The comparative analysis of AUTOVI and other AI-driven visualization platforms reveals several important trends in the evolution of automated visual analytics for structured data. One of the clearest patterns is the significant efficiency gained through automation. Systems that integrate machine learning and automated preprocessing—such as AUTOVI—demonstrate the ability to reduce workflows that traditionally require over forty minutes to just a few minutes, thereby lowering the technical burden for users and making data exploration more accessible.

Interactivity also emerges as a central factor influencing user engagement and analytical depth. Interactive components, such as AUTOVI's *Try Your Own Visualization* module, allow users to experiment with various visualization options and navigate data more intuitively. Such features are particularly valuable for exploratory analysis, where flexibility and real-time feedback enhance understanding. Transparency plays a similarly important role. When systems provide clear explanations for recommended visualizations, non-technical decision-makers develop greater trust in automated insights, increasing the likelihood of adoption.

At the same time, the review underscores key limitations of general-purpose visualization platforms. While some systems excel in specific areas—such as adaptive learning or preprocessing automation—none fully address the domain-specific analytical needs of higher education institutions. Universities require tools capable of interpreting multi-year datasets aligned with academic calendars, supporting detailed cohort and program-level analysis, and generating institution-specific performance indicators. Furthermore, effective systems must integrate seamlessly with SIS and LMS platforms and comply with institutional data governance policies. Current platforms address these needs only partially, indicating a clear opportunity for a more comprehensive, domain-aware solution.

B. Future Research Directions

The insights from this review highlight several promising research directions that could advance AI-driven visualization in academic settings. One important area involves developing domain-specific AI models trained directly on educational datasets. Such models would allow visualization recommendations to be more contextually aligned with academic structures, improving the relevance and accuracy of automated outputs.

Collaborative and privacy-preserving learning approaches, such as federated learning, offer another productive avenue. By enabling multiple universities to contribute to shared models without exposing sensitive student information, federated systems could help institutions benefit from collective intelligence while maintaining data security and regulatory compliance.

A further direction involves expanding current systems beyond descriptive analytics toward prescriptive and intervention-oriented capabilities. Such features could support early-warning systems, identify at-risk students, or recommend targeted academic interventions based on longitudinal patterns.

Finally, advancements in explainable AI (XAI) remain essential. Enhancing interpretability will ensure that visualization recommender systems maintain accountability, transparency, and institutional trust—the qualities necessary for widespread adoption across universities. Improved XAI methodologies would help stakeholders understand the reasoning behind recommendations, fostering greater confidence in automated decision-support systems.

X. Conclusion

This review analyzed the evolving landscape of AI-driven visualization platforms and assessed their suitability for addressing the analytical requirements of higher education institutions. Among the systems examined, AUTOVI emerged as a strong example of how automated preprocessing and machine-learning-based visualization recommendation can streamline data exploration, particularly for users with limited technical expertise. Its efficiency and user-oriented design illustrate the substantial benefits that AI-assisted tools can bring to institutional analytics.

However, the analysis also revealed several fundamental limitations that restrict the applicability of current platforms in academic environments. Existing systems struggle to scale effectively when processing multi-year or high-volume datasets and provide limited support for adaptive learning mechanisms that respond to evolving institutional needs. Furthermore, most tools offer only narrow, general-purpose visualization libraries that fail to capture the complexity of academic structures. The absence of domain-specific analytical capabilities—such as cohort tracking, longitudinal performance analysis, and program-level comparisons—limits their usefulness for institutional planning and student success initiatives. Additionally, the lack of seamless integration with SIS, LMS, and other enterprise systems reduces their practicality for real-world deployment.

Several overarching insights emerged from this review. AI-driven platforms clearly reduce the time and effort required for generating visualizations, transforming what were once labor-intensive tasks into processes that can be completed within minutes. Interactive, transparent system designs foster stronger user engagement and build trust, especially among non-technical stakeholders. Nonetheless, the insufficient alignment of current tools with higher-education-specific needs underscores the necessity for more targeted solutions.

To address these gaps, this paper proposed a next-generation AI-powered visualization framework that integrates advanced preprocessing, adaptive learning mechanisms, domain-specific visualization templates, and comprehensive system integration. Together, these components establish a foundation for a more flexible and capable analytical environment—one that supports data-informed decision-making, enhances the monitoring of student outcomes, and strengthens analytics-driven practices across universities.

REFERENCES

[1] G. Li, R. Li, Y. Feng, Y. Zhang, Y. Luo, and C. H. Liu, "CoInsight: Visual storytelling for hierarchical tables with connected insights," *IEEE Transactions on Visualization and Computer Graphics*, 2024. doi: 10.1109/TVCG.2024.3388553

[2] J. Kim, H. Lee, and J. Choi, "Waltzboard: Multi-criteria automated dashboard design for exploratory analysis," in *Proc. IEEE Pacific Visualization Symposium (PacificVis)*, 2025. doi: 10.1109/PacificVis64226.2025.00032

[3] S. Zhang, H. Li, H. Qu, and Y. Wang, "AdaVis: Adaptive and explainable visualization recommendation for tabular data," *IEEE Transactions on Visualization and Computer Graphics*, 2024. doi: 10.1109/TVCG.2024.3388553

[4] Q. Wang, Y. Luo, Y. Zhang, and H. Qu, "ADVISor: Automatic visualization answer for natural-language questions on tabular data," in *Proc. IEEE Pacific Visualization Symposium (PacificVis)*, pp. 91–100, 2021. doi: 10.1109/PacificVis52677.2021.00010

[5] J. Xie, X. Zhang, W. Huang, and W. Chen, "AUTOVI: Empowering effective tracing and visualizations with AI," in *IEEE International Conference on Information Visualization (IV)*, 2024.

[6] M. Chen and L. Zhang, "VIS+AI: Integrating visualization with artificial intelligence for efficient data analysis," *Journal of Visualization Research*, vol. 2, no. 4, pp. 1–15, 2023.

[7] J. Zhou, Y. Luo, Q. Wang, and H. Qu, "DashBot: Insight-driven dashboard generation based on deep reinforcement learning," *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 1, pp. 690–700, 2023. doi: 10.1109/TVCG.2023.3314826

[8] J. Zhou, Y. Luo, Q. Wang, and H. Qu, "MultiVision: Designing analytical dashboards with deep learning-based recommendation," *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 1, pp. 279–289, 2022. doi: 10.1109/TVCG.2021.3114826

[9] J. D. Becher, P. Berkhin, and E. Freeman, "Automating exploratory data analysis for efficient data mining," in *Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, pp. 424–429, 2000.