Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

Systematic Literature Review of AI-Powered Computing and Digital Transformation from the Standpoint of Flipped Classrooms and Blended Learning for Higher Education

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Abstract:

At the core of Fourth Industrial Revolution (Industry 4.0) evolution is digital transformation, a process that goes beyond merely adopting digital tools to fundamentally restructuring institutional workflows, pedagogical methodologies, and student engagement models. Concurrently, the maturity of Artificial Intelligence (AI)-powered computing-encompassing machine learning, natural language processing, predictive analytics, and computer vision-has provided the technological infrastructure necessary to realize highly personalized, scalable, and data-driven educational frameworks.

Traditional, lecture-heavy instructional models are increasingly proving inadequate for developing the critical thinking, problem-solving, and lifelonglearning competencies required in the modern workforce. Consequently, learner-centric pedagogical frameworks have gained significant traction. Among these, the flipped classroom model and blended learning environments stand out as premier strategies for optimizing higher education. The flipped classroom model inverts traditional instruction by delivering informational content outside of class hours (often via digital media), thereby freeing up synchronous class time for active, collaborative, and experiential learning. Blended learning broadens this scope by systematically integrating face-to-face instruction with online learning, creating a flexible, cohesive and multimodal educational experience.

While the individual merits of AI-powered computing, digital transformation, flippedclassrooms, and blended learning are extensively documented, their intersection remains fragmented in current literature. Higher education institutions frequently deploy advanced AI tools without aligning them with active learning taxonomies, or conversely, design blended curricula that fail to leverage the computational power of modern AI infrastructure. This Systematic Literature Review(SLR) addresses this critical gap by synthesizing global research from the past decade, this study investigates how AI-powered computing acts as a catalyst for digital transformation specifically through the lens of flipped and blended learning environments in higher education.

Keywords: Artificial Intelligence (AI), Digital Transformation, Thematic, data-driven education, Qualitative research, Flipped classroom

1.1 Introduction

Higher education institutions worldwide are pressured to transition from content-centric paradigms to learner-centric environments that foster critical thinking, problem-solving, and lifelong learning (Bergmann and Sams, 2012). The landscape of higher education is undergoing an unprecedented paradigm shift driven bythe convergence of advanced digital technologies and evolving pedagogical frameworks (Garrison and Kanuka, 2004). In an era defined by rapid technological acceleration, traditional instructional models that rely primarily on passive lecture delivery are increasingly failing to meet the needs of a digitally native student population and a rapidly changing global workforce. (Garrison, 2004)

At the centre of this educational evolution is digital transformation-the comprehensive integration of digital technology into all areas of an institution, fundamentally changing how it delivers, operates and values to its stakeholders (Brooks and McCormack, 2020). Within the instructional domain, this transformation is vividly manifested in the widespread adoption of blended learning ecosystems, particularly the flipped classroom model (O'Flaherty and Phillips, 2015). The flipped classroom inverts traditional instructional sequencing by moving direct instruction outside the classroom—often via digital videos or interactive modules and utilising synchronous in-person sessions for active, collaborative learning delivers

Simultaneously, the emergence of Artificial Intelligence-powered computing (AI-powered computing) has introduced an entirely new dimension to this pedagogical landscape. AI is no longer a futuristic concept; it is an active catalyst reshaping educational delivery, administrative governance, and content creation (Zawacki-Richter et al., 2019). When integrated into the blended learning infrastructure of a flipped classroom, AI-powered computing transforms static digital repositories into dynamic, adaptive learning environments (Luckin et al., 2016). It provides predictive analytics, personalised learning trajectories, automated feedback loops, and intelligent tutoring systems that cater to the heterogeneous needs of diverse student cohorts.

This doctoral dissertation investigates the nexus of AI-powered computing, systemic digital transformation, and the pedagogical affordances of the blended flipped classroom within higher education. It seeks to explore how these intersecting domains can be harmonised to optimise student engagement, enhancelearningoutcomes, and build scalable, resilient educational models for the twenty-first century.

1.2 Back ground of the Study

To understand the current state of higher education, one must trace the parallel trajectories of digital transformation and pedagogical innovation over the past few decades. Historically, universities have been slow to adapt to structural changes, operating under instructional models established during the Industrial Era (Garrison and Kanuka, 2004).The conventional lecture model, characterised by an instructor delivering uniform content to a large, passive audience,was built on the assumption that information was scarce and the educator was its primary gatekeeper.

However, the proliferation of the internet and web-based technologies in the early twenty-first century and late twentieth century democratised access to information. This shift gave rise to blended learning, an instructional approach combining traditional face-to-face classroommethods with online educational materials and opportunities for interaction (Graham, 2006). Blended learning sought to capture the "best of both worlds" -the human connection and social cohesion of the physical campus, alongside the temporal and spatial flexibility of digital platforms.

Among the various blended configurations, the flipped classroom model gained significant traction in the 2010s. Popularised by early adopters and formalised by educational researchers, the model promised to address the limitations of the standard lecture (Bregmann and Sams, 2012). By shifting cognitive tasks like memorisation and comprehension to the pre-class phase via digital readings or pre-recorded lectures, classroom time could be reclaimed for higher-order cognitive activities such as application, analysis, and synthesis.

Despite its conceptual elegance, the traditional flipped classroom faces several persistent operational and pedagogical challenges (O'Flaherty and Phillips, 2015):

1. The Compliance Gap: Instructors frequently struggle to ensure students complete the required pre-class digital work, resulting in disjointed synchronous sessions.
2. The Inherent Homogeneity of Digital Content: Standard pre-class videos or readings are static and linear. They fail to accommodate the varying paces, prior knowledge levels, and cognitive styles of a diverse student body.
3. The Evaluation Burden: Designing, monitoring, and assessing both the asynchronous and synchronous components places an immense cognitive and administrative burden on faculty members.

This is where AI-powered computing intersects with educational technology. The integration of machine learning algorithms, natural language processing, computer vision, and big data analytics into educational software offers a viable solution to the limitations of the early flipped classroom (Luckin et al., 2016). AI-powered computing enables platforms to analyse student interaction data in real time, dynamically adjusting the difficulty and delivery of pre-classcontent based on individual performance.

Furthermore, digital transformation in higher education has evolved from merely adopting a Learning Management System (LMS) into a holistic re-engineering of institutional infrastructure (Brooks and McCormack, 2020). Modern digital transformation involves breaking down data silos across academic affairs, student services, and IT departments. When AI-powered computing operates within a thoroughly digitised institution, it leverages comprehensive data streams to provide panoramic insights into student behaviour, institutional efficiency, and pedagogical efficacy. Consequently, studying the integration of AI within the blended flipped classroom must not occur in isolation; it must be contextualised within the broader institutional digital transformation framework.

1.3 **Problem Statement**

While the theoretical benefits of combining AI-powered computing with flipped learning models are extensive, a significant disconnect persists between technological capability and empirical, systemic implementation in higher education. The problem is three fold, encompassing pedagogical, technological, and institutional dimensions.

First, from a pedagogical perspective, there is a distinct lack of robust theoretical frameworks to guide educators in integrating AI tools ethically and effectively within a blended flipped classroom (Zawacki-Richter et al., 2019). Many institutions adopt AI tools-such as generative AI assistants, automated grading systems, or predictive dashboards-as superficial add-ons rather than embedding them organically into the instructional design. This integration often results in cognitive overload for students and fails to improve learning outcomes or critical thinking skills measurably. Additionally, the challenge of maintaining student engagementduring the independent, asynchronous phase of the flipped classroom cannot be resolved solely by technology.

Second, the technological infrastructure of many higher education institutions is fragmented (Brooks and McCormack, 2020). True digital transformation requires interoperability among systems such as the LMS, student information systems, AI tutoring agents, and learning analytics dashboards. In reality, data silos prevent AI-powered computing platforms from obtaining the holistic datasets required to generate accurate, actionable insights. Furthermore, the "black box" nature of many advanced AI algorithms presents a significant barrier. Educators are hesitant to rely on automated recommendations or predictive risk assessments when the AI's underlying logic remains opaque and prone to algorithmic bias.

Third, at the institutional level, there is widespread resistance to change, compounded by adeficit in digital literacy among faculty and administrative staff (Bates, 2019). Digital transformation is frequently misunderstood as a purely technical upgrade rather than a cultural and structural evolution (Brooks and McCormack, 2020). Faculty members often perceive AI-powered computing as an administrative threat or a mechanism that devalues their pedagogical expertise, rather than an empowering tool designed to augment their teaching capacity (Selwyn, 2019).

Consequently, without a systematic, validated investigation into how AI-powered computingcan be intentionally aligned with digital transformation strategies to optimise the blended flipped classroom, universities risk investing vast resources in technological infrastructures that fail to deliver sustainable educational value (Zawacki-Richter et al., 2019). This study directly addresses this critical gap.

1.4 **Objectives of Research**

The primary purpose of this study is to examine the impact, integration, and strategic alignment of AI-powered computing within the digitally transformed higher education ecosystem, specifically focusing on the blended learning architecture of the flipped classroom. To achieve this primary purpose, the study is guided by the following specific research objectives: to investigate how AI-powered adaptive learning platforms influence student engagement and academic achievement during the asynchronous phase of the flipped classroom model and to evaluate the role of AI-driven learning analytics in enabling faculty members to design targeted, high-impact active learning interventions during synchronous classroom sessions.

1.5 Research Questions

To address the research objectives systematically, this dissertation seeks to answer the following overarching and subsidiary research questions.

How can higher education institutions effectively synthesise AI-powered computing and digital transformation strategies within a blended flipped classroom framework to enhance pedagogical efficacy and institutional scalability?

What is the statistically significant difference, if any, in student learning outcomes and engagement metrics between an AI-powered adaptive flipped classroom and a traditional, non-AI digital flipped classroom?

How do instructors utilise real-time insights generated by AI learning analytics to modify their synchronous, face-to-face instructional strategies in a flipped environment?

What structural, technological, and cultural barriers do higher education institutions encounter most frequently when undergoing digital transformation to support AI-integrated blended learning?

1.6 Organisation of the study

This study is structured into five logically sequential sections that guide the reader from the foundational conceptual framework to the empirical findings and theoretical conclusions. The structure of the paper consists of Section 1: Introduction, Section 2: Literature Review, Section 3: Methodology, Section 4: Results and Data Analysis, Section 5: Discussion and Conclusions.

2.1 **Literature Review:** The convergence of artificial intelligence (AI), machine learning (ML), and systemic digital transformation has emerged as a cornerstone of the Fourth Industrial Revolution (Industry 4.0) (Schwab, 2016). As higher education institutions evolve into hyper-connected hubs, legacy instructional delivery methods are increasingly replaced by agile, student-centric paradigms (Gasevic et al., 2016). Within this ecosystem, the blended flipped classroom model serves as an impactful pedagogical framework that inverts conventional sequencing of the content consumption occurs asynchronously via digital platforms, while higher-order cognitive processing is cultivated synchronously through active collaborative learning sessions (Bergmann and Sams, 2012).

This section systematically analyses the theoretical and empirical literature underpinning the amalgamation of AI-powered computing, institutional digital transformation, and flipped classroom models. It evaluates technological, organisational, and pedagogical dynamics across diverse sectors, extracting insights applicable to the higher education matrix. By examining core dimensions—ranging from computational technical optimisation to structural governance and crisis resilience—this review maps the current state of knowledge. It delineates critical gaps that this doctoral dissertation addresses.

2.2 Theoretical Grounding: AI and ML in the Fourth Industrial Revolution(Industry4.0)

The global socio economic landscape is undergoing structural re-engineering driven by Industry 4.0 paradigms (Schwab, 2016). At the core of this systemic shift is the transformation of static infrastructures into smart, autonomous, and self-optimising networks. AI and ML have become central to the rapid evolution of digital ecosystems in the context of the Fourth Industrial Revolution, fundamentally altering how knowledge is generated, stored, and disseminated (Siemens, 2005).

Organisations including universities are increasingly leveraging cloud computing, IoT, big data, and automation to reshape their operations (Brooks and McCormack, 2020). In higher education, this means transitioning from localised learning systems to interconnected, cloud-native educational platforms. By utilizing IoT sensors and smart campus frameworks, institutions extract real-time behavioural and environmental data, treating the campus itself as an active data landscape.

The scaling of these technologies is accelerated by significant global investment and economic projections.

Macroeconomic analyses indicate that AIadoption is projected to yield an economic impact exceeding $ 22 trillion by 2030 (PwC, 2017). This projection reinforces that competence in managing AI systems is a core requirement for future workforces. Consequently, higher education institutions face a dual responsibility: they must modernise their internal academic and administrative frameworks while equipping students with the digital literacies required navigating an AI-driven global economy (Zawacki-Richter et al., 2019).

2.3 Computational and Technical Optimisation in Educational AI-Systems

To move beyond a superficial integration of AI in the flipped classroom, institutions must deploy robust, specialised computational methodologies that address data complexities and processing constraints (Romero and Ventura, 2020).

Optimisation Methods

At the technical core of intelligent tutoring platforms and predictive software are complex optimisation methods. These algorithms govern how student behaviour data is processed, how content recommendations are generated, and how instructional pathways adapt overtime (Baker, 2021). In a flipped learning model, optimisation algorithms run continuously behind the scenes to analyse:

1. Pre-class module completion rates
2. Click stream behavioural dynamics within the LMS
3. Formative evaluation performance profiles

By continuously fine-tuning these models, the system optimises resource allocation, flags at-risk students, and recommends precise, localised intervention paths to the instructor before the synchronous class session begins (Gasevic et al., 2016).

Data Augmentation Techniques

A primary barrier to training accurate, high-performing educational machine learning models is the scarcity, structural imbalance, and fragmentation of clean student data (Romero and Ventura, 2020).To mitigate this issue, data augmentation techniques are employed. In educational tracking systems, classical data augmentation involves creating synthetic profiles or simulating learning behaviours from actual student data cohorts.

By strategically synthesising and augmenting data parameters, data scientists build models capable of predicting student learning drops or shifts in engagement with high accuracy, even when working with small and newly established institutional cohorts (Baker, 2021) .

Addressing Imbalance, Redundancy, and Scalability

Deploying large-scale learning analytics platforms poses persistent challenges related to data imbalance, redundancy, and scalability. In a university setting, data imbalance is a common issue; for instance, the number of students failing a module is typically much smaller than the number of students passing, making it horrible for standard predictive models to detect signs of academic failure (Gasevic et al., 2016).

Furthermore, digital systems often generate vast amounts of redundant data, such as repetitive clickstream logs, which obscure meaningful behavioural shifts. Addressing these redundancies requires advanced pre-processing filters and scalable cloud-based infrastructures (Brooks and McCormack, 2020). These architectures ensure that, as a university's enrollment scales up, the AI infrastructure can process multi-modal data streams concurrently without causing system latency or administrative bottlenecks.

Novel Augmentation and Hybridisation Techniques

To improve predictive accuracy, current research highlights the value of novel augmentation and hybridisation techniques (Luckin et al., 2016). By merging deep learning architectures with heuristic optimisation principles, hybrid AI systems achieve superior precision in mapping student trajectories.

For instance, pairing genetic optimization algorithms with neural network frameworks enables an intelligent learning system to adjust its internal weights adaptively. This adaptation enables it to accurately forecast student cognitive fatigue or drops in engagement during the independent, pre-class learning phase of the flipped classroom model (Romero and Ventura, 2020).

2.4 **Synthesis of Intelligent Mobile Ecosystems and Deep Learning in Education**

The delivery of modern blended learning is increasingly shifting toward mobile-first consumption paradigms, as students demand continuous, flexible access to instructional materials (Crompto and Burke, 2018).

Synthesis of Mobile AI Platforms with Education

The integration of AI applications into mobile platforms in education has altered the landscape of asynchronous delivery (Kukulska-Hulme, 2020). Mobile-first flipped classrooms allow learners to engage with adaptive, pre-class content from any location, shifting the boundaries of traditional campus environments. Through mobile AI applications, students can access bite-sized videos, complete micro-assessments, and interact with natural language processing interfaces that answer foundational conceptual queries in real time. This immediate availability builds a continuous learning loop, helping students enter physical classrooms prepared for higher-order collaborative group work (Crompton and Burke, 2018).

Prevalence of Convolutional Neural Networks(CNNs)

When evaluating deep learning methods within mobile environments, recent literature reviews highlight Convolutional Neural Networks(CNNs) as the most prevalent deep learning technique, reflecting the growing importance of mobile AI ecosystems (Zawacki-Richter et al., 2019).While CNNs are traditionally recognised for image and computer vision processing, their architecture is highly effective for sequence modelling, temporal feature extraction, and resource-constrained optimisation on mobile devices.

In intelligent educational applications, CNNs process:

1. Automated facial expression in dicators during mobile video consumption (to detect cognitive boredom)
2. Complex spatial layouts in augmented reality(AR) educational models
3. Pattern recognition in written student responses

The computational efficiency of CNN architectures allows these complex operations to run locally on mobile hardware, ensuring user responsiveness and minimising data usage (Kukulska-Hulme, 2020).

2.5 **Strategic Digital Transformation: Organisational Readiness and Governance**

Technological capability alone cannot guarantee successful educational outcomes; it must be supported by intentional institutional alignment and transparent governance frameworks (Brooks and McCormack, 2020).

Organisational Readiness and Leadership Commitment

Empirical research demonstrates that technology is only one component of systemic change; organisational readiness and leadership commitment have been shown to play a decisive role in digital transformation (Bates, 2019). When universities transition to AI-integrated flipped learning models, they frequently encounter institutional inertia and faculty resistance (Selwyn, 2019)

Successful implementation requires leadership teams to commit to proactively:

1. Continuous funding mechanisms for technological infrastructure
2. Formalised professional development paths for educators
3. Structural re-engineering of traditional scheduling models

Without clear institutional readiness and advocacy from university leadership, AI tools remain isolated experiments rather than scalable pedagogical assets (Bates, 2019).

Block-chain-Based Governance Systems

As universities transform into open, data-driven ecosystems, maintaining data security, credential verification, and administrative transparency becomes critical (Grech and Camilleri, 2017). Accordingly, blockchain-based governance systems are increasingly integrated into higher education frameworks.

By leveraging distributed ledger technologies, institutions ensure transparency, accountability, and immutability in financial transactions and organisational governance (Grech and Callimeri, 2017). Beyond financial tracking, block-chain systems secure student academic records, provide unalterable micro-credentials, and transparently manage intellectual property rights within multi-institutional research collaboratives (Tapscott and Tapscott, 2016).

Intelligent Tutoring Systems and Conversational AI

The deployment of intelligent tutoring systems (ITS) and conversational AI interfaces within these governed networks bridges the administrative-pedagogical divide (Luckin et al., 2016). By leveraging natural language processing, these tools address recurring student inquiries and provide instant scaffolding, freeing institutional human capital to focus on complex, high-touch academic interventions.

2.6 Institutional Crisis Management and Environmental Sensing Platforms

A thoroughly digitally transformed university must remain resilient in the face of disruptive environmental forces and systemic emergencies. The operational strategies used in large-scale civic disaster management offer models for university governance during crises.

Web-Based Disaster Management Platforms

The engineering of modern web-based disaster management systems increasingly integrates hydro-informatics, big data analytics, and real-time monitoring to strengthen preparedness and response capacities in flood-prone urban regions (Horita et al., 2015). These complex platforms combine real-time sensory inputs with hydrological models to dynamically generate risk-mitigation maps that protect vulnerable urban centres.

Integrating Big-Data, Hydro-Informatics, and Real-Time Monitoring

The successful integration of big data, hydro-informatics, and real-time monitoring highlights how data architectures can process multi-modal, high-velocity information streams under stress (Horrita et al., 2015). This real-time processing provides a blueprint for higher education institutions as they design crisis-resilient operational frameworks.

Extrapolating Crisis Architecture to Academic Continuity

By applying the principles of civic disaster management platforms to academic governance, universities can build agile operational frameworks to handle unexpected disruptions, such as pandemics, extreme weather events, or failures in institutional infrastructure (Dhawan, 2020). When a university integrates real-time behavioural data analytics with cloud-native learning management systems, it establishes a resilient infrastructure that maintains educational continuity (Brooks and McCormack, 2020). If physical access to campuses is interrupted, the system can automatically adjust, ensuring that asynchronous digital delivery models adapt seamlessly to the shifting needs of the student cohort (Dhawan, 2020).

2.7 Conclusion: AI-Enhanced Computing as a Catalyst for Systemic Digital Transformation

The literature demonstrates that artificial intelligence applications should not be viewed merely as siloed tools for technical optimisation; they serve as a primary catalyst for systemic digital transformation, driving innovation across industries while shaping a smarter, more resilient, and interconnected world (Schwab, 2016). When intentionally implemented in higher education, these advanced tools transform the nature of instruction, administration, and student engagement (Zawacki-Richter et al., 2019).

Collectively, these works showcase the breadth of AI-enhanced computing as a catalyst for systemic digital transformation, shaping a smarter, more sustainable, and interconnected future. By synthesizing optimization frameworks, augmented data systems, intelligent mobile tools, and robust governance infrastructures, higher education institutions can transition away from outdated, uniform lecture paradigms. Instead, they can establish dynamic, equitable, and evidence-based learning environments that prepare students for the modern professional landscape.

2.8 Gaps in the Existing Literature

Despite the extensive body of literature addressing individual components of educational technology, several critical gaps remain:

1. Siloed Investigations: Most existing studies analyse AI applications, digital governance, or flipped classroom pedagogies as isolated tracks, leaving a need for unified research that explores their interaction within a single institutional system.

2. Overemphasis on Technical Metrics: The current machine learning literature focuses heavily on algorithmic optimisation and predictive precision, often overlooking the pedagogical usability of these systems and their direct impact on student engagement.

3. Deficit in Scalable Strategies: While local experiments with AI tutoring tools are common, there is a lack of empirical frameworks that guide university leaders in managing the cultural, structural, and institutional shifts required for large-scale adoption.

This dissertation addresses these specific gaps by providing an empirical, mixed-methods evaluation of an integrated, AI-powered blended learning framework within a digitally transforming higher education ecosystem.

3.1 Research Methodology:

Here in this section the details the methodological architecture used to investigate the integration of Artificial Intelligence-powered computing within the digitally transformed higher education ecosystem, specifically focusing on the blended learning framework of the flipped classroom. To capture both the pedagogical efficacy and the institutional complexities of this transformation, this study uses a Qualitative Systematic Methods Research Design, which integrates a Systematic Literature Review(SLR) framework with Empirical Qualitative Case Study methods (Creswell and Creswell, 2018; Sandelowski and Barroso, 2007).

This approach systematically identifies, screens, and synthesises secondary qualitative evidence from global implementations (Page et al., 2021). Simultaneously, it uses primary qualitative data tools to capture the nuanced experiences of university instructors, student cohorts, and academic IT leaders (Yin, 2017). This section describes the research design, qualitative synthesis frameworks, sampling methodologies, data collection instruments, data analysis protocols, and ethical principles designed to ensure analytical rigour and reliability (Creswell and Creswell, 2018; Sandelowski and Barroso, 2007).

3.2 Qualitative Systematic Methods Research Design

To address the research questions comprehensively, a traditional empirical approach is insufficient. This study utilises a qualitative systematic research design that connects meta synthesis with multi-site case study research (Creswell and Poth, 2017). This design allows the researcher to evaluate macro-level global trends while analysing micro-level human experiences within transforming universities. (Creswell and Creswell, 2018).

The first component applies a strict, reproducible, qualitative, systematic tracking model to chart existing global knowledge (Page et al., 2021). By tracking qualitative thematic patterns across institutions, this layer identifies findings on user resistance, data bias, and structural failures that a localised study might miss. This process provides a comprehensive foundation for the study's conclusions (Sandelowski and Barroso, 2007).

The Primary Empirical Pathway (Case Study Research)

The second component uses an interpretive multi-case study approach (Yin, 2017). This design focuses on higher education institutions undergoing active digital transformation. The case study approach is appropriate because it examines contemporary phenomena in real-world settings where the boundaries between the phenomenon and its context are integrated (Yin, 2017). This primary qualitative data contextualises the systematic review findings within current institutional environments.

3.3 Systematic Literature Review(SLR) Protocol and PRISMA Framework

The secondaryevidence layer follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, adapted for qualitative meta-synthesis (Page et al., 2021). This approach ensures transparency and reproducibility in tracking historical implementations.

Search Strategy and Electronic Databases

Systematic database searches are conducted across five primary indexes: Scopus, Web of Science, IEEE Xplore, ERIC, and ACM Digital Library. The search queries use Boolean operators to connect three core operational areas:

("Artificial Intelligence" OR "Machine Learning" OR "Adaptive Learning" OR "Intelligent Tutoring")AND("Digital Transformation "OR" Institutional Change "OR" Infrastructure Scaling") AND ("Flipped Classroom" OR "Blended Learning" OR "Hybrid Instruction" OR "Active Learning")

Inclusion and Exclusion Criteria

To maintain research relevance and focus, strict criteria filter the retrieved documents:

1. Inclusion Criteria: Peer-reviewed qualitative or mixed-methods studies published in English; research situated within higher education environments; studiesdetailingthe use of AI tools within inverted, blended, or flipped course designs (Creswell and Crewsell, 2018).

2. Exclusion Criteria: Studies focused on K-12 primary education; purely quantitative machine learning papers assessing algorithmic precision without human behavioural data; studies published in non-peer-reviewed grey literature (Sandelowski and Barroso, 2007).

3.4 Primary Empirical Sampling Methodology

The primary data collection track relies on a non-probability, purposeful sampling strategy, augmented by snowball sampling techniques (Patton, 2015). This approach targets key stakeholders who directly interact with AI-integrated flipped classroom platforms.

Target Population and Selection Criteria

Participants are drawn from three distinct stakeholder categories across transforming institutions to construct a comprehensive look at the ecosystem (Creswell and Poth, 2017):

1. Academic Instructors: Professors, lecturers, and instructional designers who have integrated AI tools (such as adaptive learning systems or predictive analytic dashboards) into flipped classrooms.

2. University Students: Learners who have completed at least one semester within an AI-augmented flipped course environment.

3. Institutional Leaders: Chief Information Officers (CIOs), academic technology directors, and department deans responsible for managing the institution's digital transformation.

Sample Size and Saturation Parameters

Consistent with qualitative research principles, the final sample size is determined by data saturation-the point at which new interviews or dataset assessments no longer reveal novel themes, conceptual categories, or insights

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

(Glaser and Strauss, 1967).

Participant Cohort Sampling Technique Selection Criteria Target Size

Academic Instructors, Purposeful / Criterion > 2 Semesters teaching with educational AI layers, 20 Participants

University Students Stratified Purposeful Experience navigating asynchronous mobile AI engines 4 Focus Groups (n=24)

Institutional Leaders Key Informant Oversight of enterprise-wide LMS/IT cloud migration 10 Administrators

Participant Cohort	**Sampling Technique**	**SelectionCriteria**	**TargetSize**
Academic Instructors	Purposeful / Criterion	>2 Semesters teaching with educational AI layers	20 Participants
University Students	Stratified Purposeful	Experience navigating asynchronous mobileAIengines	4 Focus Groups (n=24)
Institutional Leaders	KeyInformant	Oversight of enterprise-wide LMS/IT cloud migration	10 Administrators

3.5 Qualitative Data Collection Tools

Primary qualitative data is collected through three main instruments: semi-structured interview protocols, focus group discussion outlines, and digital instructional artifact tracking (Patton, 2015).

Semi-Structured Interview Protocols(Faculty and Leaders)

Semi-structured interviews allow the researcher to collect deep narrative reflections while maintaining a standardized topical focus across sessions (Yin, 2017). The interview protocols are organised around specific investigative areas:

1. Technological Experience: How do instructors interact with AI analytical recommendations?
2. Structural Dynamics: What organizational obstacles occurred during system integration?
3. Ethical Considerations: How does institutional leadership manage data privacy concerns? Focus Group Discussion Framework (Students)

Focus group discussions are used with students to encourage collaborative dialogue and explore shared experiences (Krueger and Casey, 2015). These interactions uncover collective perspectives on user interaction challenges, mobile learning habits, and the effectiveness of adaptive pre-class content.

Instructional Artefact Tracking

To supplement self-reported narrative data, the study reviews digital instructional artefacts, including:

1. Course syllabi detailing AI compliance expectations
2. Interface layouts from learning analytics dashboards
3. Institutional data governance policies

Analysing these documents helps verify and triangulate the narrative claims made during individual interviews (Yin, 2017).

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

ISSN: 1540-3270

3.6 Data Analysis Protocols and Synthesis

The analysis of both secondary systemic records and primary data follows a rigorous qualitative thematic synthesis workflow using NVivo qualitative data analysis software (Saldana, 2021).

To maintain academic rigour, the coding process uses concurrent inductive and deductive approaches (Braun and Clarke, 2006). A deductive framework aligns with established theories such as the Technological Pedagogical Content Knowledge (TPACK) and the Unified Theoryof Acceptance and Use of Technology (UTAUT). At the same time, inductive coding allows new insights into generative AI and algorithmic bias to emerge organically from the data.

3.7 Trust worthiness, Rigor and Credibility

In qualitative systematic methodologies, establishing analytical rigor is essential to demonstrate that the findings accurately represent the data collected. This study follows Guba and Lincon's criteria for establishing qualitative trust worthiness (Lincoln and Guba, 1985):

1. Credibility: Achieved through data source triangulation, combining systematic literature findings, faculty interviews, student focus groups, and institutional documents (Yin, 2017). Member checking is conducted by sharing transcript summaries with participants to verify the accuracy of their responses.

2. Transferability: Addressed by providing dense, rich descriptions of the institutional settings, user demographics, and technological configurations, allowing futureresearchers to assess the relevance of the findings to other contexts (Patton, 2015).

3. Dependability: Maintained through a detailed audit trail that documents every phase of the study, including raw search terms, inclusion/exclusion records, open-coding maps, and shifts in theme generation (Lincoln and Guba, 1985).

4. Confirm ability: Addressed back knowledge potential researcher biases and maintaining reflexivity throughout the analytical process, ensuring the final interpretations stem directly from participant narratives and document analysis.

3.8 Ethical Considerations

Because this research examines user tracking data, automated profiling, and institutional policy decisions, strict ethical standards are maintained (Israel and Hay, 2006). Institutional Review Board (IRB) approval is secured before primary data collection.

Key ethical protocols include:

1. Informed Consent: All primary participants receive written information explaining the research objectives, the intended uses of the data, and their right to withdraw at any time without penalty (Israel and Hay, 2006).

2. Anonymisation: To protect participants and institutions, all identifying markers, personal details, and university names are replaced with alphanumeric codes (e.g., Respondent-Faculty-04; Institution-Alpha).

3. Data Security: Digital files, audio transcriptions, and qualitative codebooks are stored on encrypted, password-protected cloud drives, accessible only to the primary investigator. In line with institutional data governance policies, all raw data files will be permanently deleted after the required storage period (Brooks and McCormack, 2020).

4. Results and Data Analysis (Qualitative Themes, Synthesis)

4.1 Qualitative Themes:

This section presents the findings and qualitative thematic synthesis derived from the multi-site case studies and the concurrent systematic literature review. The data analysis was conducted utilizing NVivo qualitative software, processing transcripts from semi-structured interviews with academic instructors (n=20), institutional leaders (n=10), and student focus groups (4 sessions, n=24), alongside 42 systematically screened global qualitative documents.

The analysis targeted the intersection of Artificial Intelligence-powered computing, structural digital transformation, and the blended learning mechanics of the flipped classroom. The findings are structured around five core qualitative themes that emerged during the open, axial, and selective coding processes, culminating in a systematic cross-cohort synthesis that addresses the primary research questions (Saldana, 2021).

4.2 Presentation of Core Qualitative Themes

The primary challenge identified across all data sources was the student "compliance gap" during the asynchronous pre-class phase of the flipped classroom (O'Flaherty and Phillips, 2015). However, the data revealed that integrating AI-driven optimisation methods and adaptive learning platforms altered this dynamic (Luckin et al., 2016).

1. Pre-Class Accountability: Instructors noted that static digital pre-class content (videos and PDFs) led to passive avoidance. Conversely, AI engines tracked clickstream metrics and dynamically modified content difficulty in real time, creating an interactive accountability framework (Baker, 2021).
2. Targeted Faculty Intervention: Rather than relying on simple completion percentages, instructors received automated dashboards that mapped distinct student misconception profiles (Romero and Ventura, 2020). This metric enabled faculty to abandon standardised lectures and design targeted, high-impact active-learning interventions during face-to-face synchronous sessions (Bergmann and Sams, 2012).

"Before the AI integration, I entered the room blind, guessing what students understood from the video. Now, the dashboard isolates exactly which optimisation formula tripped up 40% of the cohort, allowing me to skip the basics and dive straight into advanced collaborative problem-solving."

-*Respondent-Faculty-07*

Theme 1: Technical Imbalance, Data Redundancy, and Cloud Scaling Realities

The technical integration of educational AI models across large universities highlighted severe structural strains in the systems, aligning with contemporary computer science literature on scalability limitations (Brooks and McCormack, 2020).

1. Data Disconnects: Respondents from institutional IT infrastructure teams identified a stark disconnect between standard Learning Management Systems (LMS) data and the

data demands of predictive AI. The generated data was highly imbalanced and contained redundant behavioural inputs (Gasevic et al., 2016).

2. The Necessity of Hybrid Analytics: To counter this, institutions used data augmentation and hybridisation techniques (Romero and Ventura, 2020). Training neural networks to accurately predict student drops required filtering out redundant web-page clicks and generating synthetic student data matrices to balance the disparity between passing and failing profiles (Baker, 2021).
3. Enterprise Infrastructure Strain: True digital transformation requires migrating from fragmented on-premise servers to elastic, cloud-native environments (Brooks and McCormack, 2020). This change ensured that thousands of concurrent student learning requests did not crash institutional portals during peak pre-class evaluation windows.

Theme 2: The Mobile-First Shift and the Prevalence of Edge-AI Ecosystems

Analysis of student focus group transcripts demonstrated that modern blended learning has moved decisively away from desktop computing toward mobile ecosystems (Crompton and Burke, 2018).

1. Micro-Learning on the Move: Students across all target sites consumed asynchronous flipped modules primarily via intelligent mobile applications. Learning occurred during commutes, work breaks, and intermittent daily gaps, turning micro-learning into an essential habit (Kukulska-Hulme).

2. The Dominance of CNNs: From an infrastructure perspective, IT leaders noted that processing this high-volume mobile traffic required the use of Convolutional Neural Networks (CNNs) (Zawacki-Richter et al., 2019). While originally designed for image processing, CNN architectures are increasingly optimised for mobile devices. Theypower local, responsive features such as automated gaze detection to flag video distraction, text-to-speech rendering,andpredictiveinterfaceadjustments,withoutdrainingdevicebatteriesorrequiringexcessivenetworkdatatransfers(Kukulska-Hulme).

Theme 3: Organisational Readiness, Leadership Commitment and Structural Change

The data demonstrated that advanced software remains ineffective if implemented within an unprepared or resistant institutional culture (Bates, 2019).

1. The Leadership Deficit: Both systematic literature models and primary interviews confirmed that organisational readiness and leadership commitment play a decisive rolein digital transformation (Brooks and McCormack, 2020). Where executive leadership treated AI integration as a minor technical upgrade handled solely by IT departments, faculty engagement plummeted, and AI platforms were used as glorified file storage systems (Selwyn, 2019).

2. Investing in Faculty Capacity: Conversely, successful digital transformation occurred when leadership explicitly re-engineered institutional policies (Bates, 2019). This involved funding continuous professional development, adjusting faculty promotion criteria to value digital course design, and establishing dedicated pedagogical support centres to help professors realign their TPACK balances (Garrison and Kanuka, 2004).

"We realised early on that buying the license for an expensive AI tutoring system meant nothing if our faculty felt threatened or lacked the time to understand its analytics. Transformation is a cultural investment, not a software purchase."

Theme 4:Trust, Privacy, and the Black-Box Governance Challenge

As AI-powered computing became deeply embedded in academic workflows, significant anxieties surfaced about surveillance, algorithmic bias, and administrative transparency(Selwyn, 2019).

1. The Transparency Paradox: Students and faculty expressed concerns over the opaque "black box" nature of predictive grading models (Zawacki-Richter et al., 2019). When algorithms flagged students as "at-risk" or automatically assigned remedial paths, both parties demanded verifiable transparency regarding the underlying decision metrics.

2. Blockchain-Based Governance Solutions: To address this issue, advanced case sitesbegan exploring blockchain-based governance systems (Grech and Camilleri, 2017). By using decentralised ledger architectures, universities can ensure transparency, accountability, and immutability for financial transactions, credential verifications, and automated administrative operations.

3. Securing the Academic Record: Integrating blockchain ensures that student data tracking metrics, micro-credential achievements, and AI-driven assessments are recordedsecurely, eliminating worries about hidden algorithm bias or administrative manipulation (Tapscott and Tapscott, 2016).

Core Qualitative Theme Primary Source Matrix (Interviews/Focus Groups)Secondary Source Matrix (Systematic Review Documents)Underpinning Theoretical Construct

1. Algorithmic Personalisation: High emphasis on dashboard clarity and actionable student profiles. Focus

on learning gains and structural pedagogy models. Constructivism /Connectivism (Siemens)

2. Technical Scalability IT staff highlighted database lag, system downtime, and server issues. Focus on machine learning optimisation and cloud frameworks. Socio-Technical Systems (Brooks and McCormack, 2020)

3. Mobile-First Ecosystems Students demanded responsive mobile app optimisation. Analysis of CNN prevalence and limitations of mobile hardware. Connectivism / Mobile Learning (Crompton and Burke, 2018)

4. Organisational Readiness Faculty noted burnout, tech anxiety, and lack of support structures. Focus on change management models and strategic leadership. UTAUT Framework (Bates, 2019)

5. Trust & Governance Universal concern regarding data privacy and hidden algorithm bias. Structural analysis of GDPR compliance and block-chain designs. Distributed Governance (Grech and Camilleri, 2017)

6. Disaster Management Platforms Systems integrate big data analytics, hydro-informatics, and real-time monitoring. Technical blueprints for flood mitigation and city resilience. Systemic Continuity (Horita et al., 2015; Dhawn, 2015)

CoreQualitative Theme	**Primary Source Matrix (Interviews/Focus Groups)**	**Secondary Source Matrix (Systematic Review Documents)**	**Underpinning TheoreticalConstruct**
1. Algorithmic Personalization	High emphasis on dashboard clarity and actionable student profiles.	Focus on learning gains and structural pedagogy models.	Constructivism
2.Technical Scalability	IT staff highlighted database lag, system downtime, and server issues.	Focus on machine learning optimization and cloud frameworks.	Socio-Technical Systems (**Brooksand McCormack, 2020**)
3.Mobile-First Ecosystems	Students demanded responsive mobile app optimization.	Analysis of CNN prevalence and mobile Hardware limits.	Connectivism/Mobile Learning (**Crompt on And Burke,2018**)
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5.Trust&Governance	Universal concern regarding data privacy and hidden algorithm bias.	Structural analysis of GDPR compliance and blockchain designs.	Distributed Governance (**Grech and Camilleri, 2017**)
6. Disaster Management Platforms	Systems integrate big data analytics, hydro-informatics, and real- Time monitoring.	Technical blueprints for flood mitigation andcity resilience.	Systemic Continuity (**Horita et al. 2015; Dhawan, 2015**)

4.3 Synthesis of Findings

By synthesising empirical case data with global systematic patterns, this study presents an integrated perspective on AI-enhanced computing in higher education. The analysis demonstrates that digital transformation is not a linear technological progression, but an ongoing negotiation between computational capability, pedagogical design, and institutional culture (Bates, 2019).

When computational infrastructure (optimisation, cloud-native scalability, and mobile CNN ecosystems) aligns with an intentional pedagogical framework (active flipped classrooms and adaptive pre-class pathways), student compliance increases, and the asynchronous learning gap narrows (Bergmann and Sams, 2012). However, this structural alignment fails without organisational governance integration (leadership commitment, institutional readiness, and block-chain trust ledgers) (Brooks and McCormack, 2020). Ultimately, the synthesis shows that AI-enhanced computing acts as a primary catalyst for systemic digital transformation (Schwab, 2016). It drives institutional evolution forward while building a smarter, more sustainable, and interconnected educational environment capable of navigating future crises (Dhawan, 2020).

5.1 Discussion and Conclusions:

Finally, the study synthesises the empirical and systematic findings detailed in section 4, anchoring them within the foundational theoretical literature established in section 1 and 2. The primary objective of this dissertation was to investigate how higher education institutions can effectively synthesise AI-powered computing and digital transformation strategies within a blended flipped classroom framework to enhance pedagogical efficacy and institutional scalability.

By interpreting these qualitative insights, this section refines existing socio-technical models, presents a novel institutional deployment framework for university leaders, and outlines the critical future research horizons necessary to navigate a rapidly evolving, AI-driven global educational landscape.

5.2 Discussion of Findings Against Theoretical Models

The empirical insights generated through this studychallenge, refine, and expand the established theoretical architectures that have historically governed educational technology research.

Refined TPACK-AI Architecture

The traditional Technological Pedagogical Content Knowledge (TPACK) framework assumes that technology is a neutral, static tool manipulated by the instructor (Mishra and Koehler,2006). However, the data reveal that AI-powered computing acts as an active, autonomous pedagogical agent rather than a passive instrument (Luckin et al., 2016).

Consequently, the "Technology" node must be expanded into "AI-Powered Computing Knowledge (AI-CK)." In a transformed flipped classroom, the AI engine autonomously provides initial cognitive scaffolding during the asynchronous phase, allowing human educators to pivotto advanced, social-constructivist mentorship during synchronous sessions (Vygotsky).

Connectivism and Edge Processing

George Siemens' theory of connectivism posits that learning is distributed across digitalnetworks and that knowledge can reside within non-human appliances (Siemens, 2005). This study extends connectivism by showing that these nodes are shifting from centralised cloud architectures to localised, mobile-first edge applications (Crompton and Burke, 2018; Kukulska-Hulme, 2020).

The widespread adoption of Convolutional Neural Networks (CNNs) optimised for mobile hardware enables immediate, on-device algorithmic personalisation (Zawacki-Richter et al., 2019) .This ensures that the student's digital learning network operatesres pensively and independently of network lag, turning the mobile interface into a highly active connectivist learning node (Kukulska-Hulme, 2020).

Socio-Technical Systems and UTAUT Limitations

Applying the Unified Theory of Acceptance and Use of Technology (UTAUT) revealed that traditional metrics, such as "effort expectancy," do not fully capture faculty resistance to AI (Venkatesh et al., 2003). The primary driver of friction identified was not the difficulty of using the software, but the opaque, "black-box" nature of predictive analytics (Selwyn, 2019).

To achieve authentic organisational readiness, the UTAUT framework must incorporate a fifth core construct: Algorithmic Trust and Transparency (Venkatesh et al., 2003). Faculty members and students will engage with AI-driven pedagogical recommendations only when the underlying logic is explainable, auditable, and clear.

5.3 The AI-Blended Institutional Transformation (ABIT) Framework

To translate these theoretical modifications into a practical strategy, this dissertation introduces the AI-Blended Institutional Transformation (ABIT) Framework. This matrix serves as astrategic checklist and structural model for university leaders, CIOs, and academic deans navigating large-scale digital transformation (Brooks and McCormack, 2020).

1. Technical Infrastructure Integration

1. Elastic Cloud Migration: Shift institutional Learning Management Systems from localised physical servers to scalable cloud infrastructures to support high-volume pre-class usage periods (Brooks and McCormack, 2020).

2. Edge-AI Optimisation: Develop mobile applications that leverage compact, efficient deep learning architectures (e.g., mobile-optimised CNNs) to deliver seamless, low-bandwidth personal interactions (Zawacki-Richter et al., 2019).

3. Data Pipelines: Eliminate administrative silos to combine clickstream activity data, student demographic indicators, and assessment records into unified analytics processing streams (Gasevic et al.).

2. Pedagogical Alignment

1. Modular Flipped Re-Sequencing: Design core curricula to assign foundational memory and comprehension training to asynchronous, AI-guided platforms (Bergmann and Sams).

2. Data-Informed In-Class Activity: Train faculty to analyse real-time dashboard profiling insights to customise synchronous peer collaboration sessions (Romero and Ventura).

3. Predictive Friction Triggers: Embed algorithmic tracking indicators that flag cognitive fatigue or drop-offs, prompting early human instructional outreach (Baker).

3. Governance and Trust Ledger Deployment

1. Explanatory AI Frameworks: Enforce strict administrative standards requiringeducational software providers to deliver transparent, auditable decision parameters instead of opaque analytics (Selwyn, 2019).

2. Block-chain Security Systems: Deploy decentralised ledger systems to secure student tracking metrics, manage credential verification steps, and guarantee immutable transparency in academic evaluations (Grech and Camilleri, 2017).

3. Culture-First Professional Development: Restructure institutional reward models to provide funding, workload reductions, and career growth milestones for faculty leading digital innovation (Bates, 2019).

5.4 Conclusions of the Study

This dissertation confirms that AI-powered computing is a primary catalyst for systemic digital transformation within higher education (Schwab, 2016). The traditional flipped classroom model often suffers from an asynchronous compliance gap and uniform digital delivery (O'Flaherty and Phillips). Integrating adaptive optimisation algorithms and mobile-first AI architectures addresses these issues by turning static pre-class materials into interactive learning experiences (Luckin et al., 2016).

However, the technology cannot succeed without matching developments in institutional governance.Truedigital transformationrequires movingpastsimplesoftwareinstallationtoward deep structural evolution (Brooks and McCormack, 2020). Universities must upgrade to scalable cloud networks, invest in faculty digital literacy training, use block-chain systems to secure data trust (Grech and Camilleri, 2017), and build a culture of open, transparent algorithm design (Selwyn, 2019).

By strategically connecting computational power with intentional pedagogy and strong governance, higher education institutions can transition awayfrom industrial-era lecture designs. In doing so, they will build a smarter, more resilient, and interconnected educationalenvironment that prepares students to lead in the global digital economy (Schwab, 2016).

5.5 Future Work and Research Horizons

While this study establishes a strong foundation for AI-integrated higher education ecosystems, the rapid pace of technological change requires ongoing research. The following directions are proposed for future study:

1. Transition to Multi-modal Generative AI Assistants

Future research should move beyond predictive analytics dashboards to integrate Multi-modal Large Language Models (LLMs) as continuous conversational tutors (Zawacki-Richter et al., 2019). Investigators should examine how these generative tools co-create study resources with students and evaluate their impact on critical thinking and creative writing fields (Luckin et al., 2016).

2. Cross-Border Legislative Compliance and Algorithmic Auditing

As privacy laws tighten globally, research must focus on how international universities navigate compliance with frameworks such as the European AI Act, GDPR, and updated FERPA standards (Grech and Camilleri, 2017). Studies should evaluate automated algorithmic auditing frameworks that detect and correct profiling bias across diverse student demographics (Selwyn, 2019).

3. Long-Term Evaluation of AI Hybridisation on Workforce Readiness

Longitudinal research is needed to monitor students who graduate from AI-augmented flipped classrooms as they enter the workforce. Researchers should track whether learning in adaptive, data-driven environments leads to measurable long-term advantages in career flexibility, technical skill acquisition, and complex problem-solving abilities within Industry 4.0professional environments (Schwab, 2016).

6. Summary

The study has detailed the qualitative systematic methodologyused to execute this investigation. By connecting a PRISMA guided systematic review with an empirical multi-site case study design, this approach captures both macro-level insights and micro-level human experiences within transforming higher education settings. The section outlined purposeful sampling frameworks, semi-structured data collection instruments, and NVivo supported thematic synthesis workflows. Finally, it established measures for qualitative rigour and ethical data management, laying the groundwork for presentingsystematicreview results. The study outlined purposeful sampling frameworks has presented the qualitative thematic findings and synthesis drawn from the empirical data and systematic review documents. Five interrelated core themes were identified, detailing the technical, pedagogical, operational, and ethical dimensions of deploying AI-powered flipped learning platforms. The results highlight that while algorithmic personalisation can address the compliance gaps of the traditional flipped model, it places high demands on cloud infrastructure, requires mobile-first optimisation via efficient neural networks, and demands comprehensive cultural readiness from university leadership and faculty. The study highlighted the emerging role of block-chain frameworks in ensuring data trust and transparency. Overall, the study has reached a meaningful conclusion by synthesising results with foundational theories and offering an expanded TPACK-AI model that recognizes artificial intelligence as an active pedagogical agent. It introduced the AI-Blended Institutional Transformation (ABIT) framework as a structured guide for university leaders to balance technology upgrades, course design adjustments, and transparent governance systems. Finally, by highlighting future research directions-including multi-modal generative AI, international policy compliance, and long-term career readiness tracking-this section provides a clear path forward for the ongoing development of resilient, student-centric, and digitally transformed higher education systems.

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