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Designing an AI-Based Digital Governance Structure for Online Education Establishments: A Design Science Research Methodology Along With Practical Use of the OULAD Database

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Abstract

The exponential increase in e-learning has led to educational data landscapes of growing complexity. With this, one might wonder whether we will be getting evidence-based institutional decision-making and if the use of transparent, accountable, and responsible Artificial Intelligence (AI) will become widespread. Learning Analytics and Educational Data Mining provide the basis to predict student outcomes quite accurately, yet they have not been fully utilized in institutional digital governance. The authors of this study propose and test out a framework dubbed AI-Driven Digital Governance (AIDG), which fuses the concepts of digital governance, Artificial Intelligence, Learning Analytics, Explainable Artificial Intelligence (XAI), and Business Intelligence all under one roof in a decision-support architecture.

The paper is conducted primarily employing Design Science Research (DSR) methodology which enables designing, demonstrating, and testing the framework step by step. An empirical case study is based on the data of the Open University's Learning Analytics Dataset (OULAD). In the development process, educational data is prepared and features are engineered using two types of supervised machine learning models; namely, Random Forest, and Extreme Gradient Boosting (XGBoost) which are employed at governance level prediction. The model's accuracy, its precision rate, how well it can detect positives (recall), and their F1-score which is sort of like a harmonic mean are the criteria to assess the performance of the model. The model is further made more transparent and explanatory with the help of SHapley Additive exPlanations (SHAP) which points out the learning variables that are most heavily influencing prediction outcomes. Finally, the generated data analysis products and the explanation of model predictions are incorporated into an accessible Microsoft Power BI system so that users can interact with the tool while institutional decision-making and monitoring are being done on the back of data.

The results of the experiments show good predictive abilities of both models. In the Random Forest model, 93.34% of Accuracy, 97.06% of Precision, 90.12% of Recall and 93.46% of F1-score were

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recorded, while in the XGBoost model, the following metrics were calculated: 93.99% of Accuracy, 96.55% of Precision, 91.89% of Recall and 94.16% of F1-score. For that reason, XGBoost was identified with the best overall predictive performance between the tested models.

In addition, SHAP analysis offered evidence based on a SHAP diagram of what factors were driving different model predictions. The combination of predictive analytics, explainability, and interactive governance dashboards exemplifies how educational data can be transformed into actionable governance intelligence.

Based on Design Science Research this paper presents a novel, practically implemented AIDG Framework that, by integrating machine learning predictions, transparency, accountability, institutional monitoring, and evidence-based decision support, enhances conventional educational prediction methods. The results of the experiment have revealed that there is a practical value in the integration of technologies, such as AI, XAI, Learning Analytics, and Business Intelligence into a governance architecture of e-learning organization based on Design Science Research.

Keywords: Digital Governance; Artificial Intelligence; AI Governance; Learning Analytics; Educational Data Mining; Explainable Artificial Intelligence; Design Science Research; OULAD; Business Intelligence; Evidence-Based Decision-Making.

1. **Introduction**

The rapid digital transformation of higher education has fundamentally changed the way universities and e-learning organizations deliver educational services, manage institutional resources, and support academic decision-making. Learning Management Systems (LMSs), Virtual Learning Environments (VLEs), cloud-based services, Artificial Intelligence (AI), Learning Analytics (LA), and Educational Data Mining (EDM) continuously generate large volumes of academic, administrative, and behavioral data. These developments provide institutions with substantial opportunities to improve educational quality, monitor learner engagement, optimize resource allocation, and support evidence-based decision-making. However, the increasing complexity and scale of digital educational ecosystems have also created new governance challenges concerning transparency, accountability, data quality, privacy, security, ethical AI, and institutional responsibility.

Digital governance has become a necessary fixture in institutional digital transformation. Traditional Information Technology (IT) governance was mostly about managing infrastructure and keeping services running. Digital governance goes further. It covers organizational structures, technological platforms, data policies, and decision-making mechanisms as a single connected system. In e-learning, that means institutions need governance mechanisms that align digital tools with strategic objectives, while also ensuring responsible data use, clear accountability, transparency, and continuous performance monitoring. The rise of AI intensifies that need. AI-supported decisions may influence student support, academic intervention, resource allocation, and institutional planning, so governance has to be ready for those consequences.

Artificial intelligence brings real potential to educational governance, especially through predictive analytics and intelligent decision-support. Machine learning models can catch patterns in learner behavior, assessment activity, and engagement that ordinary reporting tends to miss. Predictive models are where this gets concrete. They can flag students who may need academic intervention early, and they give institutional decision-makers evidence for proactive planning. Learning Analytics and Educational Data Mining, then, supply an important analytical foundation, one that turns educational data into actionable institutional knowledge.

Despite the fact that educational predictive models are being developed in parallel, the actual process of integrating them in governance at institutions is slow. A large amount of academic work has gone into the prediction of students' results and their classification, including those who are at risk, and the analysis of learning behavior and digital governance issues. Such studies often focus on organizational structures, policies, digital transformation, and technology management, thus making the two research fields very distinct. Therefore, the results of predictive modeling might remain as isolated analytical ones rather than transparent,

informative, and actionable insights that could help institutions to govern themselves and to make strategic and operational decisions.

One of those challenges that AI decision-making supported by explainable AI could resolve is, the transparency & accountability challenge of the output decisions. Machine learning algorithms can often do a great job of predicting things accurately. However, when the models are very complex

or black-box like, stakeholders in the institution may find it difficult to interpret what the model is doing or why it arrived at an output decision. In a governance setting, a high level of predictive accuracy is not all; decision-makers must rely on an understanding of the underlying factors of the model's predictions to be able to use the outputs effectively as part of institution-wide procedures. Explainable Artificial Intelligence (XAI) is a technique that is capable of providing a better view of how a model is working so as to promote openness and accountability. SHapley Additive exPlanations (SHAP) has been applied in this case to figure out how each characteristic contributes to modeling predictions and provide global and local interpretability features. Therefore, besides prediction, the proposed governance framework's analytical part is going to focus on explainable governance intelligence.

We see a further limitation in the area of analytical results being able to translate into actionable insights.

While machine learning and explainable model techniques have technically informative output for practitioners, it might be hard to apply these outputs directly into organizational decisions when they are displayed primarily via statistical tables or code in scripts. Through Business Intelligence (BI) systems, this constraint might be resolved since these systems are able to convert analytical results into interactive visual displays and dashboards for governance purposes. In the paper, the Power Microsoft BI solution is chosen as a user interface or decision-support medium for the prediction data, engagement indicators, performance measures (for learners), SHAP-type justifications of model outputs, etc., for presentation to the stakeholders of the institution.

In light of these considerations, the authors introduce an AI-Driven Digital Governance (AIDG) Framework for the operation of e-learning institutions. The framework is structured as an integrated governance framework linking institutional digital governance with data analytics, learning analytics, explainable AI techniques, and interactive BI.

Contrary to viewing educational data only as raw data for algorithms, we propose in this article a way of seeing educational data as a strategic asset for decision-makers and institutional stakeholders. That is, through such data, they can keep control of the process, take pre-planned actions, base decisions on evidence, and regularly enhance their governance.

The study adopts the Design Science Research (DSR) methodology because its primary purpose is not merely to describe an existing phenomenon or compare predictive algorithms, but to design, implement, demonstrate, and evaluate a novel governance artifact. DSR provides a systematic basis for developing the proposed AIDG Framework in response to an identified research problem and for evaluating its technical and practical utility. The empirical demonstration is conducted using the Open University Learning Analytics Dataset (OULAD), which provides integrated information related to students, assessments, learning activities, and interactions within a Virtual Learning Environment. The use of OULAD enables the proposed framework to be demonstrated using real educational data rather than remaining solely at the conceptual level.

The implementation combines data preparation and feature engineering with two supervised ensemble learning algorithms, Random Forest and Extreme Gradient Boosting (XGBoost). Their predictive performance is evaluated using Accuracy, Precision, Recall, and F1-score. The

analytical workflow is subsequently extended through SHAP-based explainability to identify the factors contributing to predictive outcomes. The resulting analytical and explanatory information is then incorporated into interactive Power BI dashboards designed to communicate governance indicators and support institutional decision-making. This integrated workflow connects the technical analytical layer with the governance and decision-support layers of the proposed framework.

The empirical results demonstrate that both evaluated machine learning models achieve strong predictive performance. Random Forest achieves an Accuracy of 93.34%, while XGBoost achieves 93.99%, with XGBoost also obtaining an F1-score of 94.16%. These results provide empirical evidence that engineered educational and behavioral indicators can support reliable predictive analytics within the proposed governance architecture. However, the contribution of the study extends beyond predictive performance. Through SHAP analysis and Power BI visualization, the framework demonstrates how predictive evidence can be interpreted and transformed into governance-oriented information for institutional monitoring and decision support.

Therefore, the core contribution of this study is the creation and demonstration at empirical level one single Digital AI Governance Framework that merges Design Science Research, educational data analytics, business intelligence, and Explainable AI. Besides that, the framework allows for a step-by-step transition by e-learning companies from using fragmented analytics to implementing governance mechanisms that are both transparent, accountable, and evidence-based. From this aspect, the study proposes not only a design artifact that would be a practical implementation but also illustrates empirically the operational aspects of integrating AI in educational analytics as a piece of institutional digital governance.

Chapter 2

Related Work

2.1 **Introduction**

Digital technologies have been transforming education from within quite rapidly. Higher education is now operating and governing themselves differently due to these changes in technologies.

Among other changes is the development of e-learning environments.

Now it means that a lot is placed on Learning Management Systems (LMSs), Virtual Learning Environments (VLEs), cloud-based services, etc. Artificial intelligence, learning analytics and educational data mining (EDM) are some of the other technologies being used to produce huge numbers of various sorts of data.

There is no doubt such data are going to be very useful for enhancing educational quality, tracking learners' interests, improving institutional productivity and enabling the decision-making process by means of facts and figures.

But then again a great deal of reliance on digital tech may also be a problem for example data privacy, data quality, issues of cyber security, the requirement for transparency and accountability,

ethical concerns related to AI, regulatory compliance and how to handle education data in a proper way.

So with these kinds of questions and issues the idea of digital governance has also moved out of being mainly technology-focused to being one of the major capabilities of the whole institution where it links to all major areas: organizational strategy, data governance, technology management, risk management and making decisions based on evidence.

Artificial Intelligence has further expanded the scope of these governance challenges. Machine learning and predictive analytics can provide institutions with timely information about learner performance, engagement, and potential academic risks. Nevertheless, predictive capability alone does not guarantee responsible or effective institutional governance. AI-supported decisions must also be interpretable, accountable, and aligned with institutional policies and ethical requirements.

The existing literature reflects substantial progress in each of these areas. Research on digital governance emphasizes institutional structures and strategic alignment, whereas studies on AI and learning analytics frequently concentrate on predictive performance and learner outcomes. Similarly, international AI governance frameworks provide important principles concerning transparency, fairness, accountability, human oversight, and risk management. However, these research streams remain insufficiently integrated within an operational governance architecture specifically designed for e-learning organizations.

Accordingly, this chapter critically reviews five interconnected areas: digital governance in e-learning institutions, Artificial Intelligence as an enabler of digital governance, Learning Analytics and Educational Data Mining, international AI governance frameworks, and the use of educational data for governance-oriented decision support. The purpose is not merely to summarize previous studies but to identify areas of convergence and limitation and to establish the research gap that motivates the development of the proposed AI-Driven Digital Governance Framework (AIDG Framework).

Aftersummarizing themainpoints of thechapter theauthors point out theliterature gaps regarding governance integration, explainability, practical validation, and operational decision support as these topics are still underdeveloped in terms of research. This discovery serves as a solid theoretical basis that validates the choice to apply the Design Science Research methodology in the next chapter.

2.2 Digital Governance in E-Learning Institutions

2.2.1 Evolution of Digital Governance

The concept of digital governance has undergone a considerable development due to the rising importance of digital technologies in organizations. Early approaches to governance were linked to IT governance and were focused more on the infrastructure of technology, IT resources, service delivery and operational control. As digital technologies became more incorporated into the strategy of an organization, governance evolved to cover aspects such as digital transformation, data governance, cyber security, institutional accountability, and legal compliance.

Digital governance has acquired great value within the context of higher education. Universities and e-learning institutions function in digital ecosystems, where the process of teaching, learning, assessment, administration and communication relies on digital platforms. There is the continuous generation of data, including academic data, behavioral data, and operational data, providing opportunities for improving institutions but also posing risks connected with data management and responsible technology use. Modern digital governance is not limited to the handling of the technological framework. Digital governance relates to the coordination of digital projects with institutional goals, definition of organizational roles and responsibilities, treatment and protection of data, assessment of digital risks, and the use of relevant data to influence institutional decisions.

Recent studies show the correlation between the level of maturity of governance and the capability of organizations to assimilate technological innovations, organization learning, and continuous improvement processes. Implementing effective governance means having not only the specific policies and structures in place but also having in place the tools to monitor performance of governance, assess risks associated with governance, and adjust the governance practices based on the changes in the digital environment.

This process is the conceptual basis of the AI-based digital governance. If Artificial Intelligence becomes part of educational platforms and decision-making systems, governance tools should also meet the necessary requirements related to AI, e.g. interpretability, accountability, fairness, human involvement, etc.

2.2.2Digital Governance in Higher Education

The increasing reliance on digital technologies is really changing how governance works in higher education. Universities now need to sync technological growth with their own strategies, education quality, regulatory needs, and what stakeholders expect. Digital governance has thus turned into a key way to manage tech innovation while ensuring transparency, accountability, and responsibility within institutions.

The literature I looked at in this study shows that good digital governance helps institutional performance. It does this by making governance structures clear, outlining who does what, and setting up ways to make decisions based on evidence. Also, governance maturity seems to play a role in how well an institution can adapt to tech changes while still managing digital resources responsibly.

In e-learning settings, governance really covers a lot of ground since institutions handle various linked sources of educational info. These sources are things like LMS records, VLE interaction logs, student info systems, assessment databases, and cloud-based educational services. So, governance mechanisms need to keep data integrity, protect privacy, ensure security, maintain accessibility, and promote appropriate use.

Digital governance has a substantial connection with the quality of education. When governance systems are established, they help organizations to track how the organization is operating and assess their digital projects.

Nonetheless, there are still major challenges. Many governance models focus on organizational structures, rules, and methods of technology management leaving operational questions on how AI can be integrated into governance processes unanswered. At the same time, while more educational data are analyzed with the help of predictive methods, not so many studies provide answers on how result data can be translated into intelligible and applicable information for executive governance.

Another limitation refers to empirical validation. Many studies on governance are based on conceptual frameworks, concepts, and suggestions without bringing empirical evidence from real-life education data. Thus, the linkages between governance concepts, intelligent analytics, explainability, and institutional decision support are not yet practically illustrated.

According to the literature, technological governance has evolved beyond being simply a function of technology management and has become an institutional mechanism that includes strategy, data governance, cybersecurity, accountability, compliance, and evidence-based decision making.

Despite this progress, it appears in the literature that there continues to be a gap between governance and AI-based educational analytics. While current governance theories present valuable foundations for innovating and implementing educational processes and practices, there are limited explanations on how the theories can be enhanced with technologies such as machine learning, Learning Analytics and Explainable AI.

This restriction gives the primary basis for the suggested AIDG Framework. This framework aims to broaden digital governance and cover connections between institutional governance mechanisms and educational data, data analytics, transparency, and decision-making.

2.2.4 Implications for Research

The literature examined indicates that future digital governance system for e-learning entities should view governance as an integral institutional capability and not merely an administrative and/or technological function. Three implications deserve particular attention. Firstly, any governance mechanisms should ensure alignment between the AI initiatives and institutional goals. Secondly, the educational data should be governed throughout its entire process in life to ensure its quality, safety, and responsible use. Finally, the AI-generated analytic result must be understandable and related to the institutional decision-making activity.

The proposed AIDG Framework requires the founding principles of Institutional Digital Governance, Data Governance, AI and Predictive Analytics, Explainable AI, and Governance Intelligence.

2.3 Artificial Intelligence as a Means for Facilitating Digital Governance

The relevance of Artificial Intelligence has increased considerably in the context of higher education digitalization. This technology is employed not only for instructional purposes but also for predictive analytics, identifying student risks, providing personalized education, institutional planning, resource distribution, and decision-making.

In the context of e-learning, AI enables processing huge volumes of educational data and discovering trends not easily visible using regular reporting systems. Thus, the use of machine learning models allows institutions to gather information about students' engagement, assessment-log behavior, and academic performance on time.

Yet, the governance value of AI is not defined only by the high accuracy of predictions. Sharma et al. (2024), as seen in this work, note the importance of transparency, fairness, explainability, and ethical responsibility for reliable AI systems. If decision-makers are unable to clarify the reasons behind the outputs of a certain model, predictive accuracy is of little use in practice.

The quality of data is another major governance requirement. Shang (2025), in his study, discusses the negative impact of incomplete, inconsistent or dispersed educational datasets on machine learning and institutional decision-making, thus highlighting the importance of treating the governance of data as the basic level of governance in the area of AI.

In addition, Misra et al. (2026) argue the importance of lifecycle-based AI governance, including stakeholder accountability, risk management, fairness assessment, monitoring, and compliance with regulations. Thus, it can be concluded that AI needs lifecycle governance rather than a mere implementation technique.

OULAD has been extensively utilized for educational machine learning studies. Previous studies have implemented various algorithms such as Random Forest, Support Vector Machines, and XGBoost to forecast student's outcomes as well as pinpoint learners with potential risks. However, most of the studies in this category are prediction-centric, that is, they only emphasize classification performance.

In this context, one cannot say that there is a lack of AI usage in education; however, it would be correct to say that AI usage in education is limited.

Current predictive studies, for example, use such evaluations as Accuracy, Precision, Recall, F1-score, AUC, but the governance side of the issue remains less addressed, providing insufficient attention to elements such as transparency, accountability, governance metrics, and support in executive decision making.

2.3.1 Section Synthesis

From what has been discovered in the literature, AI proves to be a powerful tool in the hands of higher education institutions, but its success depends on how it is embedded into data governance and accountability systems of the institution.

The AIDG model presented in this study aims at overcoming the described limitation by treating machine learning as one of the elements of the complex governance framework rather

Only as a standalone predictive mechanism.

2.3.2 Implications of Research

The research literature affirms that the model for government powered by AI should harmoniously integrate predictive analytics and Learning Analytics on top of Explainable AI, institutional accountability, and decision support systems, among others.

Thus, the research is based on the use of machine learning for making predictions in the field of governance, SHAP for making predictions more interpretable, and Power BI for delivering analytical results via interactive governance dashboard

2.4 Learning Analytics and Educational Data Mining for AI-Based Governance

2.4.1 Learning analytics as a facilitator of governance

Increasing use of digital learning environments has led to the continuous production of educational data due to the use of learning management systems, online assessments, and other platforms of learning interaction. Learning analytics provides instruments that transform this data into information useful for decision-making in education.

The development of learning analytics evolved from mostly descriptive reporting and progressed to predictive approaches. Modern learning analytics solutions are able to manage detection of behavioral patterns of learners, predictions concerning their academic success level or risks of being low-performing students, and assessment efficiency of educational interventions.

Looking at governance, the significance of such capabilities lies in their contribution to educational performance monitoring, problem identification, intervention evaluation, and resource management by the institutions.

Nevertheless, the degree to which Learning Analytics is utilized in governance depends on the way analytical data is integrated into the institutional processes. If analytics is limited to monitoring individual students, its contribution to governance remains unclear.

2.4.2 Educational Data Mining for Institutional Intelligence

Educational Data Mining is a great addition to Learning Analytics as it employs computer methods to identify important patterns in educational data. Classification, clustering, regression, association analysis, and anomaly detection methods can uncover connections between learner activity, academic success, and learner participation.

Machine learning models such as Random Forest and XGBoost are especially relevant with this study since they allow modeling nonlinear relationships between educational variables and assessing the data with the help of XAI techniques.

Despite this fact, however, many EDM works exhibit continued obsession with predictive accuracy and utility. This occurs at the cost of lesser focus on the transformation of model outputs into actual indicators of governance or decision-support information for decision-makers.

The current paper seeks to enhance the role of EDM by further placing its predictive outputs within the wider context of governance induction.

2.4.3 OULAD as a Concrete Foundation for Governance-Oriented Analytics

The Open University Learning Analytics Dataset (OULAD) provides an important empirical basis for educational analytics. This is due to the fact that it incorporates data on students as well as their assessments, courses, and interactions within a Virtual Learning Environment, thus providing multidimensional analysis of student engagement and assessment behavior as well as academic results and many other educational aspects.

Nonetheless, OULAD has predominantly been utilized as a reference data source for predictive education analytics. Its capability as a basis for governance-focused analytics has received lesser attention.

Thus, in the context of this research study, OULAD is utilized not solely to evaluate classification algorithms but also to illustrate the way educational data can be converted to governance indicators using machine learning algorithms, SHAP-based explainability, and visually interactive Power BI dashboards.

Responsible AI Principles

Global Development of AI Governance

The rising application of AI globally has sparked the rise of global frameworks aimed at contributing to reliable and responsible AI. The frameworks tend to highlight the need for transparency, accountability, fairness, human supervision, privacy, risk management, and continuous evaluations alongside technical performance, emphasis.

This is important for the higher education institutions since AI can affect student assistance, academic intervention, planning of institutions, and allocation of resources.

Major Global Frameworks for AI Governance.

The Framework for Managing Risks with Artificial Intelligence as developed by the National Institute of Standards and Technology (NIST) lays stress on importance of risk management and governance during entire lifecycle of artificial intelligence application.

The UNESCO Guideline on the Ethics of Artificial Intelligence elaborates on the human-oriented perspective and mention the importance of openness, fairness, privacy, and sustainability.

OECD Principles of AI present views on the importance of human-centered values and inclusive growth.

The EU Artificial Intelligence Act sets the framework for regulating artificial intelligence by focusing on the risk profiles of applications of artificial intelligence and requirement for transparency, human supervision, and data governance.

All four frameworks are different in scope and legality, but they possess similarities on the issues critically important for artificial intelligence governance in education.

2.5.3 Comparative Synthesis of International Frameworks

The analyzed frameworks allow for different views on similar issues. NIST mainly concentrates on risk management and governance aspects of the whole process, UNESCO focuses on the ethical and human-centered concept of AI, OECD provides principles for responsible AI policies, and EU AI Act proposes the regulatory framework that is based on risk categorization principles.

Nevertheless, the frameworks are poorly designed to be applied in practice, which means that they do not suggest any principles for application of Learning Analytics, Educational Data Mining, SHAP-based explainability along with institutional dashboards in governance, which is unfortunate.

Nevertheless, the fact that the frameworks lack practical applicability does not decrease their significance for the analyzed domain but allows rethinking their integrated principles and adapting them to fit the specific requirements of e-learning organizations.

2.5.4 Research Implications

The AIDG Framework encompasses the recommendations of the above approaches including, but not limited to, accountability, transparency, human decision-making, responsible data use, risk management process, explainability, and ongoing assessment.

The AIDG Framework is not meant to replace any international governance frameworks, but rather offers a specific solution that is well aligned and thus can be connected to educational analytics and institutional decision support systems.

2.6 Synthesis of Literature and Research Gap:

The discussion of the literature reflects the development of digital governance as well as AI, Learning Analytics, Educational Data Mining, and artificial intelligence in the context of the evolution of digital technologies in higher education institutions. However, the key limitation is the lack of integration among institutional governance systems, educational analytics, explainable AI technologies, and decision support systems.

The current body of literature related to digital governance has predominantly focused on institutional framework, strategic fit, digital transformation process, accountability, and digital resources management. Although these studies establish a vital basis for institutional governance, their contribution is of little operational import with respect to the implementation of artificial intelligence and predictive analytics in governance processes.

Research in artificial intelligence and educational data mining has very clearly shown that machine learning techniques can be used for the analysis of complex educational data and for making predictions about learners' outcomes. However, educational datasets are often utilized mainly for the purposes of improving predictive performance rather than for the creation of governance indicators that can be helpful in institutional planning, evaluating policies, monitoring, and making evidence-based governance decisions.

Much like the literature on learning analytics, there is plenty of evidence demonstrating the great potential of these analytics for studying the engagement of learners and their academic performance. Nonetheless, the aspect of governance is still relatively neglected in this body of

research. In particular, there is not enough information available regarding the possibilities of transferring learner-level analytic outcomes into intelligence for the purposes of institutional governance and using it in executive decision-making processes

The analysis of international laws concerning artificial intelligence governance - the NIST AI Risk Management Framework, the UNESCO Recommendation on the Ethics of Artificial Intelligence, the OECD AI Principles, and the AI ACT of the European Union - shows a great deal of consensus regarding the significance of transparency, fairness, accountability, human intervention, privacy protection, and active risk management. Nevertheless, these acts in majority are universal or intersectoral in nature and as such provide just a little practical guidance pertaining to the use of artificial intelligence in e-learning systems.

The literature also mentions a significant issue of explainability. While machine learning algorithms can have high performances in terms of prediction, it is hard for institutional stakeholders to make sense of their results, without appropriate tools for explanation.

Explainable Artificial Intelligence could thus serve as a bridge between forecasting and accountable governance, allowing decision-makers to understand which elements affect the working of a model.

Another significant limitation is that of empirical verification. While the publicly available educational datasets (like OULAD, for example) have been used on a large scale for predictive learning analytics, their use for the practical demonstration of governance frameworks has been much more limited. Also, interactive Business Intelligence solutions such as Power BI offer a possibility of making outputs comparable and understandable for decision-makers, but how they could serve the purpose of AI-based educational governance has not been sufficiently analyzed.

As a result of this data synthesis, four key research gaps have been identified.

2.6.1 The Integration Gap:

Available literature highlights the major developments in the domains of digital governance, AI governance, Learning Analytics and Educational Data Mining, but these fields of knowledge have hardly been combined in a single framework tailored to the operational needs of e-learning organizations.

The first gap, therefore, relates to the lack of full-fledged architecture which covers institutional governance, data governance, AI governance and educational analytics altogether.

2.6.2 The Explainability Gap:

Even though machine learning is gaining popularity in the field of education, not much attention has been paid to Explainable Artificial Intelligence as an independent governance tool.

For the purposes of making decisions at an institutional level, predictive precision is not enough. Decision-makers have to access clear information on the various factors that affect the output of the model.

2.6.3 Implementation-Related Validation Gap

A large share of available research into governance is of conceptual nature while machine learning research in education tends to focus on the evaluation of available models than the application of complete governance artifacts. As a result, there is a need for empirical validation that shows how governance principles, educational data, predictive analytics, explainability, and decision support technologies can work hand in hand with each other in practical implementation. The current research closes this gap because it uses OULAD as an empirical example of analyzing AIDG Framework.

2.6.4 Decision-Support Gap:

Another gap in the area of research refers to the use of AI analytical results in governance. Machine learning results are nearly always represented according to some technical indicators while managers need looser information to carry out monitoring, intervention, planning, and policy evaluation. Therefore, Business Intelligence dashboards serve as a substantial tool to connect analytical outputs with social governance. In this research, the use of Power BI serves the purpose of converting analytical results in the governance area into tangible outcomes in the form of dashboards.

Motivation for Developing the AI-Driven Digital Governance Framework

The identified deficiencies in the existing literature have led to the development of AI-Driven Digital Governance Framework (AIDG Framework). The framework combines principles of digital governance with Artificial Intelligence, Learning Analytics, Educational Data Mining, Explainable AI, and interactive dashboards into one holistic architecture.

Different from previous studies that analyzed these technologies separately, the new framework argues that the technologies are interconnected components of the institutional governance system. Machine learning is used to predict results, SHAP to provide interpretation, and Business Intelligence to communicate findings to institutional stakeholders.

The methodology of Design Science Research constitutes the basis for the development of the framework, which is empirically verified using the OULAD dataset. Therefore, the project aims at closing the gap between governance theory and its practical implementation in institutions, while paying appropriate attention to the issues of transparency, accountability, and evidence-based decision making.

Table 2.1. Comparison of Prior Investigations with Current Study

Stream Of Study / Research	Main Area of Focus	Method of Approach	Data/Context	AI/Analytics	Defining Explainability	Governance Dimension	Practical Implementation	Biggest Limitation
Lazarenko & Hapchuk (2024)	Digital transformation and governance	Conceptual and analytical	Higher education	Digital transformation analysis	Level of explainability	Institutional digital governance	Limited	Limited integration of chat driven analytics into governance
Demartini et al. (2024)	AI in digital transformation	Conceptual and empirical	Context of organization	Transforming with the help of AI	Limited	Digital transformation	Partial	Limited scope for e-learning e-governance
Sharma et al. (2024)	Ethical and trustworthy AI	Governance oriented analysis	General AI context	Governance in AI	Level of explainability found	Transparency and accountability	Limited	Doesn't have specifications for e-learning institutions
Tawafak et al. (2025)	Learning analytics through AI	Empirical and analytical	Higher education	AI and learning analytics	Partial	Educational decision support	Partial	Limited level of integration of governance, AI-explainability and BI
Shang (2025)	AI and educational data quality	Data driven approach	Data sets	Data analytics	Level of explainability	Data governance	Limited	Prevention of governan

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								ce related issues
Misra et al. (2026)	Governance of AI and ethical AI	Governance Framework	Organization context	Governance in AI	Strong emphasis	Risk and accountability	Limited	Needs to be adjusted for e-learning use
Predictive Studies Based on OULAD	At-risk prediction using AI	Machine Learning	OULAD	Random forest and xgboost	Limited	Governance scope is limited	Experimentally employed	Focus on prediction performance
Present Study	E-governance with the help of AI in e-learning organizations	Design Science Research	OULAD	Random Forest, XGBoost, SVM and other models	Emphasis on responsible use of AI	Governance in institution, data and AI	Power BI as dashboard	Biggest Limitation

Comparative Analysis:

Examining each piece of literature reveals that while past works have provided significant insights in their own time, they mainly focus on particular aspects of the wider problem. Research on digital governance helps establish the institutional and strategic background for its model, while AI and Educational Data Mining research allows conducting analytical work.

Research on ethical AI adds associated concepts like transparency, accountability, and ethical usage of AI, while Business intelligence introduces methods to deliver information to stakeholders.

Nonetheless, all these aspects have not been put together in a single model demonstrating how e-learning organizations may function.

This research is thus different from previous works mainly due to its integrative approach of combining ideas as opposed to introducing a new algorithm.

Table 2.2. Gaps in Research and Reason for Proposed AIDG Framework:

Research Field	Existing Research	Recognized Gap	Contribution of the study
Digital Governance	Studies focus on systems of governance, policy decisions, and digital transformation processes.	Low integration levels of Artificial Intelligence.	ntegrates governance principles with AI-based institutional decision-making possibilities.
Artificial Intelligence	Studies provide strong prediction abilities in the area of educational analytics.	Very few efforts to integrate governance and explain as well as interpret it.	Leverages AI in the institutional governance processes through Explainable AI.
Learning Analytics & EDM	Studies are useful in requesting behavioral patterns of learning and making predictions.	Governance-related institutional intelligence production that is rare.	Transforms educational analytics indicators into governance indicators supporting an institution in its decision-making process.
AI Principles of Governance	Studies provide ethical, legal, and governance principles in the area of responsible AI.	Low implementation level of operations customized for e-learning institutions.	Adapts international governance rules to a real-life AI-based governance model.
Practical Verification	Existing Research	Weak integration of governance framework validation.	Illustrates and tests the AIDG Framework using OULAD, SHAP, and Power BI.

Each of the listed tables has its own role to play in the story. While Table 2.1 compares past studies to the current research effort, Table 2.2 interprets the gaps found in the literature as the motivation and contributions of the AIDG Framework. The importance of the distinction is in providing more logic to the chapter.

2.7 Summary of the Chapter:

In this chapter, we examined the recent literature on digital governance, Artificial Intelligence, Learning Analytics, Educational Data Mining, Explainable AI, and global frameworks on AI governance. Studies show that these fields have advanced significantly; however, each of them is fragmented, and none of them provides accurate indications for an integration of institutional governance, educational analytics, explainability, and interactive decision based support.

The analysis revealed four main gaps of research: the gap of integration, the gap of explainability, the gap of practical validation, and the gap of decision support. All these indicate the necessity of designing a governance framework that is beyond the analytic predictions and involves transparency, accountability, interpretability, and institutional decisions support.

The AI-Driven Digital Governance Framework that has been proposed fills these gaps by unifying governance institutions, data analytics, machine learning, Explainable AI, and Business Intelligence in the context of Design Science Research. The OULAD dataset provides the evidence necessary to show the analytical element of the proposed framework, while SHAP and Power BI are employed to interpret and visualize the framework from the governance perspective.

Thus, the pointed out gaps serve as the theoretical rationale for the research methodology elaborated in Chapter 3. The following Chapter outlines the Design Science Research methodology, research design, framework development, implementation based on OULAD, machine learning models, explanation technique, dashboard development, and evaluation method used in the research.

Chapter 3

Methodology

3.1 Introduction

The previous chapter analyzed the literature pertaining to digital governance, AI, learning analytics, educational data mining, explainable AI and worldwide AI governance standards. The chapter showed that although these fields have considerably evolved, they have not reached uniformity and do not produce sufficient practical recommendations for applying governance principles, intelligent analytics and explainability and institutional decision-making support in one method suitable for e-learning organizations.

To solve this issue, the current research employs the Design Science Research method as DSR is suitable for the research aimed at creating, developing, demonstrating and evaluating a new artifact capable of solving real organizational problems. The primary artifact for this study is AI-Driven Digital Governance Framework (AIDG Framework).

The framework in question brings together digital governance, data governance, artificial intelligence, learning analytics, educational data mining, explainable artificial intelligence, and business intelligence systems. It illustrates its framework through the use of the Open University Learning Analytics Dataset (OULAD) dataset. To generate predictions based on governance concepts, machine learning models will be employed; SHAP methods will work to explain the machine learning results, and Microsoft Power BI will transform the resulting analytical decisions into governance intelligence used for further decision-making by the organization.

Hence, the chapter will present the methodological basis of the research. First of all, it will explain the methodology of research design and provide reasons why DSR was used for this research. Then, it will describe the method of DSR that was used in the study, how the AIDG Framework was built, how the OULAD dataset was chosen and prepared, and how machine learning, explainability, dashboard creation, evaluation, and ethical considerations were applied by the author when conducting the study.

3.2 Research Approach

The major purpose of the research is to construct, develop and validate the integrated digital governance framework instead of just describing the existing governance practices. Therefore, the study is conducted following the design science research paradigm, where knowledge is generated through systematic development and evaluation of a research artifact.

The central research artifact is the AI-Driven Digital Governance Framework (AIDG Framework). The framework has been developed to tackle the limitations identified in the Chapter 2.

The research approach integrates conceptual formulation with practical validation. The study begins with establishing the framework grounded on the literature, international principles of governing AI, and institutional requirements. Secondly, the framework is validated through using data from OULAD. In the next step machine learning algorithms are created and tested. Then, the machine learning algorithms are analyzed with the help of SHAP. Finally, the analytical outcomes are turned into governance-related insights through Power BI dashboards.

The unique approach enables all aspects of the research be covered, with the theoretical aspect forming a theoretical basis for the framework.

Aim of the Research

The methodology for this study is determined by the following aims:

1. To analyze the present condition of digital governance and AI usage in organizations dealing with e-learning.

2. To uncover the shortcomings of existing governance models by means of reviewing the relevant literature.

3. To design an integrated AI-based Digital Governance Framework according to Design Science Research principles.

4. To test the framework by using Open University Learning Analytics Dataset.

5. To test machine learning models for support in governance-oriented decisions.

6. To improve transparency using Explainable Artificial Intelligence through SHAP approach.

7. To create visualizations in Power BI for facilitating governance monitoring and decision-making.

3.3 Reasons for Choosing Design Science Research

Using the correct methods of research corresponds to the topic under investigation, research aims and objectives and results needed. Given that the major aim of the current study is the development and validation of a new governance artifact, the principal method chosen for the study is Design Science Research.

In contrast to those methods of research that only analyze existing phenomena, the method of Design Science Research is concentrated on designing and creating tools used to solve the problems faced. Artificial constructs in the field of Information Systems include models, methods, architectures, algorithms, decision-support systems and integrated frameworks.

The literature review indicates the gap in the field of digital governance, AI, Learning Analytics, EDM, Explainable AI, and institutional decision support that needs to be addressed using creation of the new tool.

Table 3.1 Research Methodologies Comparison

Research Methodology	Purpose	Relevance to this Study	Justification
Survey Research	To capture the opinions and perceptions	Low	It does not help with systematic framework development and artifact validation.
Experimental Research	To clarify relationships and test interventions	Moderate	It is helpful for measuring algorithms, but not for framework production.
Case Studies	To study real-life situations	Moderate	It is appropriate for showing OULAD-related implementation, but not for artifact production only.
Qualitative Research	To investigate individual experiences and behavior in organizations	Low	It provides contextual information but does not help with the proposed artifact production.
Design Science Research (DSR)	To design, create, showcase and measure new artifacts	High	It directly helps with both systematic development and practical evaluation of the proposed AIDG Framework.

The comparison indicates that the Design Science Research (DSR) methodology has the best fit with the purpose of the study.

3.4 Design Science Research Process

The research uses a structured Design Science Research (DSR) process based on the six-stage model suggested by Peffers et al. (2007). The stages construct a structured route from the identification of the issue to dissemination (contribution) of the research.

Six stages are:

1. Identification of the Problem and Motivation.
2. Definition of Objectives of a Solution.
3. Design and Development.
4. Demonstration.
5. Evaluation.
6. Communication.

3.4.1 Stage 1: Identification of Problem and Motivation

At the first stage, the particular problem of the organization needing a solution is defined. The literature analysis has shown that digital governance, AI governance, Learning Analytics, EDM, and Explainable AI are usually studied separately.

This fragmentation prevents institutional leaders from having access to the complete, clear, and justified information concerning governance intelligence. Consequently, the problem identified is the lack of a comprehensive operational approach connecting the governance concept to predictive analytics, explainability, and decision-making support.

3.4.2 Stage 2: Specification of the Goals for the Solution

At the second stage, specific goals that the artifact has to achieve are specified. Based on previously identified research gap, the AIDG Framework is expected to do the following:

- impose the principles of institutional and digital governance on the basis of AI;
- make use of educational data in governance-oriented analytics;
- provide predictive identification of academic risks;
- provide transparency due to Explainable AI;
- turn analytical results into governance intelligence; and
- provide the basis for evidence-based decisions of the institutions.

3.4.3 Phase 3: Design and Development

At the phase three, AIDG Framework is created by taking into account digital governance concepts, data governance concepts, AI and predictive analytics, Explainable AI and Business Intelligence. The design is based on literature reviewed in Chapter 2 and regarding global AI governance principles. The resulting architecture is modular as each section of the framework will play a peculiar function in governance and at the same time be part of the whole governance process.

3.4.4 Stage 4: Demonstration

This stage concerns demonstrating the artifact in an appropriate practical context. The OULAD is the empirical case studied.

The demonstration involves:

1. Data Integration
2. Data Cleaning
3. Feature Engineering
4. Feature Selection
5. Machine Learning Model Development
6. Model Evaluation
7. SHAP Analysis
8. Power BI Development

3.4.5 Stage 5: Assessment

The fifth stage appraises the artifact through various views. Predictive performance evaluation utilizes Accuracy, Precision, Recall, and F1-score. For the evaluation of explainability SHAP is adopted, while effectiveness in governance and decision-making assistance is measured by using a combination of governance metrics and Power BI dashboards.

3.4.6 Stage 6: Projection Stage

The last stage of DSR conveys the research issue, method, artifact, results, contributions, constraints, and directions for future work.

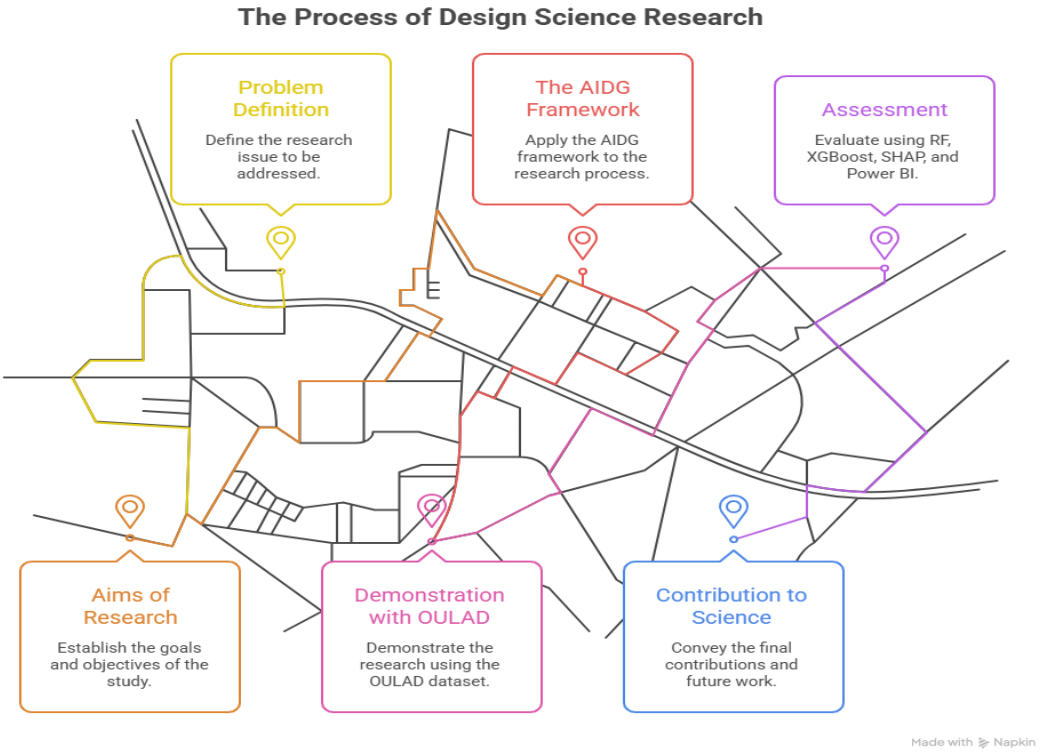


Figure 3.1. The Process of Design Science Research in This Study

The proposed framework is grounded in theory, developed systematically, prototyped in practice, and assessed empirically through the application of a six-step process.

3.5 Building the AI-Driven Digital Governance Framework

3.5.1 Framework Development Process

The AIDG Framework is the main outcome from the DSR method. The aim of the framework is to fill in the gaps in research discussed in Chapter 2 by bringing together raised issues in governance with the findings derived from the AI approach in education.

The process of designing this framework involves using literature review, analyzing international standards in AI governance, and evaluating requirements of the e-learning environment.

The architecture of the framework is modular, which indicates that its components cooperate throughout the entire process of governance. Thus, educational data is viewed not just as an input into algorithms but also as a resource for an organization.

3.5.2 Primary Elements of the AIDG Framework The framework suggested is made up of five interrelated elements.

1. Institutional Digital Governance This element provides for the institution's policies, strategy goals, duties or responsibilities of the organization, as well as the mechanisms of compliance and

performance management. It establishes the environment of governance within which AI technologies function.

2. Data Governance Data governance is responsible for data acquisition, integration, preprocessing, quality assurance, and security. Quality data is vital for the trustworthy reporting.

Artificial intelligence and predictive analytics are part of a system that employs machine learning algorithms to turn various types of data related to education into predictive knowledge. Random Forest and XGBoost detection techniques are applied to the analysis of educational settings to find links to the factors influencing students' performance, engagement, and likelihood of academic failure.

Explainable AI completes the model creating modules that estimate how significant a role the feature plays in the predictive model. The principle activity of this system is making the whole process of analysis clearer and more reliable, giving the interpretation to inputs and outputs.

Finally, governance intelligence is received thanks to the Google PowerBI technology. It provides means for the visual representation of the subjects of governance intelligence like students' participation, performance, assessment results, evaluation of the future academic outcomes based on SHAP technology, and other necessary variables.

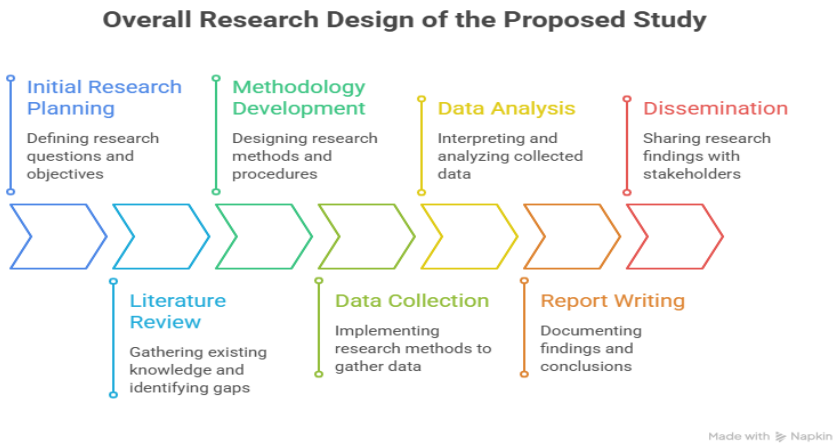
3.5.3 Integration of Frameworks

The very core of the AIDG Framework rests on the integration of all its elements.

Governance policy dictates data management and the flow of reliable data enables machine learning; predictive models provide information for governance purposes, SHAP enhances transparency, and Power BI allows for the communication of gathered intelligence to the end users.

Thus, the overall process translates educational data into governance intelligence that serves as a basis for proactive intervention, institutional monitoring, evidence-based planning, and continuous enhancement.

Figure3.2. Overall Research Design of the Proposed Study



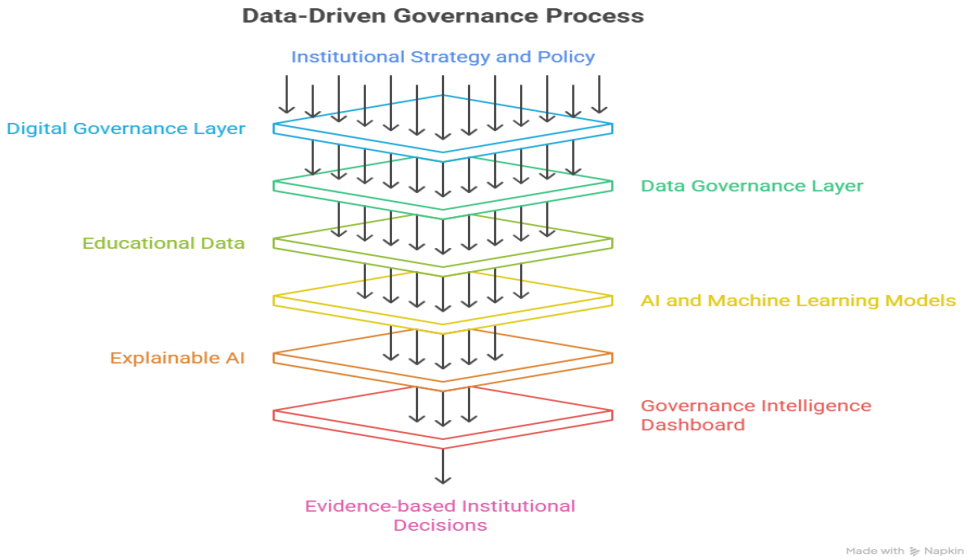


Table 3.2. Components of the proposed AIDG Framework

Component	Key Functions	Expected Governance Outcomes
Institutional Digital Governance	Strategically aligned policies and governance procedures	Alignment and accountability in governance.
Data Governance	Data quality, privacy, & integration	Decisions based on reliable data.
AI & Predictive Analytics	Risk detection and predictive modeling	Proactive governance decisions.
Explainable AI (SHAP)	Model transparency and interpretability	AI-supported governance people can trust and understand.
Governance Intelligence Dashboard	Visualization of governance indicators	Executive decision support grounded in evidence.

3.6 Case Study and Data Source

3.6.1 Selection of the Case Study

The Open University Learning Analytics Dataset (OULAD) was chosen as the empirical case study for assessing the applicability of the proposed framework. The fact that the data set is public will allow for transparency and replicability of the implemented procedures for researchers interested in repeating the analysis.

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OULAD is a great choice due to the fact that it contains data concerning learners' interactions with the material, assessment results, course registration, and educational behavior, which means that it presents the ideal setting for the demonstration of educational analytics geared to governance.

3.6.2 Description of the OULAD Dataset

The OULAD dataset consists of anonymous educational records obtained from courses offered through a virtual learning system. The relational structure of OULAD includes data on the students, their enrollment, assessment, course details, and virtual learning activities.

This dataset allows for the study of learner participation, academic achievement, assessment activity, and learning behavior within different modules and across different sessions.

In the present research, machine learning models are developed and tested using OULAD data in addition to development of governance indicators, SHAP analysis, and support for visualizations in Power BI.

3.6.3 Reasons for Dataset Choice OULAD was chosen due to the following four reasons:

1. The dataset is open to the public and allows reproducibility.

2. It consists of both assessment, behavioral, and demographic information.

3. It is complicated enough for machine learning and explainability research.

4. The information on interactions of learners makes it possible to derive indicators related to governance.

Table 3.3. Details of OULAD Dataset

Feature	Explanation
Dataset Title	Open University Learning Analytics Dataset (OULAD)
Institute Name	The Open University in the UK
Type of Data	Learning and Educational Analytics Data
Primary Tables	Student Info, Student Results, Exams and Assessments, Student VLE usage, VLE, Courses
Main Parameters	Information on population and state, registration, assessments, activity of students, resources for learning
Core Usage	Learning Analytics and Educational Data Mining
Utilization	Testing AIDG framework using AI-based methodology

3.7. Data Preparation and Feature Engineering

3.7.1. Data Preparation

Data preparation is crucial as it determines how reliable the analytic results are, which in turn largely depends on the quality and consistency of the data used.

The OULAD dataset was thoroughly prepared prior to the machine learning stages. The preparation process involved merging required tables, checking for consistency, identifying duplicates, treating missing values if needed, standardizing the formats of variables, encoding categorical variables, and eliminating unnecessary and redundant variables.

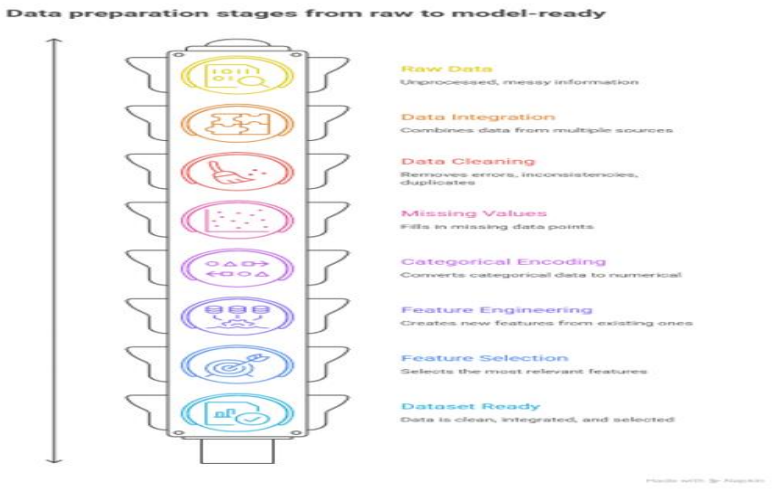
These procedures helped formulate a trustworthy base for future analytics.

3.7.2. Feature Engineering

Feature engineering has been done in order to create the indicators that enable to understand the learner engagement level, academic achievements and behavioral patterns in a more effective way than with the help of the original variables.

The most important newly created features were:

- Total Interactions - number of interactions of the learner in the online learning environment.
- Active Days - number of days the learner accessed the platform.
- Assessments Submitted - number of assessments that were done.
- Average Assessment Score - the mean score for all assessments taken.
- Late Submissions - number of assessments that were submitted after the deadline.



- Unique Learning Resources - number of unique learning resources accessed.
- Assessment score variability: This means variability in assessment outcomes.
- Registration gap: The registration gap is defined as the length of time from registration to the start of learning.
- Module presentation time: duration of the modules presentation time in academics.

All of these functionalities represent student engagement and academic behavior and may serve as potential governance tools.

3.7.3 Feature selection

This feature selection process was employed to minimize unnecessary complexity whilst allowing the identification of relevant variables.

This approach allows computing efficiency, minimizes redundancy, and improves the interpretability of the model. This is crucial for governance-oriented studies because the decision-makers have to realize the variables with the most significant influence on the model results.

The identified features triggered the development of the Random Forest and XGBoost models.

3.7.4 Workflow of Data Preparation

Figure 3.4. Workflow of Data Preparation

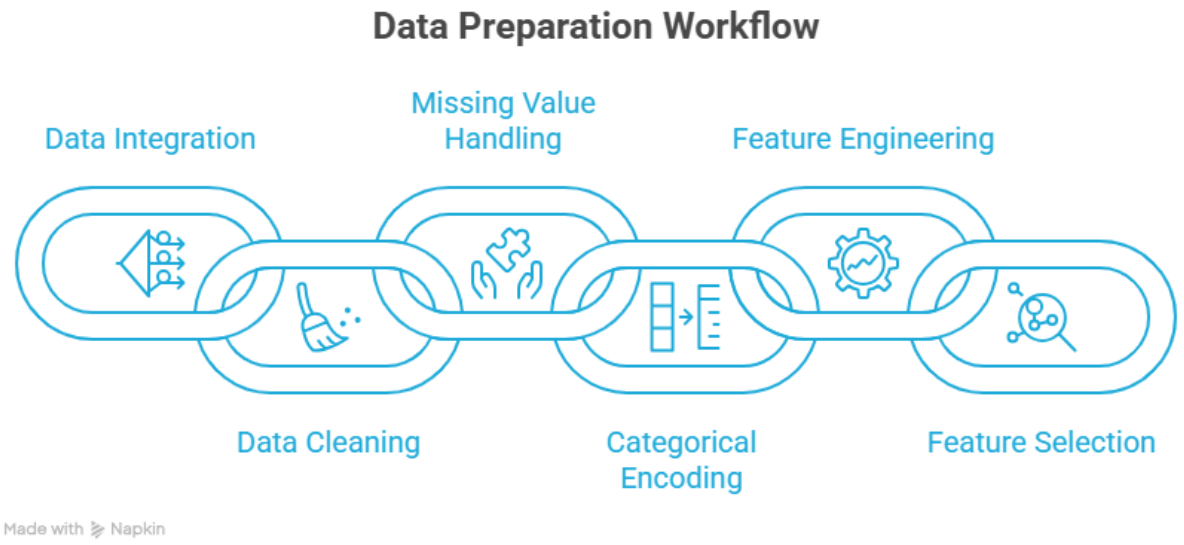


Table 3.4. Features That Have Been Designed for the Current Research

Feature	Description	Governance Significance
Cumulative Interactions	Total number of interactions	Level of student engagement
Days of Activity	Active learning days	Continuity of learning
Number of Assessments	Completed assessments	Level of participation in the educational process
Average Score	Average performance level	Performance indicator
Instances of Late Submission	Cases of late assessment submission	Indicator of academic success
Unique Learning Resources	Unique resources used	Level of resource usage
Variability in Assessment Score	Measurement of stability in assessment performance	Indicator of stability of learning
Delay in Registration	Time lapse between registration and participation	Indicator of early involvement in learning
Duration of Module	Duration of learning activity	Governance Significance

3.8 Machine Learning Model Development

3.8.1 Model Selection Strategy

Machine learning acts as the analytical backbone of the framework of AIDG. The goal of using machine learning is to transform data from education into predictive knowledge which will be beneficial for making decisions.

For the purpose of this study two methods from the family of ensemble learning were chosen: Random Forest and Extreme Gradient Boosting (XGBoost).

The choice was made based on four criteria:

1. Good performance in predicting in the educational domain.
2. Reliability of working with different educational data types.
3. Ability to be used together with Explainable AI technology.
4. Applicability for supporting the practices linked to governance.

3.8.2 Random Forest

Random Forest refers to the ensemble learning method constructed using different decision trees and combining them together to form conclusions based on the decisions made by authoritative source. As an ensemble method with the power of combating overfitting and helping accomplish high precision in classification tasks, Random Forest is widely used in the field of educational analytics to build models that can establish non-linear linkages between learner features and behavioral indicators. In the context of AIDG framework, Random Forest is applied to conduct governance-related forecasting and risk estimation through identifying some elements of importance of the developed model in terms of explanatory analysis.

3.8.3 Extreme Gradient Boosting (XGBoost)

XGBoost is recognized as the gradient boosting approach that builds individual decision trees while minimizing the prediction errors. Due to its capability to apply complex models for predictive purposes XGBoost could be successful in educational analytics framework.

3.8.4 Training and Validating the Model

After preparing the data and engineering the features, the data was divided into two sets, training and testing.

Both Random Forest and XGBoost were constructed using the same features according to the prepared dataset.

To assess the quality of models, a combination of Accuracy, Precision, Recall, and F1-score was applied.

Finally, a SHAP interpretation was carried out for better transparency of the decision-making process concerning the selected variables.

3.8.5 Contribution to Governance-Oriented Decision Support

The machine learning models should not be viewed as autonomous prediction mechanisms. Their results transform into governance-related indicators that provide assistance in early risk detection, institution monitoring, proactive intervention, and planning.

The results of the prediction are then analyzed using SHAP and presented in the Power BI dashboards.

Table 3.5. Models of Machine Learning Employed in the Research

Model	Type	Main Characteristics	Role in the AIDG Framework
Random Forest	Ensemble Learning	Stable, assists with overfitting, provides feature importance	Cross-cutting prediction and risk identification
XGBoost	Gradient Boosting	Powerful predictive ability, efficient optimization, able to model complex relationships	Advanced predictive analytics and advanced organization support

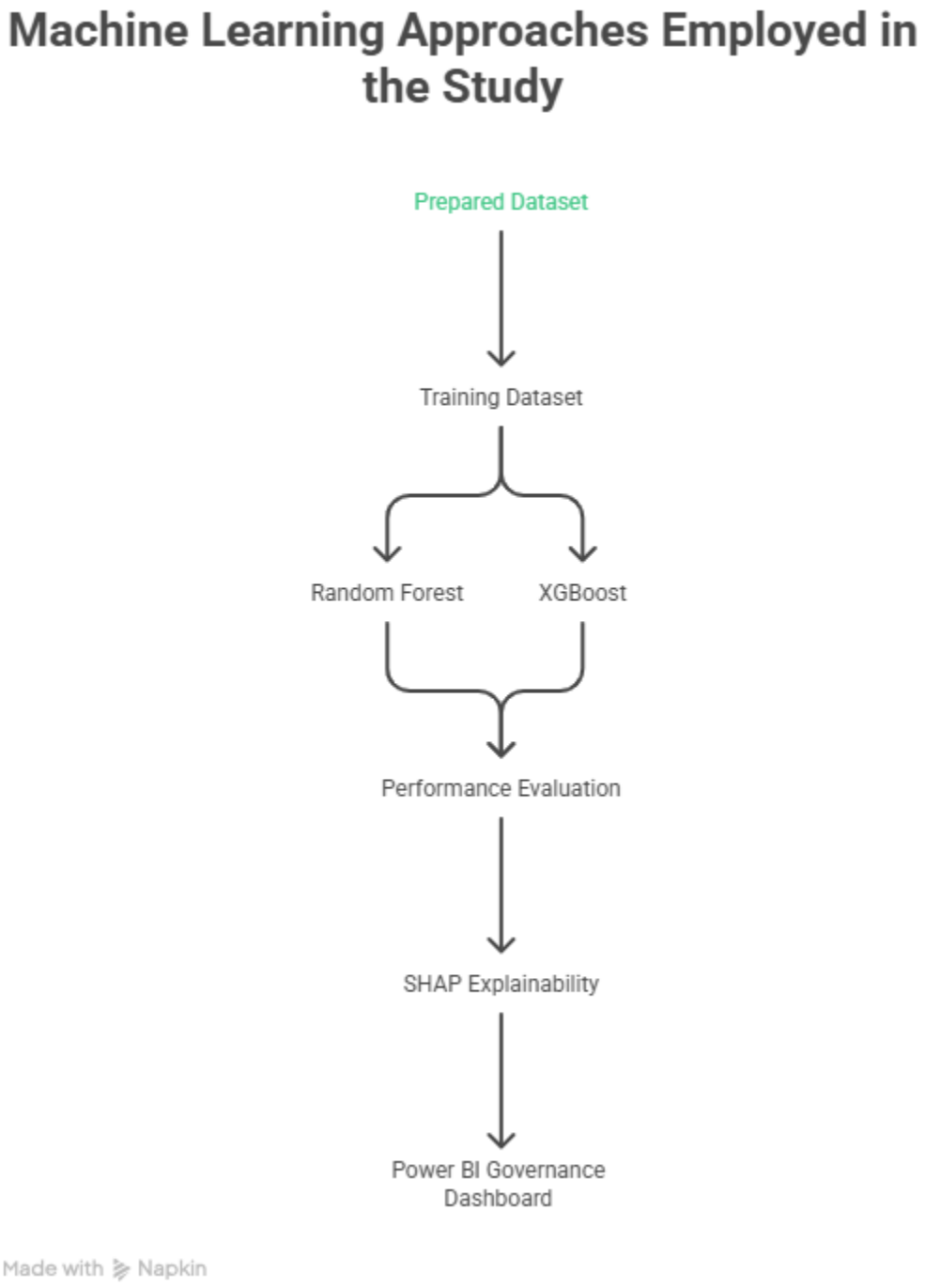

Machine Learning Approaches Employed in the Study
Prepared Dataset
Training Dataset
Random Forest
XGBoost
Performance Evaluation
SHAP Explainability
Power BI Governance Dashboard
Made with Napkin

Fig 3.5. Machine Learning Approaches Employed in the Stud

3.9.Explainable Artificial Intelligence

3.9.1 Function of Explainable AI in Digital Governance

The growing intricacy of machine learning models presents difficulty in terms of transparency and accountability. Merely achieving high prediction rates is not enough in terms of using AI effectively in making decisions at an institutional level.

Explainable Artificial Intelligence gives an opportunity to stakeholders to comprehend the reasons leading to specific predictions from the model. This is crucial in governance, as institutional decisions need to be transparent and accountable.

Thus, we consider XAI to be an integral element of the AIDG framework and not just an auxiliary processing element.

3.9.2 Choice of SHAP

SHAP was chosen because it proposes a theoretically justified method for evaluating the influence of particular features on the outcome.

Another advantage of SHAP as compared to simply feature-importance measures is that SHAP provides:

- global explanations, showing which features are major contributors to the general behavior of the model
- local explanations, which clarify particular outcomes of the model.

Furthermore, SHAP can be employed in tree-based models used in this research like Random Forest and XGBoost.

3.9.3 SHAP in the Context of AIDG Framework

SHAP has three main functions in governance.

The first task is to detect the variables having the most significant impact on prediction.

The second function is concerned with its ability to improve transparency by elucidating individual predictions.

The final function of SHAP lies in the support of evidence-based governance allowing stakeholders to grasp the reasons for the predicted results.

Thus, SHAP makes its contribution to transparency, accountability, and trustworthiness of AI-assisted governance.

Explainability Workflow 3.9.4

Figuer3.6 illustrates the flow of explainability in artificial intelligence procedures C.

Machine Learning Model

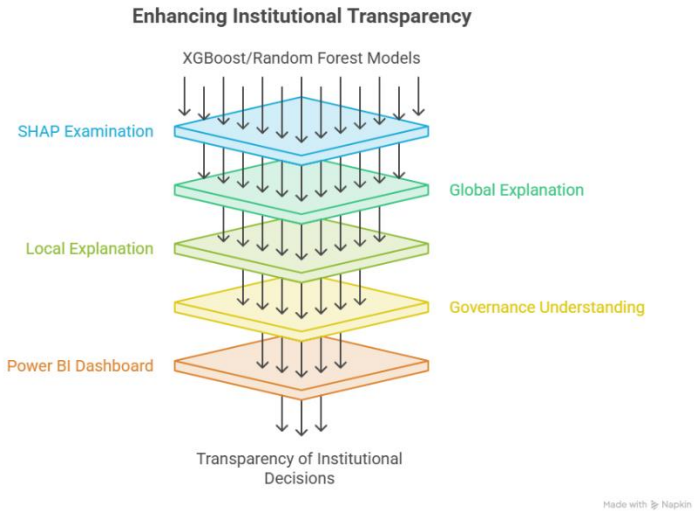


Table 3.6. Governance Contribution of SHAP Analysis

SHAP Function	Technical Contribution	Governance Contribution
Overall Analysis	Reveals effective features	Promotes governance motives
Particular Analysis	Clarifies single decision	Facilitates clear case decisions
Feature Assessment	Estimates effect of features	Aids in ranked implementation of governance policy
Model Clarity	Diminishes non-transparent nature	Boosts institutional trust and accountability

3.10 Development of the Governance Dashboard with Power BI

3.10.1 Applicability of Business Intelligence in Digital Governance

The use of predictive analytics has allowed for the generation of important data and information, but the results must be presented in a way that is understandable and applicable to decision-making processes. Thus, business intelligence can be defined as an operational level needed to link the outcomes obtained from AI to the sphere of governance.

Power BI was used to depict various indicators of governance, forecasting outputs, measures of engagement of learners, results of studies, and the elements of explanations based on SHAP.

Process for Developing the Dashboard

Subsequent to the prediction and the analysis of SHAP, the analytical output is arranged in the form of governance-oriented visual elements that form the dashboard.

Thus, the dashboard presents descriptive information, predictive results, explanatory evidence, and indicators of governance so that institutional stakeholders can proceed from observation to prediction and interpretation.

3.10.2 Dashboard Development Procedure

3.10.3 Governance Key Performance Indices

The dashboard encompasses:

- indicators of student engagement;
- in indicators of academic performanc
- dictionaries of predicted outcomes;
- determination of at-risk students;
- utilization of educational resources;
- studying of assessment results;
- importance index based on SHAP; and
- governance indices.

The indices mentioned are appropriate to interpret education performance and governance effectiveness.

3.10.4 Dashboard Contribution to Institutional Governance

The Power BI dashboard extends beyond conventional static reporting. It provides a governance intelligence environment in which predictive and explanatory information can be explored interactively.

The dashboard supports institutional stakeholders in identifying trends, monitoring performance, examining potential risks, evaluating interventions, and prioritizing improvement initiatives.

Within the AIDG Framework, Power BI therefore represents the final operational layer through which analytical outputs are transformed into accessible governance intelligence.

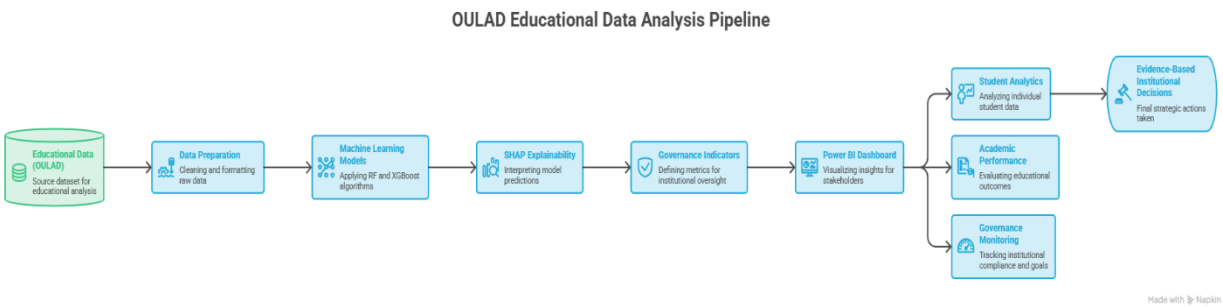


Figure 3.7. Architecture of Governance Intelligence Dashboard

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Table 3.7. Governance Dashboard Components

Dashboard Element	Source of Data	Purpose of Governance
Dashboard for Student Engagement	VLE use of students	Track engagement and participation of learners
Dashboard for Academic Success	results of assessment	Assess outcomes of learning
Dashboard for Predictions	results of RF and XGBoost	Spot students at risk
SHAP Dashboard for Interpretation	SHAP findings	Clarify predictions made by AI and make it transparent
Governance Dashboard for KPI	combined indicators for governance	Facilitate executive monitoring and strategic planning words

3.11 Evaluation Strategy

3.11.1 Evaluation Objectives

Evaluation is an essential part of DSR since the created artifact should be able to show that it is useful for resolving the problem defined in the research.

By conducting this study, the evaluation will also be extended beyond predictive outcomes and will assess the application of the AIDG Framework in decision-making for governance.

A comprehensive method of evaluation will be employed in this case with many dimensions, which means that the following aspects will be assessed:

1. Predictive efficiency
2. Explainability
3. Governance effectiveness
4. Dashboard-based evaluation

3.11.2 Evaluation of Predictive Efficiency

Machine learning models are assessed based on four basic metrics of classification.

Accuracy refers to the percentage of correctly classified instances.

Precision indicates the percentage of correctly identified positive samples in relation to all samples predicted as positive.

Recall shows the capacity of the model to recognize the actual positive samples.

In turn, F1-score is the harmonic mean of Precision and Recall scores which allows a more equitable evaluation.

Utilization of different metrics prevents the analysis from being overly dependent on overall accuracy.

3.11.3 Evaluate Explainability

In order to evaluate the level of explainability, the SHAP method will be employed. The role of SHAP is to evaluate the factors that impact the predictions most strongly.

This approach is investigating the contributions of features and providing insights into governance and decision-making processes.

As such, SHAP is more of a mechanism of evaluation in terms of transparency and accountability than simply a tool for technical explanations.

3.11.4 Evaluation Based on Governance

Governance evaluation investigates the extent to which the framework is able to:

• improve transparency in AI-based decision making;

• improve accountability through transparent analytics;

• enable proactive identification of academic risks;

• make evidence-based strategic planning more efficient;

• convert educational data into governance intelligence;

• allow continuing monitoring of institutions via interactive dashboards.

These factors make it possible to assess how successfully the framework turns analytical results into useful institutional decision-making tool.

3.11.5 General Evaluation Model

The overall evaluation takes into consideration predictions, explanations, governance performance, and visualization.

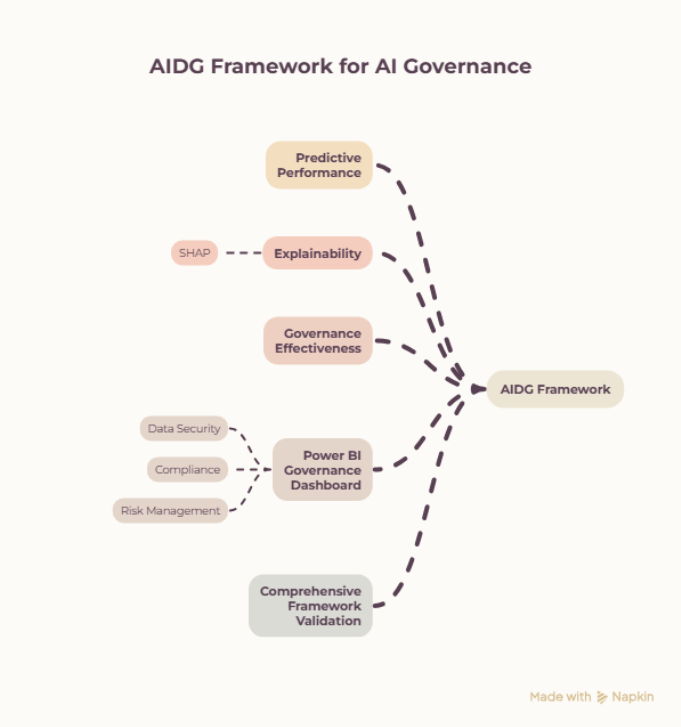
Machine learning statistics indicate prediction performance; furthermore, SHAP is the one creating transparency and Power BI works as an instrument for transmitting governance knowledge.

Thus, this multi-aspect method gives the opportunity to evaluate the AIDG Framework from technical and institutional points of view.

Table 3.8. Evaluation Criteria of the Proposed AIDG Framework

Dimension of Evaluation	Methods of Assessment	Expected Result
Predictive ability	Measures of performance (accuracy, precision, recall, F1 score)	Reliable prediction of academic outcomes
Interpretability of the outputs	SHAP values	Clear and explainable AI decisions
Effectiveness of governance	Governance efficiency indicators	Enhanced governance in the institution
User-friendliness of interface	Data visualization in Power BI	Available governance intelligence
Validation of the framework	Combination of the evaluation measures	Confirmation of the AIDG Framework

Figure 3.8. Multi-Dimensional Evaluation framework



3.11.6 DSR Progression and its Relation with Implementation

Table 3.9. Correlation between Design Science Research Progression and Implementation

DSR Phase	In this study, the methodologies adopted include:	Chapter/Section
Recognition of the Problem and Drive	Detecting the research issue via literature analysis and identifying the gaps in the research process	Chapters 1-2
Identification of Goals	Determining objectives and requirements for the AIDG Framework	Sections 3.2-3.3
Development and Design	Formulating the AIDG Framework by combining governance, AI, LA, EDM, SHAP, and BI	Section 3.5
Exposition	Demonstrating through OULAD, data preparation, becoming able to handle features, machine learning application, SHAP, and Power BI	Sections 3.6-3.10
Assessment	Performing predictive analytics, explainability, governance, and dashboard evaluation	Section 3.11
Communication	Presenting and discussing the results, contributions, limitations, and possible future research paths	Chapters 5-6

This mapping shows that there is a direct connection between stages of the methodology and actual implementation of the research artifact.

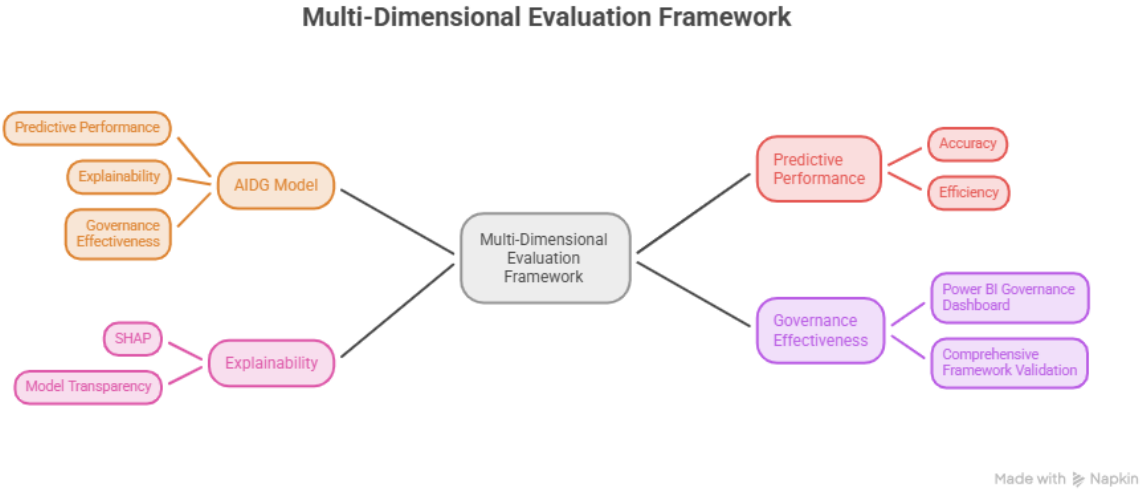
3.12 Ethical Considerations

In studies involving educational data and Artificial Intelligence, it is necessary to consider ethic and morals since the findings affect the work of an educational institution.

In the current research, the use of OULAD is fully in compliance with the principles of responsible data usage.

First of all, only anonymized educational data is used in this research. No identification information can be used in the process of using the data.

Secondly, AIDG framework will assist but not replace human intellect. The predictions received through Random Forest and XGBoost will be applied as auxiliary information for the decision-makers. Human decision-makers will be responsible for all executive decisions made.



Thirdly, SHAP will be used in the research to improve openness and accountability by allowing stakeholders to understand the reasons which lead to the prediction.

Finally, the research process will be based on principles of fairness, openness, responsible data usage, and presence of human in the whole process which are the ideas introduced in Chapter 2.

3.13 Summary of the Chapter

The current chapter has presented the methodological background of the study and rationalized the choice of Design Science Research as the main method for undertaking design, development, demonstration, and evaluation of the proposed AI-Based Digital Governance Framework.

The chapter first presented the research design and demonstrated that the research issue and objectives are compliant with the DSR methodology. Six stages of DSR were mapped onto crafting the research artifact.

Later on, the chapter presented the stages of formulating the AIDG Framework and outlined its five pillars: institutional digital governance, data governance, AI and predictive analytics, Explainable AI, and governance intelligence dashboards.

Chapter 4

Proposed AI-Enabled Digital Governance Model

4.1 Introduction

The methodology utilized in this research is highlighted in Chapter 3, which also outlines the essence of using 'Design Science Research' as the research approach in developing and assessing an innovative governance tool for e-learning organizations. Based on this methodology, the present chapter brings forward the 'Proposed 'AI-Driven Digital Governance Framework', which is the centerpiece of this research.

This model was developed in light of the research gap mentioned in Chapter 2. The literature review showed that digital governance, as well as Artificial Intelligence (AI), Learning Analytics (LA), Educational Data Mining (EDM), Explainable Artificial Intelligence (XAI), and Business Intelligence (BI), are treated as separate areas of the study. However, despite the contributions of these areas, they do not have any recommendations about the use of these technologies in a common governance framework.

The suggested AIDG framework successfully tackles this challenge by incorporating principles of institutional governance, the concept of governance of educational data, and predictive analytics into one system. The aim of the framework is to convert the educational data from a mere analytical tool into value-enhancing governance intelligence that would be able to serve the purposes of accountable, transparent, and data-based decision-making in institutions of higher education.

The framework incorporates the governance lifecycle that starts with the definition of institutional strategy and governing objectives, and goes through the entire process of collecting and processing educational data through the use of artificial intelligence, and ends with the creation of governance information dashboards.

Thus, in the chapter, we will outline the key design principles of the AIDG framework, explain its layered architecture, tell about the governance workflow, present the proposed governance performance indicators, and underline the theoretical novelty and contribution.

Data usage and validation of the AIDG framework will be discussed in Chapter 5.

4.2 Design Principles of the Proposed AIDG Framework

Based on a combination of various design principles gathered during the review of existing literature and in connection with the analysis of widely known AI governance frameworks and following the Design Science Research approach, the AIDG Framework has been completed.

These principles emphasize that this framework is not just the new technological architecture, but rather an innovative governance-oriented model which presents a concept of aligning AI with the institutional goals, ethical requirements, good data quality, transparency, accountability, and data-driven decision-making.

The main idea is not only to concentrate on the predictive performance of the framework, but also to cover other governance needs connected with the safe and sustainable AI use.

4.2.1 Strategic Alignment

The crucial principle concerns the alignment of AI initiatives with its institutional strategy.

AI should not be perceived as an isolated technological tool. Implementation of AI technologies should lead to the realization of institutional objectives, such as improvement of educational quality, promotion of student success, increase in organizational performance, and advancement of evidence-based governance.

Thus, all the analytical procedures implemented within the AIDG framework are in line with the objectives of the institutional governance. This way, it is ensured that the investments into AI and the conducting of analytical procedures lead to fulfilling the institution's priorities, rather than creating a technically advanced, but useless output.

4.2.2 Transparency and Explainability

Transparency is a crucial principle of responsible digital governance.

Participants in the institutional process should have a clear understanding of the workings of AI models and how their predictions may impact governance decisions. The AIDG Framework implements Explainable Artificial Intelligence through the concept of SHAP.

SHAP allows assessing and analyzing the contribution of independent variables into the prediction of the model, thus eliminating a major complication usually associated with machine learning models and giving stakeholders the understanding necessary to obtain informative proof of AI-based results.

Thus, the importance of explainability is rather related to governance than to a technical aspect.

4.2.3 Accountability

In digital governance, institutions need to have clearly stipulated responsibilities regarding the creation, implementation, observation, and operation of AI systems.

The AIDG Framework then has AI predictions seen as helping rather than executing decisions. The relevant institutions' leaders, education institutions' management bodies, and responsible governance structures are expected to make sense of the analysis results and decide what steps the relevant institutions should take.

This human involvement in the process is crucial for proper governance as it is supposed to support rather than give the power of making decisions to AI.

4.2.4 Quality of Data and Data Governance

Governance is dependable based on reliable data

Therefore, the educational data governance framework integrates the process of data governance in all phases of educational data cycle, including data sourcing, integration, data quality assurance, verification of data consistency, data privacy, feature engineering and data security management.

Good educational data ensure the reliability of AI model outputs as well as trustworthy data governance decisions.

4.2.5 Responsible Artificial Intelligence

The AIDG Framework adopts principles associated with responsible AI, including fairness, transparency, reliability, explainability, and ethical implementation.

These principles are intended to reduce risks associated with inappropriate or biased AI-supported decisions while strengthening stakeholder confidence.

Responsible AI is therefore embedded within the governance architecture rather than being treated as a separate compliance activity.

4.2.6 Human-Centered Decision Support

The framework adopts a human-centered approach in which Artificial Intelligence augments rather than replaces human expertise.

Institutional administrators, academic leaders, and governance committees remain at the center of the decision-making process. Predictive models, SHAP explanations, and dashboards provide evidence that assists human judgment.

This principle is particularly important in educational governance because analytical predictions may require contextual interpretation before an institutional intervention is implemented.

4.2.7 Continuous Improvement

Digital governance is a process that is constantly changing and requires constant monitoring and evaluation.

That is why AIDG Framework has feedback mechanisms through which governance outcome monitoring, intervention evaluation, model performance assessment, and governance process refinement based on new educational data becomes possible.

Feedback processes make it feasible for the framework to make changes in response to changes in students' behavior, institutions' priorities, technological advancements, and governance requirements.

4.2.8 Sustainability and Digital Transformation

The last principle is connected with sustainability.

The framework is intended to support digital transformation in the institution with an emphasis on long-term sustainable results rather than short-term analytical solutions. The innovative feature of the framework is an approach that brings together governance policies, educational analytics, AI, Explainable AI, and Business Intelligence.

Table 4.1. Core Principles of the Proposed AIDG

Principles of Design	Definitions	Governance Impact
Strategic Alignment	AI practices should align with the goals of the institution	Supports governance strategy
Transparency and Understandability	Use SHAP to gain insight into AI-generated outputs	Improves transparency
Responsibility of Governance	Keep humans in charge of governance decisions	Enhances accountability
Data Preservation and Quality Control	Provide valid, safe, and good-quality educational data	Makes decision-making reliable
Responsible Use of Artificial Intelligence	Implement principles of fairness, ethicacy, reliability, and transparency	Supports responsible governance of AI
Decision Support from the Viewpoint of Humanism and Social Responsibility	AI should assist rather than replace human judgment	Improves quality of decision-making
Ongoing Improvement	Carry out performance assessments and improvement of governance	Increases governance advancement
Sustainability	Facilitate long-term digital transformation	Contributes to sustainable governance

The principles described in Table 4.1 serve to form a conceptual basis upon which the AIDG Framework is built, as well as providing a rationale for distinguishing the proposed framework from any methods of assessing AI on the basis of predictability alone.

4.3 Structure of the AIDG Framework

The AIDG Framework is constructed in layers that include institutional governance, educational data management, AI, explainable AI, and business intelligence in a single framework of governance.

This structure is aimed at converting educational data to governance knowledge, which can utilize transparency, accountability, and evidence-based decisions.

Thus, the developed framework has five layers of interrelated processes, each of them being responsible for a certain process of governance.

4.3.1 Layer 1: Institutional Digital Governance

The first layer sets up the framework and structure of the governance policy.

This layer comprises:

- policy guidelines
- success target settings
- guidelines for operations
- quality assurance system
- risk management
- regulatory compliance

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- define priorities in governance affairs.

This layer defines institutional objectives and is instrumental in guiding further actions referring to data and AI.

The main function of this layer is to make sure that AI works in line with institutional priorities and policies rather than independently with respect to governance.

4.3.2 Layer 2: Data Governance and Educational Data Management

The second layer deals with educational data in all possible aspects.

In this layer educational data derives from:

- Learning Management Systems
- Virtual Learning Environments
- students' information systems
- assessment data management systems
- institutional information systems
- other educational platforms

Data governance in this layer implies data integration, its cleaning, preprocessing, quality assurance, features formation, confidentiality and security guarantee.

It is crucial to underline that the efficiency of the governance intelligence based on AI depends on the quality and accuracy of the input data.

4.3.3 Level 3: Artificial Intelligence and Predictive Analysis

The analytical engine of the framework is represented by this level.

The educational data is analyzed using machine learning models that can identify patterns related to:

- learners' engagement;
- academic success;
- students' risk;
- learning habits;
- governance-related outcomes.

In empirical research, Random Forest and XGBoost are the main predictive models used in the analysis.

The information produced by this level is transformed into indicators related to governance that can promote intervention and institutional planning.

The framework does not see prediction as an end in itself; rather, it is regarded as an analytical ability in the context of the overall governance process.

Layer 4: Explainable AI

Section 4.3.4 elaborates on the transparency and interpretability of AI-generated outcomes.

SHAP has been included to determine the role that various factors play in predicting models. This will help institutional actors in assessing not only the significance of these factors, but also the impact that different factors have on modeling outcomes.

Explainability promotes:

- transparency;
- claritude;
- comprehensibility;
- credibility; and
- rational governance of AI.

Therefore, this section leads to transforming predictions into comprehensible proofs useful for making decisions at institutions.

4.3.5 Layer 5: Intelligence and Support of Governance

The last, fifth layer is taking analytical results and creating them into useful governance intelligence.

Microsoft Power BI is used as the Business Intelligence environment for reporting:

- governance metrics;
- predicted results;
- learner engagement;
- institutional performance;
- SHAP-based explanations;
- information about risks.

The dashboard gives an actionable interface to institution actors for monitoring their performance, recognizing emerging risks, analyzing their strategic decisions, and making right decisions based on evidence.

4.3.6 Layers of the Framework

The main advantage of the AIDG Framework is the interaction of all five layers.

Institutional governance sets strategy and responsibilities. Data governance ensures the quality and availability of educational data. AI changes data into predictive knowledge. Explainable AI makes predictions understandable. Business Intelligence gives a picture of created governance intelligence to decision makers.

The communication between these layers makes it possible to develop beyond common reporting and to achieve proactive and transparent digital governance.

Figure 4.1. AI-Based Framework of E-Governanc

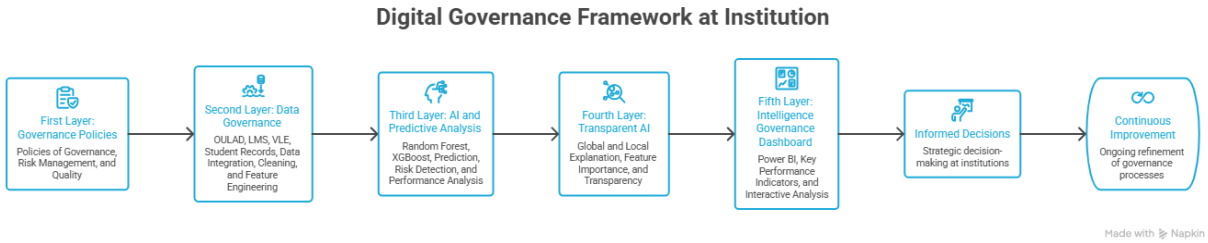


Table 4.2. Functional Layers of AIDG Framework

Layer	Main Function	Expected Governance Outcome
Institutional Digital Governance	Plan governance policies and strategic goals	Governance conformity and responsibility
Data Governance	Solve education data quality and integration problems	Correct institutional data
AI and Predictive Analytics	Forecast learner success and institutional risks	Preventive governance solutions
Explainable AI (SHAP)	Understand models predictions	Transparency and confidence
Governance Intelligence Dashboard	Show governance indicators by means of Power BI	Evidence-based support for executive decisions

4.4 Governance Flow of the Proposed Framework AIDG

The efficiency of the framework AIDG is determined not only by the presence of separate architectural layers but also by their constant collaboration.

Thus, the framework has a governed workflow for transforming the educational data into transparency governance intelligence and institution action.

The workflow starts from institution governance objectives and passes through data management, predictive analytics, explainability, visualization, and decision-making; and eventually comes back to the governance planning stage thanks to feedback mechanism of improvement.

4.4.1 Stage 1: Governance Planning

The process starts from an institutional strategy and governance objectives, regulatory requirements, and KPIs.

The institution top management set the priorities in governance that give directions what information must be collected, processed, analyzed and reported.

This stage allows making sure that AI applications are used in accordance to real requirements of the institution and not merely for the sake of technology itself.

4.4.2 Stage 2: Educational Data Collection and Management

The next phase involves the gathering of educational data from pertinent institutional systems.

The data collected undergoes integration and preparation via:

- integration of data;
- cleansing of data;
- validation;
- engineered features; and
- selection of features.

The goal is the creation of a strong analytical foundation that can effectively describe learner behavior and institutional performance.

4.4.3 Stage 3: Artificial Intelligence Analysis

The data ready is analyzed with the help of machine learning models.

Random Forest and XGBoost will be used in this research to find the relations between learner engagement and academic performance as well as how these characteristics could indicate possible academic risk.

4.4.3 Stage 3: Artificial Intelligence Analytics

After preparation, the data are fed into machine learning models for analysis.

In this study, Random Forest and XGBoost do the pattern-hunting. They look for clues in learner engagement, academic performance, and potential academic risk.

Once generated, the predictions turn into governance-oriented indicators. They are meant to guide proactive intervention at the institutional level.

4.4.4 Stage 4: Explainability and Governance Interpretation

In stage four, SHAP is used to make sense of the model predictions.

Instead of telling decision-makers only that a learner is high or low risk, the framework unpacks the factors behind that label.

That approach bolsters transparency and accountability. It also lets institutional stakeholders review the AI-supported evidence before they act.

4.4.5 Stage 5: Governance Intelligence Visualization

The interpreted outputs are integrated into Power BI dashboards.

The dashboards combine:

- governance indicators;
- predictive outcomes;
- learner engagement metrics;
- academic performance information; and
- SHAP-based explanations.

This integrated visualization enables institutional leaders to monitor governance performance, identify emerging risks, and examine areas requiring intervention.

4.4.6 Stage 6: Institutional Decision-Making and Continuous Improvement

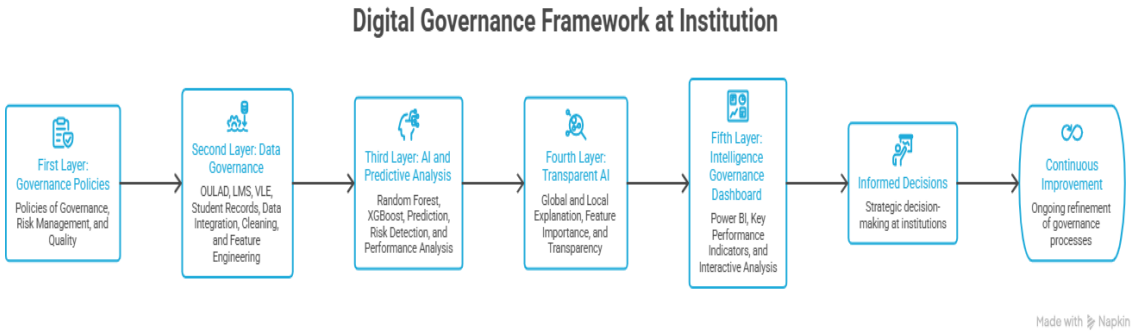
The final stage transforms governance intelligence into institutional action.

Decision-makers can use the analytical evidence to:

- implement targeted interventions;
- revise governance policies;
- allocate resources;
- improve educational quality;
- monitor academic risk; and
- evaluate the effectiveness of previous interventions.

The outcomes of these actions are continuously monitored and returned to subsequent governance cycles through the feedback mechanism. This creates an iterative governance process supporting institutional learning and maturity.

Figure 4.2. Governance Workflow of the Proposed AIDG Framework



governance objectives are the ones that inspire doing analytics, the analytical reports in turn produce the evidence needed for taking the governance actions, interpretation of the analytical data is assisted by explainability, taking decisions is the result of working on dashboards, and ultimately the decisions lead to feedback which is the basis of ongoing governance development.

Governance Performance Indicators are part of the AIDG Framework.

The indicators, referred to as Governance Performance Indicators (GPIs), aim to extract governance information through transforming educational data and analysis results.

Conventional educational indicators mainly center around a students' academic results. However, these new indicators bring together different areas: institutional governance, educational performance, learner participation, AI governance, and governance intelligence.

Such a multifaceted structure helps institutional stakeholders assess governance from planning, education, technology, and operations perspectives.

4.5.1. Governance indicators related to institutions

Governance policy effectiveness and organizational management are captured through governance policy effectiveness indicators.

Among the main indicators are:

- policy compliance;
- institutional performance;
- quality assurance;
- decision making;
- strategic goal achievement; and
- continuous improvement of governance

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These indicators give us insight into how mature an institutional governance system is, whether organizational goals and operational results are in line, and how they can be better aligned.

4.5.2 Educational Performance Indicators

Educational performance indicators measure learner achievement and academic effectiveness.

They include:

- average assessment scores;
- assessment completion rate;
- student academic performance;
- learning progression;
- student retention; and
- completion status.

These indicators provide evidence for academic quality assurance and educational program evaluation.

4.5.3 Learner Engagement Indicators

Learner engagement is particularly important in online learning environments because interaction patterns can provide early evidence of potential academic difficulties.

The proposed engagement indicators include:

- total VLE interactions;
- number of active learning days;
- learning resource utilization;
- assessment participation;
- learning activity consistency; and
- late submission frequency.

Monitoring these indicators enables institutions to identify changes in learner engagement and support early intervention.

4.5.4 Artificial Intelligence Governance Indicators

The framework extends conventional educational analytics by incorporating indicators related specifically to AI governance.

These include:

- prediction accuracy;
- prediction confidence;
- model transparency;
- feature importance;
- explainability level; and
- governance reliability.

These indicators help ensure that AI is evaluated not only according to predictive performance but also according to its suitability for trustworthy institutional governance.

4.5.5 Governance Intelligence Indicators

The final category measures the practical value of governance intelligence generated through the integration of predictive analytics, Explainable AI, and Business Intelligence.

Representative indicators include:

- decision-support effectiveness;
- dashboard usability;
- governance insight accessibility;
- early risk identification capability;
- evidence-based intervention support; and
- continuous governance monitoring.

These indicators assess whether analytical outputs can be effectively transformed into actionable institutional information.

4.5.6 Integrated Governance Measurement

The indicators may belong to separate classes; nonetheless, they operate together within an integrated governance measurement system.

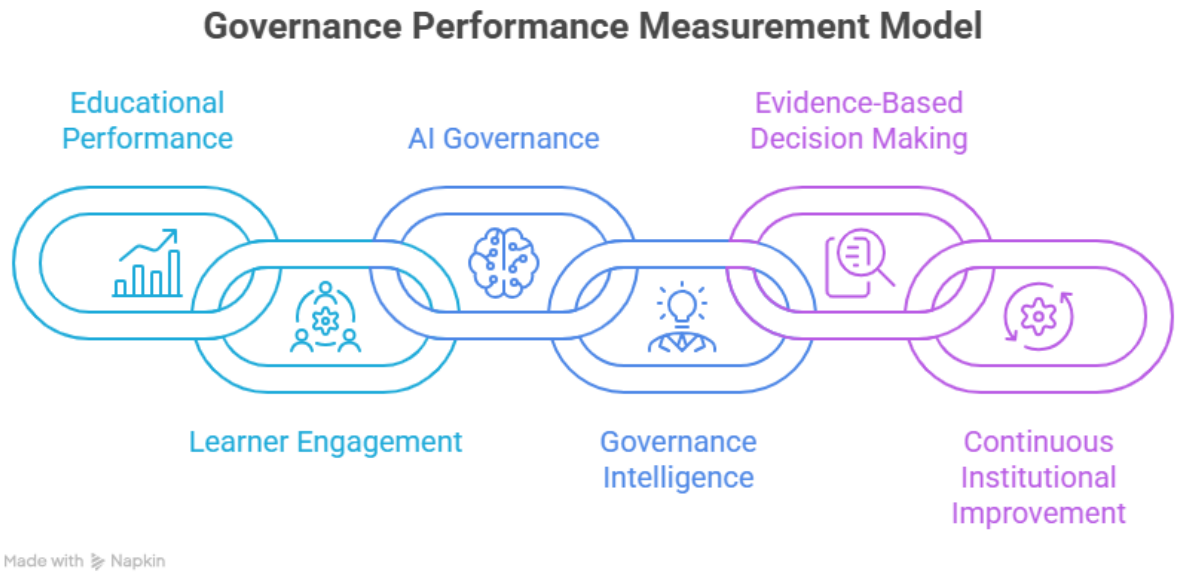
For instance, indicators measuring learner engagement may be used to identify predictive risks, AI governance indicators measure how trustworthy and transparent the models are, while governance intelligence indicators gauge the extent to which the generated information informs the decisions of the institution.

The integrative nature of the system enables multi-faceted evaluation of governance performance, resulting in the continuous improvement of institutions.Table 4.3. Governance Performance Indicators of the Proposed AIDG Framework

Table 4.3. Governance Performance Indicators of the Proposed AIDG Framework

Categories of Indicators	Illustrative Indicators	Reason for Governing
Institutional Governance	Adherence to policy, maturity of governance	To assess the effectiveness of governance in institutions.
Educational Results	Results of assessment and percentage of success in education	To oversee quality of education.
Involvement of learners	Days of active use, interactions, usage of resources, late delivery	To identify engagement trends and academic risks.
AI-based governance	Correctness of information, importance of given features, SHAP explanations, addressing models.	To guarantee efficient governance with the use of AI.
Smart governance	KPIs from the dashboard, decision helping ability, alerts on possible risks	To assist in making the right decisions.

Figure 4.3 Governance Performance Measurement Model



4.6 Contribution and Original Work.

Research Framework.

The AIDG Framework is the central research output and academic input of this paper. The new contributions of the framework should be considered in the context of integration and operationalization rather than creation of a novel machine learning method.

In the previous studies, many valuable findings have been presented in different fields of digital governance, AI, Learning Analytics, Educational Data Mining, Explainable AI, and Business Intelligence.

The aim of the framework is to provide relevant means for connecting various areas of studies in order to offer more effective solutions for digital governance for learning organizations.

4.6.1 Merging Governance and Artificial Intelligence

AIDG Framework's initial contribution is the merger of institutional digital governance and AI-driven learning analytics.

Rather than viewing AI as an independent technological tool, the AIDG Framework incorporates AI into institutional governance procedures.

This development transforms predictive analytics from an isolated technological procedure into governance intelligence.

4.6.2 Incorporation of Explainable AI into Governance

Another feature of the framework is the integration of SHAP-based Explainable AI technology into the whole governance cycle.

This development leads to moving from prediction accuracy to interpretability, thus providing a solid piece of evidence regarding those factors that led to AI predictions.

Thus, this merger increases the level of:

- Transparency;
- Accountability;
- Interpretation;
- Stakeholder confidence in the technology; and
- Responsible use of AI.4.6.3 The Alteration of Predictive Analytics into Governance Intelligence

The third contribution concerns the turning of outputs of machine learning into an institution's governance intelligence.

Power BI has an operational interface through which it is capable of providing the predictions, indicators of governance, metrics of engagement, and explanatory data to the policymakers.

As such, it becomes possible for an institution to progress from descriptive reporting to proactive governance with the help of analytical evidence.

4.6.4 The Perspective of Multidimensional Evaluation

The fourth contribution is the perspective of multidimensional evaluation present in the model.

The AIDG Framework does not assess success only through accuracy of prediction.

In other words, it takes into account:

- the quality of predictions;
- a possibility to explain the predictions;

- the efficacy of governance processes;
- the ability to support decisions made.

This wider point of view responds to practical needs of digital governance in organizations, whereby the high level of technical performance would not produce a significant benefit without the capacities of interpretation of models.

4.6.5Theoretical Contribution

The contribution made by means of this framework from the theoretical point of view could include the provision of an integrated governance framework that connects the theories of digital governance and AI-supported educational analytics.

It shows in theoretical terms how the principles of governance, educational data, predictive AI, Explainable AI, and Business Intelligence may function as parts of one ecosystem of the organization in practice.

4.6.6 Practical Contribution

From a practical standpoint, the framework offers educational technology organizations a systematic way of establishing their AI-powered governance practices. The stakeholders in an educational institution can make use of this framework in order to:

- increase the transparency of governance;
- watch the engagement of students;
- detect possible academic problems;
- facilitate the implementation of evidence-based practices;
- observe the performance of the institution;
- make decisions more effective, and
- enable a place for ongoing development of the organization.

Thus, the practical contribution is in linking technical analytics with the practice of institutional governance.

4.6.7 Summary of the Innovation to the Framework

Thus, the main innovation of the AIDG Framework can be summarized in five intertwined contributions:

1. Governance Integration: institutional digital governance is linked with AI and educational analytics.

2. Transformation of Data into Governance: educational data is transformed into governance-oriented intelligence.

3. Transparent Governance: SHAP is introduced into the governance life cycle for purposes of transparency enhancement.

4. Operationalization of Decision Support: Power BI provides a means for transforming analytical outcomes into governance information.

5. Multidimensional Evaluation: the framework evaluates its predictive, explanatory, governance, and decision-support components.

Thus, the framework provides educational analytics approaches with opportunities to go beyond prediction and to employ an integrated, accountable, transparent, and proactive model of digital governance.

4.7 Synopsis of Chapter

In this chapter, a detailed description of AI-Driven Digital Governance Framework (AIDG Framework) is provided, which is the most important idea of the research as per the principles of Design Science Research.

The proposed framework is developed on the basis of research issue disclosed in Chapter 2, which is mainly concerned with the void between digital governance and several concepts like Artificial Intelligence, Learning Analytics, Educational Data Mining, Explainable AI, and Business Intelligence.

Initially, the chapter introduces eight design principles pertaining to the framework: strategic alignment, transparency and explainability, accountability, quality of data and governance, responsible AI, human factor in the decision support, continuous improvement, and sustainability principles.

The chapter gives information on the five-component composition of AIDG Framework with its first part of institutional digital governance and the second part of the system of educational data management.

Chapter 5

Practical Implementation and Experimental Evaluation

5.1 Introduction

In this chapter, a practical implementation and empirical evaluation of the proposed AI-Driven Digital Governance Framework (AIDG Framework) is presented, with the Open University Learning Analytics Dataset (OULAD) serving as the empirical case study.

Following the theoretical elaboration of the framework set out in Chapter 4, the chapter illustrates a practical implementation of the suggested governance scheme in an e-learning context through the combination of educational data analytics, machine learning, Explainable Artificial Intelligence (XAI), and Business Intelligence transformation technologies.

The case study aims to assess the practical effectiveness of the proposed AIDG Framework in facilitating evidence-based digital governance. The process of implementation includes

integration, preprocessing, feature selection, development of predictive models, evaluation of the models, SHAP explainable analysis, and visualization of governance intelligence in dashboards built in Microsoft Power BI.

The OULAD dataset was used to apply two supervised machines learning techniques: Random Forest algorithm and Extreme Gradient Boosting (XGBoost). Predictive performance was analyzed based on accuracy, precision, recall, and F1-score. Moreover, beyond predictive capability, SHAP technique was used to find out about the interpretability of the model and dashboards from Power BI were created to convert analytics into governance intelligence.

Different from ordinary Educational Data Mining research where the focus is on predictive ability, this evaluation takes a multidimensional perspective which combines predictive ability, explainability, governance intelligence, and capability to support decision-making. This approach is inline with the Design Science Research methodology used in the research since the research artifact needs to have both technical effectiveness and usefulness in practice.

The rest of the chapter will be divided into the case study dataset, data integration and preprocessing, features engineering, application of machine learning algorithms, predictive results, SHAP analysis and Power BI dashboards, as well as validation of the suggested framework in practice. 5.2 Case Study Dataset: OULAD

5.2.1 Overview of the Dataset

OULAD or the Open University Learning Analytics Dataset is the case study investigated in this research.

The OULAD dataset is an anonymous educational data collected by the Open University across its courses many of which are being delivered via a Virtual Learning Environment (VLE). OULAD integrates various information about students, their course enrollment, assessment score information, learning resources as well as interaction of students.

OULAD is structured in a relational way that enables it to depict many dimensions of the learners around aspects of their characteristics, learning outcome, participation and course context that make it useful for any analytical undertaking in education as well as in this research study for governance-based analyses.

5.2.2 Variables and Contribution Towards Governance of OULAD

The main variables that were used for analysis include student data, student enrollment, student assessment data, assessment results, student learning records, records of interaction with VLE, student course data, and resources.

Table 5.1. OULAD dataset variables and contribution towards Governance.

Primary Factor/Table	Details	Governance Contribution
studentData	Sex, age group, area of residence, educational qualification, handicap, final grade	Uneconomic Governance
studentEnrollment	Date of registration and date of quitting	Governance in regard to studentLife
Exams	Type of exam, level of importance, deadline	Academic Governance
studentExam	Date of submission and result	Monitoring of performance
studentVleSystem	Number of clicks, type of activity, date of activity	Learning Analytics
VleSystem	Type of resource and description of the activity	Resource Governance
Classes	Code of module and presentation	Planning of organization

The combination of the tables yields a cohesive analytical base that can illustrate various aspects of both academic performance and interaction with education within the learning environment.

5.3 OULAD Data Integration and Analysis

5.3.1 Data Integration

The available OULAD data is organized in a number of relational tables that each provide certain pieces of information about students, assessments, learning activities, courses, and activities carried out within the virtual learning environment.

In order to support the analysis, an integration of the required tables was performed on the basis of common IDs, for instance:

• ID_student

• Code_module

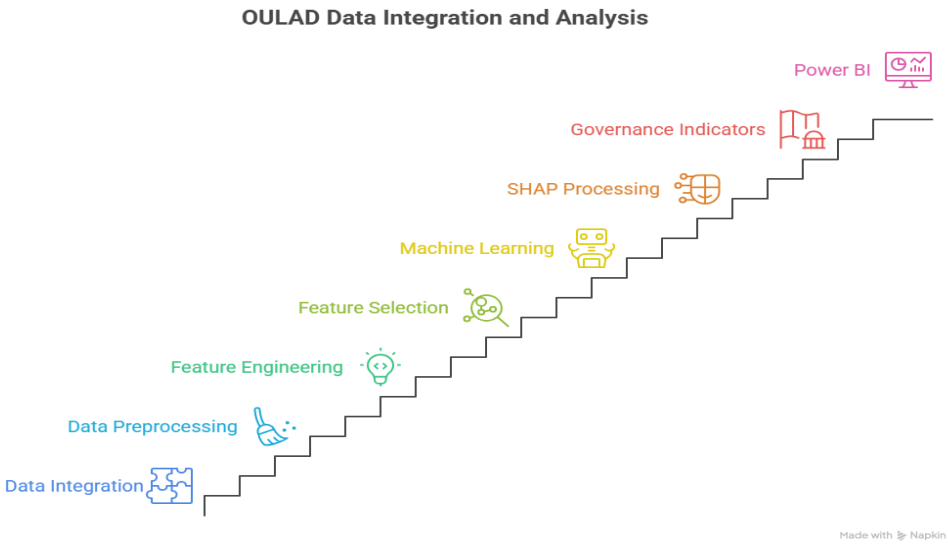
• Code_presentation

The integration process also shaped up an analytical model where one is able to see the students' characteristics, registration, assessment performances, actions in regard to learning resources, and course's parameters.

The established integrated database has become the ground for future data processing.

Figure 5.1. OULAD Data Integration and Analysis Working Methods

5.3.2 Cleaning of Data



After completing the data integration process, the new dataset went through a series of checks to find quality problems that might hurt predictive performances or governance reliability.

The cleaning process contained several steps:

- the removal of duplicate records;
- the identification and treatment of missing data;
- the correction of inconsistent values of the categorical variable;
- the removal of observations that cannot be used for predictive analysis due to their incompleteness;
- the checking of the consistency of the data in databases..

The above-mentioned actions enhanced the quality of data and minimized possible analytic bias caused by incomplete or inconsistent educational data.

Data Transformation, in this case, involved the conversion of non-numerical variables to appropriate numerical ones for machine learning purposes. Continuous variables were checked for consistency while irrelevant and duplicated variables were eliminated.

The purpose of the data transformation was to make the dataset ready for the machine learning and the SHAP methods that were to be employed in the study.

Feature Engineering was applied in order to create meaningful analytical features out of the original educational data whereby we did not only strive to obtain better prediction results but also to create meaningful indicators for governance in the AIDG Framework.

Some of the engineered features include:

- Total Interactions the total number of interactions of the students in the virtual learning environment.
- Active Days the number of days the student logged in to the learning management system.
- Assessments Submitted the total number of assessments done.
- Average Assessment Score the average assessment results.

- Late Submissions the number of assessments submitted late.
- Unique Learning Resources the number of different types of educational materials used.
- Assessment Score Variability the standard deviation of the assessment scores.
- Registration Gap the time interval between registration to the beginning of the learning process.
- Module Presentation Length: length of education period.

These features measure learner behavior more precisely compared to the initial patterns and allow for effective patterns matching in terms of governance models.

Table 5.2. Characteristics of Engineered Features and their Relevance for Governance

Characteristics	Explanation	Given Relevance
Total Interaction	All interactions of users	Engagement of learners
Active Days	Days users have been active	Continuity of learning
Number of Assessments submitted	Completed assessments	Participation in academics
Mean Assessment Scores	Average performance of users	Academic performance
Number of Late Submissions	Number of late submissions	Early academic risk
Resources used	Number of unique resources used	Utilization of resources
Variation in Assessment Scores	Consistency of user performance	Stability of learning
Time between Registration Gap	Delay in registration and participation	Early engagement
Time in the course	Duration of a course	Academic scheduling

5.4.2 Feature Selection:

Despite the fact that attribute preprocessing led to getting an extensive dataset, not each of the attributes turned out to be equally important for prediction. Feature selection was carried out in order to choose effective attributes, eliminate redundancy and facilitate the processes of computation and understanding of the model. The features that were chosen became the basis for running Random Forest and XGBoost algorithms and were further analyzed in terms of their contribution to prediction using SHAP method.

5.5 Employed Machine Learning Techniques and Predictive Assessment

5.5.1 Selection of Models

Two ensemble methodologies were selected for the purpose of the empirical testing:

1. Random Forest

2. Extreme Gradient Boosting (XGBoost)

The models were selected due to their performance in prediction tasks, ability to deal with heterogeneous educational data types, compatibility with SHAP, and usability for decision-making in the field of governance.

5.5.3 XGBoost

This XGBoost technique relies on the principle of sequential gradient boosting in order to develop decision trees and reduce the occurrence of errors in predictions.

On the one hand, the AIDG Framework benefits from this new method, as the XGBoost model can give valuable insights into complicated relations between the behaviour of learners and educational parameters.

5.5.4 Preparation of the model and assessment of its performance

The initial dataset was split into two separate groups, namely training and test sets Moreover, Random Forest and XGBoost were run on the same set of features to ensure comparability between the results.

The assessment of the work done is made through the indicated indicators:

- accuracy,
- precision,
- recall, and
- F1-value.

These indicators offer different viewpoints with respect to the predictive abilities of the models and help to avoid over-reliance on the use of only one measure.

5.5.5 Predictive Performance Results

Table 5.3 shows the Predictive Performance Results for the Machine Learning Models Selected

Model	Accuracy	Precision	Recall	F1 score
Random Forest	0.9334	0.9706	0.9012	0.9346
XGBoost	0.9399	0.9655	0.9189	0.9416

The experiment showed that both models successfully predicted results.

Random Forest had an accuracy of 93.34 percent, a precision of 97.06 percent, a recall of 90.12 percent, and an F1 score of 93.46 percent.

XGBoost had an accuracy of 93.99 percent, a precision of 96.55 percent, a recall of 91.89 percent, and an F1 score of 94.16 percent.

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Analysis of Results

The small divergence noted between both models suggests that the educational indicators made an impact in the outcomes generated.

The performance of both models shows that student engagement, assessment habits, registration habits, and academic performance contribute toward achieving the already defined objectives.

XGBoost had the highest Accuracy and F1-score values meaning that in comparison with Random Forest, it has the better predictive capabilities, but the difference is not so big so we can deem Random Forest inefficient.

Interpretation from the Perspective of Governance

Results from the models are vital from the governance point of view as the data provided may serve as early-warning signals.

The models can allow institutions to operators to understand the situation with regard to the students who may need additional academic assistance. Thus, the institutions can move on from reactive measures to proactive governance.

The data provided can facilitate:

- early intervention in education;
- special assistance to students;
- appropriate allocation of resources;
- monitoring results;
- evidence-based planning.

The researcher views the findings as indicating that the AIDG Framework establishes an association between feature engineering, predictive analytics, and decision support that is aligned with governance functions. In addition, the results suggest that the framework does not rely solely on the use of one specific machine learning algorithm. Indeed, Random Forest and XGBoost demonstrated very similar outcomes of work.

5.5.6 Comparative Assessment of the Models

Table 5.4. Comparative Assessment of the Chosen Machine Learning Algorithms

Parameter	Random Forest	XGBoost
Predictive Accuracy	Above Average	Quite High
Generalization Capability	Above Average	Quite High
Feature Importance Analysis	Present	Present
SHAP Affordability	Exemplar	Exemplar
Governance Adequacy	Above Average	Quite High

The assessment displays that both algorithms are valid for implementation. XGBoost shows better predictive ability, however, Random Forest is a strong and interpretable candidate as well. Therefore, the key advantage of the comparison is finding not just the “best” algorithm, but showing that the analytical workflow oriented to governance achieves success irrespective of the methods relied on.

5.6 SHAP-based analysis of explainability

5.6.1 The aim of SHAP analysis

The power of predicting is not enough to ensure trustworthy electronic governance. The stakeholders in an institution need explanations regarding why AI produces a specific prediction. Therefore, SHAP is used to explain how every educational factor contributes to the final output of the model. SHAP enables global and local explanation of the results and makes it possible to receive solid evidence for good governance.

5.6.2 Summary Analysis Using SHAP

Figure 5.2. Summary Plot of the Proposed AIDG Framework

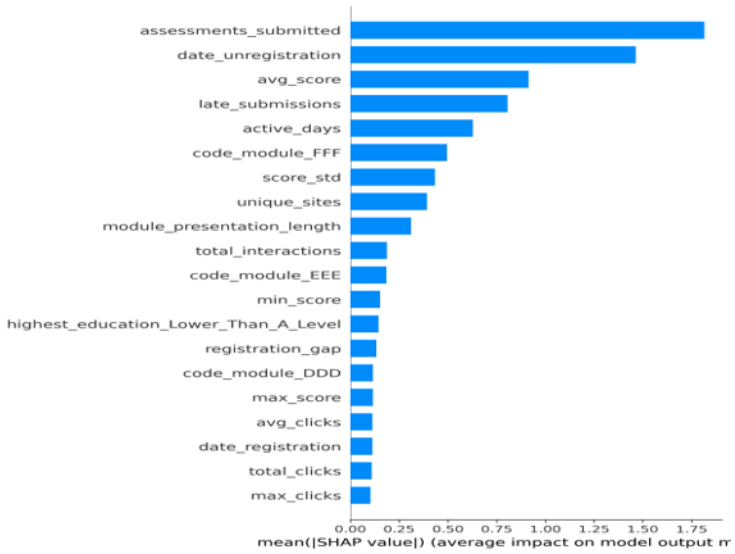


Figure 5.2 illustrates the SHAP summary plot which has been produced by the prediction model. The plot provides an overall view of how much each of the input features has contributed to the prediction made by the model. Input features are arranged in the order of their overall contributions and the distribution of SHAP values gives an idea of the strength as well as the type of input features' influence on the individual observations. Thus, the visualization gives better insights into the prediction process than standard feature-importance methods that take into account all input features.

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5.6.3 SHAP-Based Global Feature Importance

In order to provide additional insight into how the machine learning model behaves in terms of making predictions, a global SHAP feature-importance assessment was carried out. Normally, classical feature importance presents the relative contribution of the model variables but SHAP perceives the contribution of each feature in relation to the modeling output for each analyzed instance. In our research we assess the overall size of the contribution through the mean absolute SHAP value which does not depend on whether the contribution is positive or negative. This analysis helps trace the most significant educational, behavioral, and contextual features of the model results and enables it to be easily interpreted for policy purposes in the context of AIDG Framework proposed in the given research.

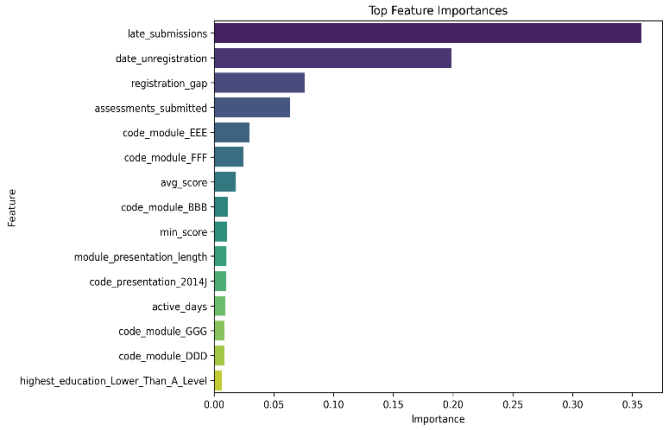


Table-5.5. Importance and Explanation of Features According to SHAP Values

Rank	Feature of interest	Mean Absolute SHAP Value	Governance Interpretation
1.	assessments_submitted	1.8156	Learning commitment
2.	date_unregistration	1.4646	Student retention
3.	avg_score	0.9141	Academic performance
4.	late_submissions	0.8054	Early risk indicator
5.	active_days	0.6281	Student engagement
6.	code_module_FFF	0.4953	Course context
7.	score_std	0.4330	Learning consistency
8.	unique_sites	0.3925	Learning diversity
9.	module_presentation_length	0.3114	Academic scheduling
10.	Interactions	0.1877	Overall participation

The analysis of the significance of global features by SHAP makes it possible to quantitatively assess the contribution made by all the features in terms of the output made by the model. The results obtained point to the fact that the feature assessments_submitted is the most significant, as

it has the highest mean absolute SHAP value. After it, we have the features date_unregistration, avg_score, late_submissions, and active_days. The above-stated order means that these features assess the level of participation of the student in assessments, retention behavior, academic performance, and engagement in the study process.

Considering the fact that from the perspective of governance, this finding is important because the features mentioned are related to the observable educational behavior in the e-learning environment. In this respect, some of the good examples could be the results of assessment submissions along with the results of late submissions, as it would signal about the students' engagement in learning process, and unregistration would allow to inform the institutions about retention processes.

Thus SHAP analysis helps carry out the predictive analysis by getting insight into the factors that influence predictions made by the model.

The SHAP outputs indicate that assessments_submitted is the most important variable, with a mean absolute SHAP value of roughly 1.816.

The second most important variable is date_unregistration, which has a mean absolute SHAP value of around 1.465, followed by avg_score with approximately 0.914 and late_submissions with about 0.805.

This has been revealed that aspects of academic participation, student retention behavior, academic performance, and delayed submission are the major components creating predictive information.

5.6.4 Interpretation of SHAP Results in Relation to Governance

In terms of governance, SHAP analysis yields a number of very relevant conclusions.

First, the prominent role of submission behavior indicates that frequent academic engagement may serve as an important parameter for monitoring the organization.

Second, the impact of unregistration behavior shows the significance of retention of students as a governance issue.

Third, the relevance of overdue submissions confirms the idea that late learning can be regarded as an early signal.

Finally, the value of active days, different resources used, and total interactions together stands for the importance of behavioral learning analytics in the context of governance.

The above-mentioned results indicate that educational behavior can be transformed into useful governance parameters instead of being just employed for forecasting purposes.

5.6.5 Interpretation of Results by the Researcher

The researcher views the results obtained through the SHAP framework as empirical proof of one of the key design principles in the AIDG framework, namely, that AI-assisted governance must be actionable and explainable rather than just predictive.

SHAP converts outputs of the model into interpretable data that can be analyzed and confirmed by stakeholders for their intervention design purposes.

As a result, explainability is acting as one of the governance mechanisms that enhance governance quality in terms of transparency, accountability, and trust.

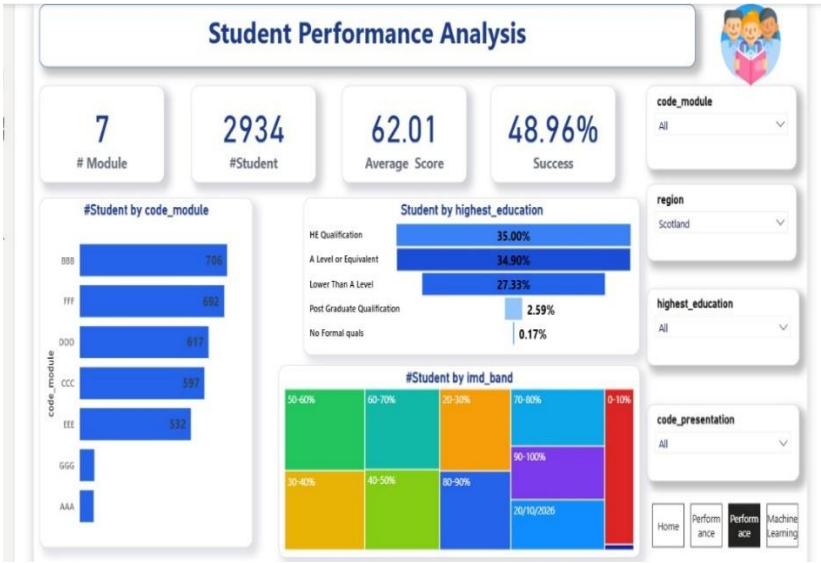
5.7 The Implementation of Governance Dashboard through Microsoft Power BI

5.7.1 The Introduction:

Machine learning and SHAP analysis are sources of useful analytical information, but decision-makers in institutions still require an easy to use environment for monitoring and interpreting these analytical results. Because of this, the implementation of Microsoft Power BI was achieved as a Business Intelligence layer in the AIDG Framework. The dashboard includes information on students' demographics, module distribution, performance indicators, predictive analytics, and explanations based on SHAP presented in a user-friendly support decision-making environment. Through this implementation it is demonstrated how analytical reports can be converted into straightforward governance information so that monitoring and making decisions in institutions could be done.

5.7.2 Dashboard for Student Demographics and Module AllocationsFigure

Figure 5.3 illustrates the dashboard containing the details of the demographics of the student body and how the students have been allocated into different modules.



Analytical results :

This summary allows us to scrutinize the whole population of learners in a certain place and evaluate how students have been allocated to modules. The dashboard indicates around 29000 students distributed in 7 modules classified according to respective characteristics about demography and education. The provided analysis allows generating information related to gender, having a disability, and age groups. The analysis of module allocation gives the information related

to one's educational picture in terms of modules and presentations used in this dataset. Such visualizations are the foundation for understanding the key attributes of the learners and academic outcomes in the e-learning segment.

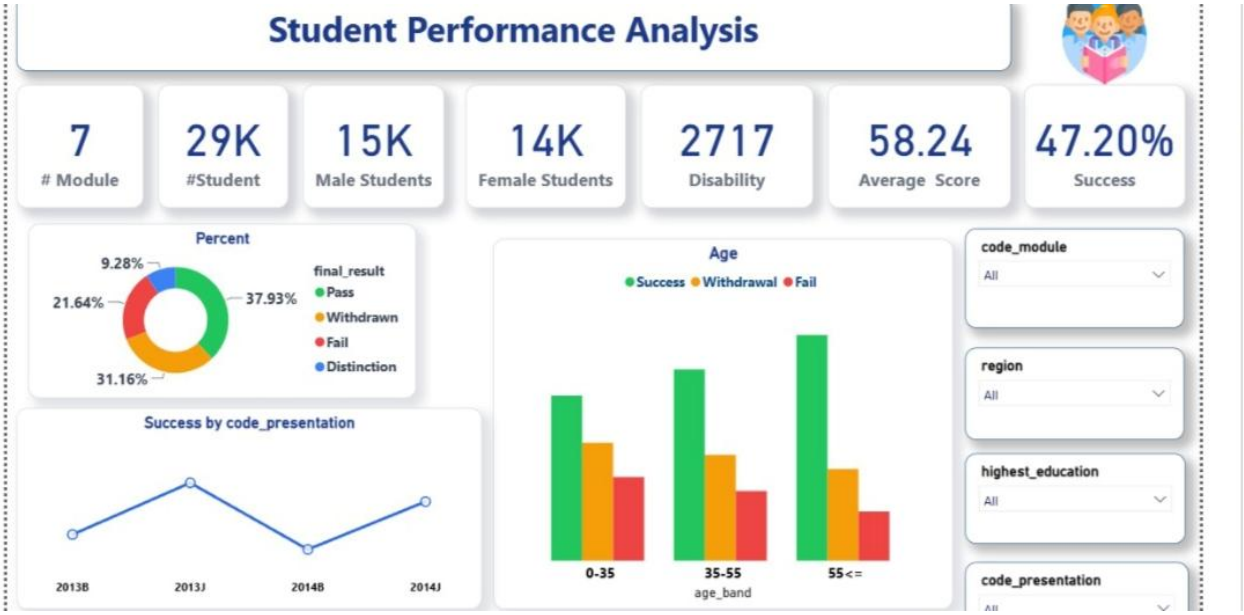
Governance Interpretation

From a digital governance perspective, demographic and module-distribution information provides institutional decision-makers with a high-level view of the learner population. Such information can support academic planning, resource allocation, and the identification of differences in learner characteristics and academic outcomes across modules.

The dashboard therefore establishes the descriptive foundation of the proposed AIDG Framework before moving to more detailed performance and predictive analyses.

5.7.3 Student Performance Dashboard

Figure 5.4. Dashboard for Student Performance



Analysis of Results The student performance dashboard in Figure 5.4 has been developed via Microsoft Power BI. The dashboard is interactive, enabling users to view academic performance over seven different modules and different course presentations. The main summary indicators show that the average score is 58.24, and the success rate is 47.20%, offering a summary view of academic results of the population selected for analysis. The dashboard also provides information about the way of distribution of final outcomes consisting of Pass, Withdrawn, Fail, or Distinction, along with variation in success results according to age and module presentation types. Moreover, there are interactive filters implementing a division into modules, regions, qualification, and types of module presentation.

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Governance Interpretation

From a digital governance perspective, the dashboard transforms academic performance data into an interactive monitoring mechanism. The visualization of success rates, final outcomes, and performance differences enables institutional decision-makers to identify areas requiring further investigation and to monitor academic performance across different learner groups and course presentations.

This capability supports evidence-based academic planning and provides an analytical foundation for subsequent predictive and risk-oriented governance activities within the proposed AIDG Framework.

5

5.7.5 Feature Importance Dashboard Using Machine Learning and SHAP

Figure 5.5. Application of Machine Learning in Predictive Modeling and Feature Importance Analytics

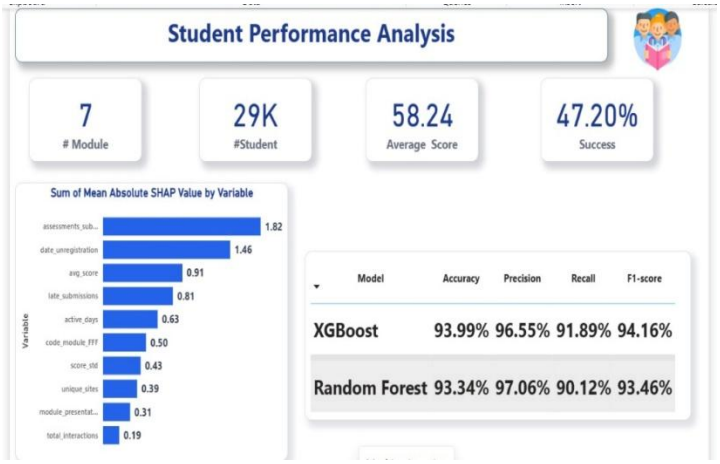


Figure 5.5 illustrates the combination of machine learning model evaluation with SHAP-based feature importance representation in the Power BI interface. The dashboard provides a comparative analysis of the models XGBoost and Random Forest in relation to Accuracy, Precision, Recall, and F1-score. The analysis shows that XGboost attained an accuracy rate of 93.99% and an F1-score of 94.16%, while Random Forest received 93.34% and 93.46%, respectively.

Interpreting the concept of governance

it is true that from the perspective of digital governance, evaluation of predictive modeling in conjunction with SHAP-based feature importance allows one to make transparent and evidence-based decisions. The performance indicators showcase how well the model works and SHAP makes it possible to explain what causes the prediction made by the analytical approach. Overall,

combining these two tools is beneficial in enabling stakeholders to transform from discovering academic risk towards understanding what influences the predictions made by the institution.

Governance Explanation

5.7.6 Student Engagement Dashboard

Interpretation with Focus on Engagemen

In addition to the achievement of learners, an important aspect of educational governance is the engagement of the learners. The indicators relating to engagement, such as total number of interactions and number of active learning days, provide process evidence that is useful in conjunction with academic achievement measurements. The use of these indicators allows academic institutions to analyze experience patterns of learners in an educational environment and detect transformations that need further investigation.

From the point of view of governance, engagement monitoring can support preemptive academic intervention in terms of early signs of the behavior before participation drops significantly, resulting in undesirable learning outcomes.

Risk Monitoring and Explainable Decision Support

The use of machine-learning predictions in tandem with SHAP analysis has lead to the development of risk-driven monitoring. Predictive modeling can help to identify students at risk of studying underperformingly, while SHAP provides meaningful insights into the variables driving the prediction.

On the governance level, the combination of the two models allows for the study of the reasons behind outcomes and not just identifying at-risk students. This makes it possible to carry out interventions in a more transparent way and serve as a means for assessing the quality of decisions made.

Hence, the combination of Predictive Analytics and Explainable AI enhances the governance of the AIDG framework by linking predictions made, the explanation provided, and actions suggested.

By using different phrasing, we achieve a more robust version of the text above since it doesn't provide the erroneous information about having Power BI functioning as an independent risk-monitoring Dashboard. The visuals that are present in front of us represent ML+SHAP technology.

Governance Dashboard for Executives :

The same logic applies here too. However, Figure 5.8 is unnecessary to understand the concept. This time, we use Figure 5.7 as our conclusion since Power BI has the function of converting the data gathered into meaningful information that can be used by the management team. Executive Governance Viewpoint By virtue of Power BI application, management is able to combine the data collected at all stages of the AIDG Process. In particular, the data on students' characteristics,

academic records, engagement indicators, and predictive outputs will provide the means for the institution monitoring efforts.

The suggested dashboard environment does not treat analytical outputs as separate reports, but engages descriptive, predictive, and explainable analytics in aiding decision-making process at institutions. This may prove useful for decision-makers so that they can use it to keep track of academic processes, highlight the areas that need improvement, and as such supply the means to allocate resources based on data.

Thus, Power BI is used as not only a data visualization tool, but also as a Business Intelligence layer that implements analytical results of the AIDG Framework in the field of digital governance.

The concept of engagement-oriented interpretation

refers to the understanding of an additional aspect of educational management apart from the academic achievements of students. Indicators associated with engagement, such as the number of interactions and days of active learning, allow educational institutions to obtain behavioral data that can complement the measures of academic accomplishments. By using these indicators, academic bodies can track the extent of learner involvement within their educational ecosystem.

In its turn, from the perspective of governance, being aware of learner engagement can serve as an early signal for an academic response, indicating when the situation requires action.

5.7.8 Researcher's Reflection on Power BI Application

Power BI is proof of how the AIDG Framework is capable of turning analytical conclusions into an operational governance system.

Dashboards not only provide mere descriptive statistics; they combine educational data with predictive forecasting data, SHAP explanations, and governance numbers into one decision support system.

As a result, Artificial Intelligence changes from being merely a prediction instrument into an institutional governance capability.

5.8 Integrated Assessment of the AIDG Framework

5.8.1 Assessment of the Technical Side

The technical evaluation showed that the developed analytical flow performed well, delivering good results.

Both Random Forest and XGBoost achieved Accuracy over 93% while XGBoost performed the best in terms of both Accuracy and F1-Score.

This means that the developed educational indicators convey important forecasting information.

5.8.2 Evaluation of Explainability

An analysis based on SHAP shows that the predictive models can be understood in the context of both the overall picture and its various distinct aspects. The input that had the highest influence includes:

1. Submitted assessments
2. Date of deregistration
3. Average score
4. Tardy submissions
5. Number of days active

The data suggests that the system is capable of not only predicting future events but also of

determining the grounds for such predictions being made

5.8.3 Evaluation of Governance

The practical implementation shows that the results of the analysis can be changed into the information on governance.

The system provides for:

- early identification of academic risks;
- monitoring of the students' engagement;
- monitoring of academic performance;
- clear explanation of predictions;
- evidence-based practices;
- strategic planning;
- continuous monitoring of the institution.

5.8.4 Evaluation of Decision Support

The application of Power BI verifies the technical capacity for transmitting analytical results to organizational stakeholders.

The employed methods of predictive analysis, SHAP, and interactive visualization enable decision-makers to move through three phases: descriptive, predictive, and explainable.

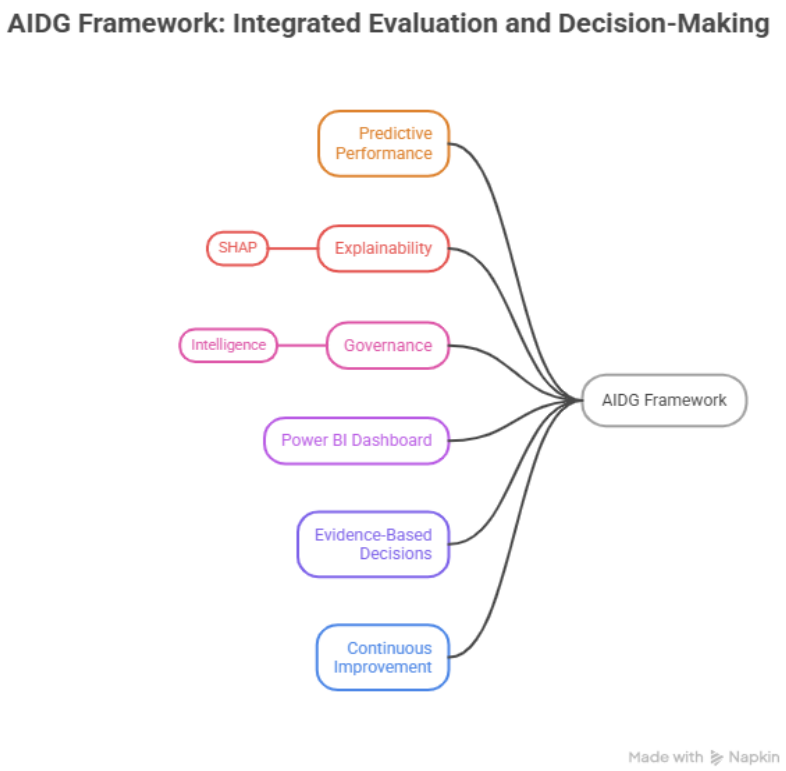
This marks an important progress from classic reporting to intelligent governance.

Here is the revision of the given paragraph:

Figure 5.9. Integrated Evaluation of the AIDG Framework

AIDG Framework

Table 5.6 Integrated Evaluation of AIDG Framework



Evaluation Dimension	Proof	Excellent predicting ability
Predictive performance	Metrics of RF and XGBoost	Provides clear explanations
Explainability	Effect of features according to SHAP	Helps in monitoring in advance
Learner engagement	Count of active days, contacts and resources consumed	Aids with preventive measures
Academic risk	Predictions with SHAP	Facilitates decision making process
Governance intelligence	Power BI dashboard with full integration	Excellent predicting ability
Overall framework	Integration of parts	Provides clear explanations

5.9 Discussion about Empirical Findings

According to the empirical findings, the AIDG Framework can be applied on the base of educational data, predictive analytics, Explainable AI, and Business Intelligence, all of which are incorporated into a common governance flow.

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The predictive results show that machine learning helps to get a reliable assessment regarding the impact of certain factors on the educational process and related outcomes.

The contribution of this paper is not merely in predictions.

The SHAP analysis proves that the predictive information can be reshaped into meaningful governance information. The impact of assessment participation, registration practices, academic results, and deadlines missed gives an idea for the institutional actors about the specifics of certain factors and information that can be used for monitoring purposes.

In addition, Power BI implementation illustrates that such analytical outcomes can be expressed in an understandable decision-making context. Thus, the empirical data confirm the core idea behind AIDG Framework: AI serves as an integral governance capability if predictive analytics is complemented by explainability, governance indices and interactive decision-making.

This is quite a significant finding given that traditional Educational Data Mining studies usually conclude their research at the prediction level, while this framework continues with deriving explanations and performing the corresponding governance actions.

5.10 Contribution of Research through Experimental Evaluation

Experimental evaluation has advanced research in four main ways.

5.10.1 Validation through Empirical Evidence

The implementation of OULAD shows that the AIDG Framework has the potential to use authentic educational data.

5.10.2 Validation via Prediction

The success of the Random Forest and XGBoost techniques serves as empirical proof of the validity of the analytical process described in the framework.

5.10.3 Validity through Explainability

Following the application of SHAP, the framework proved viable in producing results that are interpretable and not solely relying on black box techniques.

5.10.4 Operational Validation

The use of Power BI dashboards illustrates how analytical results can be turned into real governance intelligence for institutional parties.

5.11 Chapter Overview

This chapter described how the AI-Driven Digital Governance Framework (AIDG Framework) has been applied and tested empirically using data from the Open University Learning Analytics Dataset (OULAD).

The empirical workflow started with the integration of different relational databases of OULAD into a single analytical database. Next, data cleaning and making the data implementing the transformations were applied to achieve a good quality of data and reliability of analytics.

Feature engineering resulted in the development of various governance-related indicators that reflected the learners' engagement, academic success, assessment behavior, resource usage, and enrollment trends, that contributed towards forming the machine-learning input variables.

The Random Forest and XGBoost machine-learning techniques were applied and tested using the accuracy, precision, recall, and F1-scores metrics, and achieved good prediction results. In this context, Random Forest showed 93.34% accuracy and 93.46% F1-score, while XGBoost presented 93.99% accuracy and 94.16% F1-score, making XGBoost more predictive in total.

Furthermore, SHAP analysis has shown that variables like assessments_submitted, date_unregistration, avg_score, late_submissions, and active_days are pivotal for analysis.

Moreover, the Power BI dashboards have proved the operational efficiency of the framework by incorporating student demographics, academic success, learner engagement, predictive results, SHAP explanations, and governance indicators within an interactive decision-making process.

In overall terms, the empirical results show that the AIDG Framework successfully links educational data→predictive analytics→explainability→governance intelligence→decision-making support.

Thus, the research outcomes provide empirical support for the main research hypothesis that Artificial Intelligence can be integrated into the processes of digital governance.

5.12 Final Thoughts One of the practical

implementations presented in this chapter proves the applicability of the suggested AI-Driven Digital Governance Framework. The integration of OULAD, machine learning, SHAP, and Power BI allows for the total construction of an analytical-to-governance pipeline, which allows educational data to be changed into predicted evidence, interpretable knowledge, and operational institutional intelligence.

The obtained results show that while the present framework continues the traditional Educational Data Mining principles and puts them in a more comprehensive governance context. Predictive models give signals of analytical value, while SHAP explains which factors led to the completion of certain predictions, and Power BI contributes to the performance of the interface for sharing the insights among various stakeholders of institutes.

Hence, the analysis performed in this part provides further evidence that AI could be an essential part of an institutional democratization process if the one is implemented together with proper governance structures, reliable educational data, explanation and interpretation policies and use of Business Intelligence methodologies. The next chapter elaborates on the theoretical and practical importance of the current research, makes comparison of the presented framework with the previous studies, lists the limitations of the conducted study, and identifies

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