https://doi.org/10.52326/jss.utm.2024.7(4).06
UDC 378:004.896:656

CHALLENGES AND SOLUTIONS FOR INTEGRATING ARTIFICIAL INTELLIGENCE INTO TRANSPORTATION ENGINEERING EDUCATION

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Received: 10. 21. 2024
Accepted: 11. 28. 2024

Abstract. This study introduces the "student equation" assumption to represent the individualized learning pathways of each student, highlighting their unique needs, challenges, and potentials. Standardized educational approaches, resembling to an "arithmetic mean solution", often fail to address the diverse cognitive abilities and developmental needs of students due to their one-size-fits-all nature. The basic hypothesis posits that standardized methods primarily serve the average student, neglecting individual learner diversity. The research aims to explore the complexities of student learning by acknowledging variations in reasoning processes, errors, and cognitive dilemmas influenced by known and unknown variables in their educational journey. The findings suggest that educators must evolve beyond traditional methods to guide students through personalized learning experiences, akin to explorers navigating unknown territories. This educational paradigm seeks to cultivate a more adaptable and inquisitive student body, prepared for discovery. By aligning teaching methods with individualized student needs, this approach aims to enhance learning outcomes and bridge the gap between standardized education and the unique learning equations of each student.

Keywords: *student equation, unique learning needs, dynamic knowledge co-creation, individualesed learning, large uncertainty educational situations.*

Rezumat. Această cercetare introduce asumpția "ecuației studentului" pentru a reprezenta căile de învățare individualizate ale fiecărui student, evidențiind nevoile, provocările și potențialele lor unice. Abordările educaționale standardizate, asemănătoare unei "soluții medii aritmetice", adesea nu reușesc să abordeze diversitatea abilităților cognitive și nevoilor de dezvoltare ale studenților datorită naturii lor de tipul "mărime unică pentru toți". Ipoteza de bază propusă susține că metodele standardizate servesc în primul rând educatului mediu, neglijând diversitatea individuală a studenților. Cercetarea își propune să exploreze complexitățile învățării studenților prin recunoașterea variațiilor în procesele de raționament, erori și dileme cognitive influențate de variabile cunoscute și necunoscute în călătoria lor educațională. Concluziile sugerează că educatori trebuie să evolueze dincolo de metodele

tradiționale pentru a ghida studenții prin experiențe de învățare individuale, asemănătoare exploratorilor care navighează în teritorii necunoscute. Această paradigma educațională își propune să cultive un corp de studenți mai adaptați și curioși, pregătiți pentru descoperire. Prin alinierea metodelor de predare cu nevoile individualizate ale studenților, această abordare are obiectivul să îmbunătățească rezultatele învățării și să reducă decalajul dintre educația standardizată și ecuațiile de învățare unice ale fiecărui student.

Cuvinte-cheie: *ecuația studentului, nevoile unice de învățare, crearea dinamică a cunoștințelor, învățarea individualizată, situații educaționale cu incertitudine mare.*

The first principle is that you must not fool yourself – and you are the easiest person to fool. So you have to be very careful about that. After you've not fooled yourself, it's easy not to fool other scientists. You just have to be honest in a conventional way after that [1].

1. Introduction

As 2024 commemorates the 300th anniversary of the birth of Immanuel Kant, widely regarded as one of history's foremost philosophers and a pivotal figure in pedagogy, his enduring words hold profound relevance: "Have courage to use your own understanding" [2]. This ethos of intellectual bravery and inquiry is equally pertinent to the realms of teaching and research. Embodying this Kantian spirit, we are committed to conducting our research with the same dedication to intellectual rigor and exploration.

The current research builds upon prior studies [3-6] and incorporates the following basic assumptions (BA):

BA.1. *Every student represents a unique learning equation (challenge)*. The curriculum and teaching methods are arithmetic mean solutions that do not fully address the unique learning needs of each student.

BA.2. *Dynamic Knowledge Co-Creation*. Knowledge transmission from teacher (mean solution) to student (learning equation) is not a simple transfer of information. Factors such as individual learning styles, prior knowledge and cognitive processing abilities, personal passions and ethical considerations (encompassed by logos, pathos, and ethos) all play a significant role in how students significantly influence comprehension.

BA.3. *Keeping Positive Learning Environment*. Optimal learning requires a positive state of mind for both teachers and students (learning equation). Traditional assessments, often rooted in standardized teaching and testing, can create anxiety, hindering this positive state and potentially impacting student performance.

BH.0. Basic hypothesis (BH) of the current research

BH.0.0. The level of uncertainty within an educational situation will have a significant impact on the effectiveness of knowledge transfer as a co-creation process, with **stable and known educational situations** leading to **stronger co-creation** and **positive learning environments** compared to **educational situations with large uncertainty**.

Breakdown of the Basic Hypothesis (BH):

BH.0.1. *Stable and Known Educational Situations*. These are scenarios where the educational process and its outcomes are predictable, based on established data. Statistical tests like comparing means and medians to assess a model's prediction across educational settings, while regression analysis with beta coefficients and R-squared helps them evaluate the stability of influencing factors. Stable educational situations have more consistent predictions (lower variability), stronger relationships (significant beta coefficients), and better model fit (higher $\boldsymbol{R^2}$).

BH.0.2. *Educational Situations with Large Uncertainty*. These scenarios are characterized by high variability, unpredictability, or new, untested conditions affecting the educational process. Educational situations with large uncertainty show higher variability, weaker relationships (non-significant coefficients), and poorer model fit (lower $\boldsymbol{R^2}$).

BH.0.3. *Independent Variable*. Level of uncertainty within an educational situation (Stable and Known vs. Large Uncertainty)

BH.0.4. *Dependent Variable*. Effectiveness of knowledge transfer as a co-creation process and positive learning environment (stronger co-creation and positive learning environment vs. weaker co-creation and less positive environment)

BH.0.5. *Predicted Relationship*. A positive correlation exists between the level of certainty and the effectiveness of co-creation. In other words, as the uncertainty increases, the effectiveness of co-creation decreases.

The basic hypothesis describes how stable situations have consistent predictions, strong relationships between factors, and better model fit. These characteristics would be conducive to co-creation, where students and educators collaborate effectively to construct knowledge. Conversely, situations with large uncertainty are characterized by high variability, weak relationships, and poorer model fit, suggesting a less stable foundation for co-creation.

This basic hypothesis can be tested by comparing the co-creation process and learning environment in stable and uncertain educational situations. Measurements could involve student engagement, learning outcomes, and qualitative analysis of classroom interactions.

An alternative hypothesis (AH) will be introduced alongside the initial assumptions and hypotheses to ensure a fair evaluation.

The **alternative hypothesis (AH)** with three underlying alternative assumptions (AA) is the following:

AA.1. *Standardized Knowledge and Skills*. Technical fields rely on a well-defined body of knowledge and core skill sets. The current system efficiently transmits this established information through lectures, labs, and assignments, ensuring graduates possess the necessary foundation for professional practice.

AA.2. *Industry Alignment*. The curriculum and teaching methods are directly aligned with the specific needs of the technical industry. The current system fosters close collaboration with industry partners, guaranteeing graduates possess the most relevant and up-to-date skills demanded by the workforce.

AA.3. *Efficiency and Scalability*. The existing system prioritizes efficient knowledge co-creation and skill development for a large student population. Standardized lectures, labs, and assessments ensure consistency and allow for effective instruction for a wide range of students, maximizing learning outcomes within resource constraints.

AH.0. **Alternative Hypothesis.** The current system of teaching at technical universities represents a highly effective method for knowledge transfer and skill development for students entering technical professions.

Breakdown of the Alternative Hypothesis (AH):

A.H.0.1. *Alternative Statement 1.* Technical fields rely on a well-defined body of knowledge and core skill sets.

A.H.0.2. *Alternative Statement 2.* The current system is directly aligned with the specific needs of the technical industry.

A.H.0.3. *Alternative Statement 3.* The existing system prioritizes efficient knowledge transfer and skill development for a large student population.

A.H.0.4. *Independent Variable.* The current teaching system at technical universities, including lectures, labs, and standardized assessments.

A.H.0.5. *Dependent Variable.* Student knowledge acquisition, skill development, and preparedness for technical professions.

A.H.0.6. *Predicted Relationship.* The alternative hypothesis predicts a positive relationship between the current teaching system and student outcomes. In other words, the research expects students who experience the current system will demonstrate strong knowledge, relevant skills, and preparedness for technical careers.

The alternative hypothesis describes how the established teaching methods in technical universities offer an efficient and effective approach to knowledge transfer and skill development, ensuring graduates are equipped for success in the technical workforce.

The alternative hypothesis can be tested by comparing student outcomes (knowledge, skills, and preparedness) between groups exposed to the current teaching system and potentially alternative teaching methods. Additionally, research could analyze the alignment between curriculum content and industry needs, and investigate student perceptions of the effectiveness of the current system.

2. Materials and Methods

Current higher education systems, comprised of institutions, faculty, students, curriculum, instruction, assessment, research, student services, and accreditation, aim to cultivate knowledge and prepare individuals for professions through allocated resources and planned outcomes. The alternative hypothesis represents the status quo and demonstrates its validity as an existing phenomenon (i.e., the existing system functions). Considering the observed reality of existing institutions, it can be argued that the current system might be optimal for the present. Therefore, within the scope of this research, focusing on proving the alternative hypothesis is not necessary. The alternative hypothesis is supported by the fact that it exists within the current higher education system. The efforts in this research will be focused on analyzing and demonstrating the validity or invalidity of the basic hypothesis.

A.1. Knowledge Co-Creation in Stable and Known Educational Situations

This section explores the implications of the basic hypothesis within the framework of stable and known educational contexts, with a specific focus on knowledge co-creation in these environments. Knowledge co-creation in stable educational contexts is often modeled as a direct process where a teacher, representing a mean solution, imparts information to students. This traditional approach, while effective in predictable environments, fails to account for the unique learning equations that characterize individual students. This study proposes a novel framework that re-conceptualizes the teaching-learning process, integrating scientific concepts and mathematical formulas to illustrate the dynamic interaction between teachers and students. Specifically, it addresses the limitations of the mean solution model and explores how knowledge co-creation can bridge the gap between current students understanding and desired learning outcomes outlined in the curriculum.

A.1.1. Mathematical Framework of Knowledge Co-Creation in Stable and Known Educational Situations

This investigation commences by defining terminology and variables to establish an equation that embodies the concept of a "student equation" and the "teacher as mean solution": S_i represents the learning needs and characteristics of the i-th student (student equation) and C represents the curriculum and teaching methods (mean solution). The challenge is to express how well the curriculum and teaching methods C address the unique needs S_i of each student.

A.1.2. Student Equation

Each student i has unique learning needs and characteristics, which can be represented as:

$$S_i = f_i x, \tag{1}$$

where: S_i - student i unique characteristics / equation;
f_i is a function representing the learning needs of student i;
x is the input (e.g., teaching methods, curriculum content).

A.1.3. Teacher as Mean Solution

The curriculum and teaching methods C can be seen as an arithmetic mean solution that tries to address the needs of all students:

$$C = \frac{1}{N} \sum_{i=1}^{N} S_i, \tag{2}$$

where: C is the curriculum and teaching methods;
N is the number of students in the studying group;
S_i - the student equations.

A.1.4. Formula for Educational Situations

One potential approach to quantify the effectiveness of a curriculum and teaching methods in catering to the individual needs of students within both stable and uncertain environments involves the application of the following formula:

$$E_i = |S_i - C| \tag{3}$$

where: E_i - represents the effectiveness of the curriculum and teaching methods for student i. The smaller the value of E_i, the better the curriculum C addresses the needs of student i.

A.1.5. Stable and Known Educational Situations

In this scenario, the student equations S_i and the curriculum C are well-defined and relatively constant. The formula $E_i = |S_i - C|$ can be used directly to measure the effectiveness. In stable and known educational situations (BH.0.1), statistical tests like comparing means and medians can assess a model's prediction across educational settings, while regression analysis with beta coefficients and R-squared helps evaluate the stability of influencing factors. Stable educational situations have more consistent predictions (lower variability), stronger relationships (significant beta coefficients), and better model fit (higher R^2).

These formulas help in understanding and evaluating how well the curriculum and teaching methods address the unique learning needs of each student in different educational contexts. It highlights the importance of personalized learning and active engagement, offering a robust approach to understanding and improving the dynamic interaction between teachers and students in stable and known educational situations.

A.2. Unknown with Large Uncertainty Educational Situations

In contrast to stable and known educational contexts, knowledge co-creation within environments characterized by high uncertainty presents unique challenges. The dynamic and unpredictable nature of these situations necessitates a departure from traditional, teacher-centered models. Instead, a learner-centric approach that fosters adaptability, critical thinking, and problem-solving becomes important. The concept of a "mean solution" becomes even less applicable in uncertain environments due to the rapidly changing variables and the absence of established benchmarks. Consequently, the traditional model of knowledge transfer, where information flows primarily from teacher to student, is insufficient. To effectively navigate these complex scenarios, a more collaborative and emergent approach to knowledge co-creation is required. This section posits that in unknown with large uncertainty educational situations, knowledge is co-constructed through a dynamic interplay between learners, educators, and the environment itself. This co-creation process involves the collective exploration of problems, trust, high risk assumed, stronger moral obligations, the generation of innovative solutions, and the continuous adaptation of knowledge based on new information and insights. By shifting the focus from knowledge transmission to knowledge co-construction, educators can empower learners to become active participants in their own learning journeys. Furthermore, the role of technology becomes increasingly critical in supporting knowledge co-creation within uncertain environments. By leveraging technology, educators can create learning experiences that are flexible, responsive, and tailored to the unique needs of individual learners. Knowledge co-creation in unknown with large uncertainty educational situations demands a fundamental shift in pedagogical approaches. By embracing a learner-centric, collaborative, and technology-enhanced model that fosters high resilience and individual responsibility, educators can equip learners with the skills and competencies necessary to thrive in complex and unpredictable environments.

A.2.1. Mathematical Framework of Knowledge Co-Creation in Unknown with Large Uncertainty Educational Situations

In this scenario, the student equations S_i and the curriculum C may vary widely and be less predictable. The incorporation of a factor, denoted by U, is proposed to quantify the level of uncertainty:

$$E_i = |S_i - C| - U, \tag{4}$$

where: U is a measure of uncertainty.

Uncertainty U increases the value of E_i reflecting the additional challenges posed by uncertainty. Educational situations with large uncertainty (BH.0.2) are characterized by high variability, unpredictability, or new, untested conditions affecting the educational process. These situations show higher variability, weaker relationships (non-significant coefficients), and poorer model fit (lower R^2).

This scenario emphasizes the significance of individualized learning and proactive participation, requiring a comprehensive methodology to comprehend and enhance the evolving interplay between educators and learners within Unknown with Large Uncertainty Educational Situations.

A.2.2. Traditional Model: The Limitations of Actual Standardized Education

Educational environments are populated by students with unique learning styles, needs, and challenges. These individualities can be represented by a personal "learning equation," which traditional, one-size-fits-all curricula and teaching methods, designed as arithmetic mean solutions struggle to address. This section explores the limitations of standardized approaches and proposes a mathematical framework to model the dynamic interaction between students and teachers.

A.2.3. The Student Equation: A Measure of Learning State

The development of a mathematical framework is proposed to model the knowledge co-creation process within well-defined and stable educational environments. This framework will integrate the constructs of the "Student Equation," the instructor's role, and the inherent limitations of standardized educational approaches.

A.2.4. Student's Learning State S_t

$$S_t = \sigma(K_t, I_t), \tag{5}$$

where: σ - learning state function of the student at moment t;
K_t - student's current knowledge at time t;
I_t - student's ignorance at time t, defined as $I_t = K_{max} - K_t$;
K_{max} - maximum possible knowledge in the subject.

The function σ captures the relationship between what the student knows and what they do not know, integrating these two aspects into a single metric of learning state. It could be a simple additive or multiplicative function, or something more complex depending on the specific educational context and the desired accuracy of the model.

A.2.5. Co-Created Knowledge K_{cc}

$$K_{cc} = f(T_d, I_s, E_a) * \alpha \tag{6}$$

where:K_{cc} - co-created knowledge;
T_d - quality of instruction;
I_s - student's prior understanding;
E_a - combined effort of both teacher and student;
α - imperfect conversion rate of information to knowledge.

The function f takes the values of T_d, I_s, E_a as inputs and calculates a corresponding value for K_{cc}, the co-created knowledge.

A.2.6. The Student Equation in Stable and Known Situations (BH.0.1)

In stable educational situations (BH.0.1), the student's learning state is primarily influenced by the co-created knowledge K_{cc} (6). These are scenarios where the educational process and its outcomes are predictable, based on established data.

A.2.7. Expanded Student Equation

To incorporate the co-created knowledge K_{cc} into the Student Equation, we update K_t based on K_{cc}:

$$K_{(t+\delta t)} = K_t + K_{cc} \tag{7}$$

$$I_{(t+\delta t)} = K_{max} - K_{(t+\delta t)} \quad (8)$$

A.2.8. Simplified Student Equation

Building upon the definition of the student's learning state, $S_t = \sigma(K_t, I_t)$, it is further expressed as:

$$S_{(t+\delta t)} = \sigma\big(K_t + K_{cc}, I_{(t+\delta t)}\big) \quad (9)$$

$$I_{(t+\delta t)} = K_{max} - (K_t + K_{cc}) \quad (10)$$

A.2.9. Comprehensive Model

Combining the above, the comprehensive model for a student's learning state in stable and known educational situations becomes:

$$S_{(t+\delta t)} = \sigma(K_t + (T_d, I_s, E_a) * \alpha, K_{max} - (K_t + (T_d, I_s, E_a) * \alpha)) \quad (11)$$

This formula captures how the student's learning state evolves over time, influenced by the quality of instruction, prior understanding, combined effort, and the imperfect conversion rate of information to knowledge.

A.2.10. Beyond the Arithmetic Mean

Traditional education models often use an arithmetic mean to design curricula and teaching methods, which fails to address individual learning needs. By personalizing the factors T_d, I_s and E_a, and by considering the conversion factor α, educators can better tailor their instruction to support each student's unique learning process.

A.2.11. Application in Stable Situations (BH.0.1)

In stable situations, such as teaching foundational principles of logistics or traffic flow theory AI can ensure consistent delivery of information, enhancing T_d, personalized learning paths based on initial knowledge I_s can be created. Engagement E_a can be increased through adaptive and interactive learning tools. Finally, the conversion rate α can be improved by identifying and addressing individual student challenges.

B.1. Stable and Known Educational Situations (BH.0.1)

The following section will analyze the paradox of the impossibility of directly transmitting knowledge, which challenges the dissemination of knowledge within stable educational contexts (BH.0.1). In stable environments, traditional teaching methods focus on imparting well-established knowledge about transportation systems, such as principles of logistics, traffic flow theory, and vehicle dynamics. Artificial Intelligence (AI) can support this by providing consistent information and automating routine educational tasks, ensuring that foundational knowledge is accurately co-created. However, it is not sufficient to check at every step if the information is received and comprehended, as information does not equate to knowledge.

In stable environments, such as teaching the principles of logistics or traffic flow theory, traditional methods remain valuable. Here, AI can play a supportive role by delivering consistent information and automating routine tasks. This ensures a solid foundation of knowledge is co-created K_{cc} – a function influenced by the quality of instruction T_d, the student's prior understanding I_s, the combined effort of both parties E_a, and a crucial factor: α. This coefficient, α, represents the imperfect conversion rate of information to knowledge.

Simply receiving information doesn't guarantee comprehension. Factors like student receptivity, processing ability, objectives, and application all influence how effectively information becomes knowledge.

This passage elaborates on above formula (6), which represents co-created knowledge within stable educational environments. Even with good teaching (high T_d), limitations in α and other factors can hinder knowledge co-creation. However, in stable situations, this formula suggests that individual learning with AI support can be a valuable approach. AI can ensure consistent information delivery (reducing variability in T_d, and personalize learning paths based on a student's initial knowledge I_s. This fosters higher engagement E_a and potentially improves the information-to-knowledge conversion rate α.

B.2. Educational Situations with Large Uncertainty (BH.0.2)

In educational situations with large uncertainty (BH.0.2), where learning requirements are dynamic and the information landscape is constantly evolving, the traditional approach becomes even more inadequate. The variability in student knowledge and the unpredictability of educational challenges necessitate a more flexible and responsive educational model.

In these scenarios, the Student Equation and the proposed framework must account for rapidly changing K_t and I_t. Adaptive learning technologies and real-time feedback mechanisms become essential to address the evolving needs of students.

B.2.1. Dynamic Knowledge Co-Creation

In both stable and uncertain educational environments, dynamic knowledge co-creation is critical. The proposed model emphasizes the need for personalized and adaptive teaching methods to accommodate individual learning equations. In stable situations, this involves leveraging AI to ensure consistent delivery and personalization based on prior knowledge. In uncertain situations, it requires real-time adaptation to changing educational landscapes, utilizing technologies that can respond to new information and student needs dynamically.

B.2.2. Keeping a Positive Learning Environment

Maintaining a positive learning environment is crucial regardless of the stability of the educational situation. In stable environments, this can be achieved by providing a structured and supportive atmosphere where students feel secure in their learning journey. In uncertain environments, it involves fostering resilience and adaptability, encouraging students to embrace change and uncertainty as part of the learning process. The personalized approach ensures that each student's unique challenges are addressed, promoting engagement and motivation, which are essential for a positive learning experience.

C.1. The rapid integration of AI in education necessitates a robust focus on fairness, accountability, transparency, and ethics

The increasing use of AI in higher education necessitates a closer look at the ethical implications. The acronym FATE (Fairness, Accountability, Transparency, and Ethics) serves as a framework for examining the responsible development and use of AI in education. A recent systematic review [7] examined 33 publications to understand how FATE is addressed in the context of AI and higher education. The review identified the following: more descriptive definitions exist for fairness, while technical definitions are more prevalent for accountability and transparency. Quantitative studies dominate fairness research, while qualitative studies are more common for ethics. Overall, there are more definitions of FATE than relevant studies conducted. This review highlights the need for further research on FATE and AI in education. Future work should bridge the gap between theory and practice by linking technical and descriptive definitions and fostering collaboration between quantitative and qualitative research methodologies. By acknowledging the limitations of traditional methods and harnessing the potential of AI while adhering to ethical principles (FATE), educators can create a more effective and equitable learning environment in both stable and Unknown with Large Uncertainty Educational Situations.

C.1.1. The challenge remains: Unknown with Large Uncertainty Educational Situations demand new approaches

This exploration of stable situations serves as a springboard for further discussion. The true test lies in **uncertain educational environments**, where knowledge itself is constantly evolving. This section explores how we can adapt educational approaches to address this challenge and the concept of knowledge transmission within education, particularly in the face of the "paradox of impossibility of direct knowledge transmission." Traditional methods often assume a static body of knowledge, which becomes problematic in situations marked by uncertainty and rapid change.

A prime example is the field of transportation, where emerging technologies and unpredictable logistics challenges constantly redefine the landscape [8]. Here, the question arises: how can knowledge be effectively conveyed when it is still under development? AI can analyze vast amounts of data to identify patterns and trends, offering valuable predictive insights. This information can be used to foster **adaptive learning strategies**, allowing educators and students to adjust their approach based on the evolving nature of the subject matter. Drawing inspiration from research on uncertain reverse logistics [8], this section proposes several approaches for educational settings characterized by unknown variables:

C.1.2. Embracing uncertainty as the new normal

Traditional, fixed curriculums struggle in uncertain environments. The solution lies in acknowledging uncertainty from the start. By emphasizing critical thinking, problem-solving frameworks, and adaptability as core skills, we can equip students to navigate unfamiliar territory with confidence. This includes fostering a comfort level with "not knowing" and focusing on the process of exploration and discovery.

Preparing for every single scenario is impossible. However, integrating dynamic simulations and scenario planning exercises into the curriculum can expose students to a variety of unpredictable situations. Similar to the fuzzy optimization model used in reverse logistics, these simulations allow students to test different approaches and develop vital decision-making skills. In situations where no single individual possesses all the necessary knowledge, collaborative learning environments become crucial. By encouraging students to share their diverse perspectives and experiences, we foster a sense of community and facilitate peer-to-peer learning. This collaborative approach mirrors the importance of teamwork in uncertain logistics situations. The rapid pace of change in many fields renders rigid knowledge sets obsolete quickly. The key lies in emphasizing lifelong learning and adaptability. Equipping students with the skills to learn independently, critically evaluate information, and adapt their approaches based on new data empowers them to thrive in this ever-changing world.

C.1.3. Leveraging digital tools and resources

Keeping pace with the latest advancements in uncertain fields can be a challenge. Digital tools and resources offer a solution. These tools provide access to real-time data, research updates, and new methodologies, similar to how digitalization is vital in Industry 4.0 logistics, encompassing real-time visibility, supply chain optimization, data-driven decision making, predictive analytics, order tracking, automation, and increased productivity. By incorporating these lessons gleaned from the field of reverse logistics, we can transform education into a dynamic and adaptable system. This, in turn, equips students with the skills necessary to not only survive but thrive in a world brimming with uncertainty.

D.1. Stable and Known Educational Situations: Refining Existing Knowledge (BH.0.1)

The effectiveness of teaching methods hinges on a fundamental paradox: how to balance established practices with the ever-changing nature of knowledge. In well-defined fields like railway engineering or air traffic management, traditional lecture-based methods have proven effective. These methods provide a solid foundation in core principles, ensuring a clear co-creation of knowledge K_{cc} – a function influenced by the quality of instruction T_d, the student's prior understanding I_s, and the combined effort of both parties E_a and finally by α, which is imperfect conversion rate of information to knowledge. This concept was previously conveyed through the formula:

$$K_{cc} = f(T_d, I_s, E_a) * \alpha \quad (12)$$

However, this formula highlights a limitation – it doesn't account for individual learning styles. Here, AI can play a crucial role by personalizing learning experiences (represented by a variable P_i for individual student needs) and providing additional resources tailored to these needs. This personalization can be integrated into the formula as:

$$K_{cc} = f(T_d, I_s, E_a, P_i) * \alpha \quad (13)$$

By personalizing learning, AI can enhance the effectiveness of traditional methods in stable situations (BH.0.1). Statistical tests like comparing means and medians of $K_{cc}(P_i)$ across educational settings can assess the model's prediction accuracy. Additionally, regression analysis with beta coefficients and R-squared helps evaluate the stability of influencing factors (e.g., $T_d,$) on student outcomes. Stable educational situations, as characterized by BH.0.1, typically have more consistent predictions (lower variability in $K_{cc}(P_i)$, stronger relationships between factors and outcomes (significant beta coefficients), and better model fit (higher R^2).

D.2. Bridging the Gap: Teaching Critical Skills in Uncertain Environments (BH.0.2)

Traditional methods struggle to keep pace with the ever-evolving knowledge base of fields like autonomous vehicles and smart city logistics (BH.0.2). In uncertain educational situations, the focus of education must shift towards equipping students with the critical thinking and problem-solving skills necessary to navigate uncertainty. How to navigate educational uncertainty? This passage outlines six elements that may be employed to navigate educational uncertainty. Educational uncertainty can present an opportunity for the identification of intrinsic interests. This may involve the utilization of career aptitude assessments, research into various academic disciplines, or engagement in discussions with professionals in fields that elicit curiosity. Through such exploration, students can potentially discover educational pathways that align with their inherent skills and passions. Regardless of the eventual academic or professional trajectory chosen, the cultivation of valuable transferable skills, such as critical thinking, communication, and problem-solving, is demonstrably beneficial across diverse educational paths. Seeking guidance from advisors, educators, or mentors can provide valuable insights and support. The accumulated experience of these students can serve to illuminate options and facilitate informed decision-making. An open and adaptable approach to educational planning is recommended. The ideal educational path may not be linear, and deviations from the initial course can lead to the discovery of unforeseen opportunities. The knowledge landscape is subject to continuous evolution. Therefore, irrespective of the extent of formal education attained, a dedication to lifelong learning is essential to ensure preparedness for future uncertainties. The incorporation of artificial intelligence (AI) tools within educational frameworks holds promise in navigating educational uncertainty. AI-powered systems may offer personalized learning recommendations, curate educational resources, and provide adaptive feedback mechanisms, potentially enhancing the process of educational exploration and decision-making for individuals. It is important to acknowledge that the efficacy of AI-powered educational tools in mitigating educational uncertainty is an ongoing field of research, and further investigation is required to fully understand their potential impact.

D.3. Active learning in a dynamic world of Unknown with Large Uncertainty Educational Situations (BH.0.2)

Unknown with Large Uncertainty Educational Situations (BH.0.2), characterized by high variability, unpredictability, or new untested conditions, demand new approaches. Problem-based learning (PBL) emerges as a powerful tool for this purpose. By engaging students in active learning processes, PBL fosters critical thinking and decision-making skills in uncertain contexts (U_c). This approach is reflected in the formula:

$$K_{cc} = f(P_i, S_u, U_c) = g\ (PBL, T_d, I_s, E_a), \tag{14}$$

where:

K_{cc} - the co-creation of knowledge;

P_i - individual student needs;

S_uS_- captures the complexity of simulated scenarios used in PBL activities;

U_c - represents the level of uncertainty in the subject matter;

T_d - quality of instruction;

I_s - student's prior understanding;

E_a - combined effort of both teacher and student.

The function "g" highlights the effectiveness of PBL (in combination with traditional methods like T_d for teacher quality, I_s for student knowledge, and E_a for common effort) in addressing these complexities. Educational situations with large uncertainty (BH.0.2) show higher variability in $K_{cc} = f(P_i, S_u, U_c)$, weaker relationships between factors and outcomes (potentially non-significant coefficients), and poorer model fit (lower R^2).

This integration clearly distinguishes between stable and uncertain educational situations, referencing the provided basic hypotheses, and explains the application of AI and personalized learning in each context while focusing on the co-creation of knowledge. The need for effective decision-making in uncertain environments extends beyond education [9]. In the field of autonomous vehicles (AVs), the challenge lies in developing driving policies that ensure both safety and traffic flow efficiency. This is where the innovative Human as AI

Mentor-based Deep Reinforcement Learning (HAIM-DRL) framework comes into play. Inspired by human learning, HAIM-DRL leverages a "Human as AI Mentor" (HAIM) paradigm. An expert acts as a mentor to an AI agent, allowing the agent to explore but intervening in critical situations to demonstrate safe and efficient behaviors. This combined learning approach utilizes data from both free exploration and partial human demonstrations.

Significantly, HAIM-DRL bypasses the need for complex reward function design. Instead, it directly derives guidance for the agent's policy learning from the human demonstrations. Furthermore, minimal intervention techniques are employed to reduce the burden on the human mentor. Both the PBL approach in education and the HAIM-DRL framework in autonomous vehicle development showcase the importance of human-in-the-loop learning for navigating uncertain environments. By effectively combining human expertise with AI capabilities, we can equip both students and machines with the critical thinking and decision-making skills required to thrive in a world of constant change.

The effectiveness of teaching is not a one-size-fits-all proposition. By understanding the inherent paradox of stable vs. evolving knowledge, educators can tailor their methods to the specific learning environment. Traditional methods with AI-powered personalization remain valuable in stable situations, while fostering problem-solving and critical thinking through simulations becomes paramount in uncertain environments. This adaptability, coupled with the power of AI, is key to navigating the ever-changing landscape of knowledge and ensuring successful learning outcomes.

E.1. Assessment with AI in Stable and Known Educational Situations

In stable areas of education, such as testing knowledge of transportation regulations, basic mechanics, or fundamental concepts in "Transportation Engineering Fundamentals," assessments are relatively straightforward. For instance, courses like "Policy and Economics of ITS," and "Traffic Management Systems," often have well-defined learning outcomes that can be assessed using standardized methods. Given the assumption that knowledge cannot be directly transferred from a teacher to a student, even in stable learning environments, the assessment process must acknowledge the unique learning path of each student. Traditional assessments might fail to capture the nuances of individual understanding and application of knowledge. However, AI can streamline the evaluation process by automating grading and providing instant feedback, ensuring consistency and efficiency. AI can adapt its feedback to each student's responses, offering personalized insights and helping bridge the gap between standardized curricula and individual learning needs.

Incorporating ***Curriculum Subjects*** according to the assumption ”knowledge cannot be directly transferred from a teacher (as a mean solution) to a student (as a learning equation)” the following outcomes may be achieved:

- *Transportation Engineering Fundamentals***.** AI can evaluate students' grasp of basic principles and applications, providing tailored feedback to address specific areas of misunderstanding.
- *Communication Technologies for ITS*. Automated assessments can test students' understanding of communication protocols and technologies, offering simulations to demonstrate real-world applications.
- *Sensor Technologies for ITS*. Practical assessments can include AI-driven simulations where students apply their knowledge of sensor technologies in various scenarios.

- *Traffic Management Systems***.** AI can help students model traffic scenarios and manage simulations, providing immediate feedback on their decision-making processes.
- *Advanced Driver Assistance Systems (ADAS).* Students can be assessed on their understanding of ADAS technologies through interactive AI tools that simulate real-world driving conditions.
- *Connected and Autonomous Vehicles (CAVs).* AI-driven simulations can test students' knowledge of CAVs, assessing their ability to program and troubleshoot these systems.
- *Travel Information Systems***.** AI can evaluate how well students design and implement travel information systems, providing instant feedback on usability and efficiency.
- *Public Transportation Systems.* Assessments can include AI simulations where students optimize public transportation networks, receiving feedback on their strategies.
- *Data Analytics for ITS.* AI can assess students' proficiency in analyzing transportation data, offering personalized feedback on their analytical techniques.
- *Traffic Modeling and Simulation.* Automated tools can test students' skills in traffic modeling, offering immediate feedback on their simulation outcomes.
- *Cybersecurity for ITS.* AI can simulate cybersecurity threats and evaluate students' responses, providing detailed feedback on their problem-solving approaches.
- *Policy and Economics of ITS.* Standardized tests can assess students' understanding of policies and economic principles, while AI can provide tailored feedback to address individual learning gaps.
- *Project Management for ITS.* AI-driven project simulations can evaluate students' project management skills, offering real-time feedback on their decision-making processes.

In conclusion, while stable areas of education allow for straightforward assessments, the application of AI can enhance the process by providing personalized feedback and ensuring consistency. By integrating subjects from the curriculum and recognizing the unique learning equations of each student, educators can create a more effective and individualized learning environment. This approach not only improves the accuracy of assessments but also supports the continuous intellectual growth of students, aligning with both hypotheses that challenge the traditional knowledge transfer model.

E.2. Assessment in Intelligent Transportation Systems (ITS): Learning with AI

Traditional assessment methods struggle to capture student understanding in the dynamic field of Intelligent Transportation Systems (ITS). Uncertainties surrounding the impacts of new transportation policies or innovations in freight logistics pose significant challenges. This section proposes a solution that leverages Artificial Intelligence (AI) to create personalized learning experiences that address these uncertainties.

The Challenge of Traditional Assessment

Our analysis is guided by one basic hypothesis and three assumptions:

- ✔ *Uniqueness of the Learning Equation*. Every student possesses a unique learning equation requiring a personalized approach. A set curriculum, even with diverse topics like Communication Technologies for ITS and Public Transportation Systems, cannot fully address these individual needs.
- ✔ *Knowledge Co-Creation as a Dynamic Process*. Simple knowledge transmission from teacher (mean solution) to student (learning equation) is insufficient. Factors like individual learning styles and prior knowledge (e.g., Transportation Engineering Fundamentals) influence comprehension.
- ✔ *Positive Learning Environment*. Optimal learning hinges on a positive state of mind for both teacher and student (learning equation). Traditional assessments can create anxiety, hindering this positive state.

E.3. AI-powered Assessments for Unknown with Large Uncertainty Educational Situations

AI offers a path forward with simulations and scenario-based evaluations that align with individual learning styles. These methods assess critical thinking and problem-solving skills, providing a more comprehensive picture of student comprehension and adaptability within the context of ITS.

Challenges of Traditional Assessment in Uncertain Environments

- *Limited Scope*. Traditional assessments often focus on static knowledge, neglecting the dynamic nature of ITS. Emerging technologies and evolving policies can render past knowledge obsolete, making assessments based on rote memorization less relevant.
- *Difficulty in Simulating Uncertainty*. Traditional assessments struggle to replicate the real-world uncertainties students will encounter in the ITS field. They often present clear-cut problems with predetermined solutions, failing to prepare students for the complexities of the real world.
- *Dynamic Scenario-based Evaluations*. AI allows for the creation of adaptable and dynamic simulations that incorporate various uncertainties. Students can be presented with scenarios that evolve based on their decisions, forcing them to think critically and adapt their knowledge to address unforeseen challenges. This approach better reflects the dynamic nature of ITS and prepares students for a constantly evolving field.
- *Personalized Learning through AI*. AI can personalize assessment experiences by tailoring scenarios to individual student strengths and weaknesses. This ensures a more meaningful learning experience for each student, allowing them to focus on areas requiring further development. Analysis of AI assessment benefits in specific its subjects of curriculum as following:
- *Traffic Flow and Infrastructure Planning*. Simulations can model real-world scenarios with evolving traffic patterns and unexpected disruptions, requiring students to adapt their planning strategies.
- *Communication Network Integration and Optimization*. Scenario-based assessments can evaluate students' ability to maintain network reliability under varying conditions, such as unexpected surges in data traffic.

- *Sensor Deployment and Effectiveness*. Simulations can assess students' ability to adapt sensor deployment strategies based on unforeseen environmental changes (e.g., extreme weather events) that may impact sensor performance.
- *Traffic Management Strategy Design and Optimization*. AI-driven assessments can introduce unpredictable events (e.g., accidents) within simulations, requiring students to adjust their traffic management strategies on the flow.

AI-powered simulations and scenario-based assessments create personalized learning experiences, overcoming the limitations of traditional methods. This approach acknowledges the dynamic nature of knowledge co-creation and the importance of catering to individual learning styles. Ultimately, it fosters a deeper and more adaptable understanding of ITS, preparing students to navigate and innovate within this rapidly evolving field.

F.1. Practical Challenges in Education

F.1.1. Stable and Known Educational Situations

One of the practical challenges in education is addressing bias and fairness, particularly within stable and known educational situations. In the domain of Intelligent Transportation Systems (ITS), effective education necessitates both the acquisition of knowledge and the assurance of fairness in the assessment process. This section examines the limitations of traditional assessment methods in mitigating potential biases and proposes the application of Artificial Intelligence (AI) as a solution. AI can play a pivotal role in ensuring fairness when teaching established transportation knowledge. By providing uniform content delivery and standardized evaluations, AI reduces the potential for human bias that often infiltrates traditional educational practices. This is particularly relevant in the context of ITS, where precise and unbiased knowledge transfer is crucial.

Traditional assessment methods are constrained by several key factors:

- *Static Knowledge Evaluation*. Traditional assessments often rely on static knowledge tests that do not account for the dynamic and evolving nature of ITS. These assessments can fail to capture the breadth and depth of a student's understanding and adaptability in real-world scenarios.
- *Standardized Methods*. The use of standardized methods in traditional assessments can overlook individual learning styles and needs. This one-size-fits-all approach may not accurately reflect the diverse capabilities and potential of each student.
- *Human Bias*. Inherent biases in human evaluation can introduce unfairness into the assessment process. For instance, a teacher's unconscious bias towards a particular learning style might disadvantage a student who excels with a different approach.

These limitations highlight the necessity for more adaptive and impartial assessment mechanisms. Traditional assessments, with their reliance on static and standardized methods, often fall short in effectively evaluating the dynamic and multifaceted knowledge required in ITS.

✔ ***AI as a Solution***

AI offers a promising solution to the limitations of traditional assessment by providing:

- *Uniform Content Delivery*. AI ensures that all students receive the same information, minimizing discrepancies that may arise from varied teaching styles and human error. This uniformity helps create a level playing field, where each student has equal access to the same educational resources.

- *Standardized Evaluations.* AI can administer standardized evaluations that are free from human bias. These evaluations can be designed to adapt to the individual learning pace and style of each student, offering a more accurate assessment of their knowledge and skills.
- *Reduction of Human Bias.* By removing the subjective element of human evaluation, AI can significantly reduce the potential for bias. This ensures that assessments are based solely on the student's performance and understanding, rather than extraneous factors such as the evaluator's personal biases or preferences.
- *Addressing the Shortcomings of Traditional Methods.* Effective education in ITS requires addressing the shortcomings of traditional assessment methods. AI can provide a more equitable and accurate evaluation process, ensuring that all students are assessed fairly and on the same criteria. This approach not only enhances the fairness of the assessment process but also improves the overall quality of education by accurately identifying and addressing each student's unique learning needs. The paper [10] explores potential solutions to the limitations of traditional assessment in ITS education. This study investigates methods to validate real-world AI systems by analyzing existing literature and proposes a classification scheme, highlighting the need for more continuous validation techniques.

The integration of AI into the educational assessment process in stable and known educational situations within ITS can significantly enhance fairness and accuracy. By leveraging AI, educators can ensure that all students are evaluated impartially, thus fostering a more inclusive and effective learning environment. This approach aligns with the broader goals of ITS education, which aims to prepare students for the dynamic and complex challenges of the field by equipping them with both the necessary knowledge and the assurance of fair assessment practices.

F.1.2. Unknown with Large Uncertainty Educational Situations

In uncertain contexts, AI might perpetuate biases present in training data, leading to unfair treatment of students. Addressing these biases is crucial to maintain fairness and equity in education.

In the context of Intelligent Transportation Systems (ITS) education, various practical challenges arise, particularly concerning bias and fairness. This issue becomes pronounced in uncertain and unknown situations, where Artificial Intelligence (AI) systems might inadvertently perpetuate biases inherent in their training data. These biases can result in unfair treatment of students, thus undermining the principles of equity and fairness in education. To address these biases, it is essential to ensure that AI systems used in ITS education are trained on diverse and representative datasets. This effort can help minimize the risk of bias propagation and promote a more equitable learning environment. The challenge of bias and fairness can be particularly critical when teaching subjects within the ITS curriculum, such as: "Transportation Engineering Fundamentals", "Communication Technologies for ITS", "Sensor Technologies for ITS", "Traffic Management Systems", "Advanced Driver Assistance Systems (ADAS)", "Connected and Autonomous Vehicles (CAVs)", "Travel Information Systems", "Public Transportation Systems", "Data Analytics for ITS", "Traffic Modeling and Simulation", "Cybersecurity for ITS", "Policy and Economics of ITS", "Project Management for ITS".

To implement basic hypotheses in ITS education, educators must adopt adaptive teaching methods that cater to the individual needs of students. This approach involves continuous assessment and modification of teaching strategies to ensure that each student's unique learning equation is addressed. Additionally, fostering a positive learning environment is crucial for both teachers and students, as it enhances the overall effectiveness of the educational process. As autonomous vehicles become more complex and rely heavily on AI, a new safety concern - Safety of the Intended Functionality (SOTIF) - is hindering their deployment. The study [11] explores SOTIF across its lifecycle, examining academic research and learning process, industry practices, challenges, and future directions. The provided study [11] highlights the limitations of traditional assessment methods through the lens of AV safety and the concept of SOTIF. Here's how it aligns with the three key assumptions: Dynamic Knowledge Co-Creation assumption. The mentioned above work emphasizes the complexity of AV systems, encompassing high-dimensional and dynamic environments. This complexity mirrors the "learning equation" of an individual student. Traditional assessments, often static and standardized, fail to capture the nuances of such a complex system (AV) or the individual learning styles of students aiming to understand AV safety. Uniqueness of the Learning Equation assumption. The investigation [11] discusses the limitations of a set curriculum in addressing the diverse challenges of SOTIF. Similarly, traditional assessments often rely on a "one-size-fits-all" approach, neglecting the unique needs and learning styles of students. This mismatch between the assessment and the student's individual learning process can hinder effective evaluation. The investigation [11] mentions real-world accidents involving AVs, which can create anxiety and public fear surrounding the technology. Similarly, traditional assessments rooted in standardized testing can create anxiety in students, potentially impacting their performance and hindering a positive learning environment. By highlighting the complexities of AV safety (similar to a student's learning equation), the limitations of a set curriculum (mirroring a one-size-fits-all assessment), and the potential for anxiety surrounding AV accidents (analogous to test anxiety), the text effectively demonstrates the shortcomings of traditional assessment methods in the context of understanding and ensuring AV safety.

Addressing bias and ensuring fairness in ITS education requires a multifaceted approach that incorporates diverse datasets, adaptive teaching methods, and a focus on the positive mental states of both educators and learners. By doing so, we can better equip students with the knowledge and skills necessary to excel in the field of Intelligent Transportation Systems.

G.1. Confidentiality and Information Assurance in Education

G.1.1. Stable and Known Educational Situations

Managing student data for stable topics in transportation education is relatively straightforward. However, ensuring data protection and ethical use remains crucial to maintaining trust. Fortunately, sufficient policies are currently in place to ensure privacy and data security for these stable and well-defined situations. The study [12] explores the potential of a novel active learning approach that leverages both Teaching Assistants (TAs) and generative AI (ChatGPT) to provide feedback during in-class exercises for Computer

Science courses. The study found that TAs were adept at identifying student progress and challenges, particularly in areas like "backtracking." This ensures students receive targeted feedback on specific areas of difficulty. High student engagement and satisfaction levels suggest the approach fostered a positive learning environment. The analysis suggests that integrating human and AI in the feedback process has the potential to significantly improve traditional teaching methods by creating a more dynamic and responsive learning environment. Future research should investigate how to leverage the unique strengths of both human and AI to further enlarge educational practices, particularly in the field of computing.

G.1.2. Unknown with Large Uncertainty Educational Situations

When AI systems analyze large and varied datasets to predict future transportation trends, ensuring the privacy and security of sensitive information becomes more complex and critical, requiring robust safeguards and ethical practices. While Artificial Intelligence (AI) offers significant potential for analyzing large and diverse transportation datasets to predict future trends, it introduces significant challenges regarding privacy and data security. This section explores these complexities, particularly in the context of the following Intelligent Transportation Systems (ITS) subjects: "Transportation Engineering Fundamentals", "Communication Technologies for ITS", "Sensor Technologies for ITS", "Traffic Management Systems", "Advanced Driver Assistance Systems (ADAS)", "Connected and Autonomous Vehicles (CAVs)", "Travel Information Systems", "Public Transportation Systems", "Data Analytics for ITS", "Traffic Modeling and Simulation", "Cybersecurity for ITS", "Policy and Economics of ITS", "Project Management for ITS". Increased complexity in educational situations with large degrees of uncertainty requires a specific approach. Unlike traditional, static transportation knowledge, AI systems often analyze vast and dynamic datasets. These datasets may encompass real-time sensor data, historical traffic patterns, and individual user information. Our analysis is guided by three key assumptions that highlight the challenges associated with such large and dynamic datasets: Dynamic Data and the Learning Equation assumption. The dynamic nature of transportation data (analogous to the unique learning equation of a student) necessitates a flexible approach to privacy and security. Static policies designed for "mean solution" scenarios (e.g., traditional transportation knowledge) may not adequately address the complexities of AI-driven analysis. As AI systems delve deeper into individual user behavior to predict future trends, ensuring the privacy of each user becomes paramount (analogous to respecting the unique learning needs of each student). A "one-size-fits-all" privacy approach fails to consider the unique privacy concerns of individual data points within the larger dataset. Public trust in the ethical use of transportation data is crucial for effective research and development (analogous to maintaining a positive learning environment for students).

Addressing these challenges necessitates the development of robust safeguards and ethical practices for data collection, storage, and analysis. The study [13] suggests a generally receptive environment for learning analytics implementation in higher education. However, fostering trust and transparency regarding data practices remains crucial. Future research should explore ways to effectively communicate the value of learning analytics and empower students as data owners within the learning process. By acknowledging the unique privacy and security challenges associated with AI-driven transportation analysis, and by implementing robust safeguards and ethical practices, we can unlock the full potential of AI for the future of transportation, while ensuring the privacy and security of individual data.

H.1. *Transparency and Accountability*

H.1.1. Stable and Known Educational Situations

In predictable educational contexts, AI systems can enhance transparency by clearly explaining how decisions are made, fostering trust among educators and students. The research [14] examines factors influencing undergraduate students' intention to use ChatGPT for assessment support in Hong Kong's highly competitive education system. The study identifies trust as the strongest factor influencing students' willingness to use ChatGPT for assessment support. Students' beliefs about ChatGPT's potential to improve their performance (performance expectancy) and the ease of using the tool (effort expectancy) positively impact their intention to utilize it. This analysis highlights the importance of building trust and addressing ethical concerns to encourage the responsible adoption of AI tools like ChatGPT for assessment support in higher education. Furthermore, considering the limited influence of social factors, targeted strategies might be needed to promote ethical use of such tools among students.

H.1.2. Unknown with Large Uncertainty Educational Situations

In uncertain scenarios, AI's "black box" nature can hinder transparency, making it difficult for educators and students to trust AI-generated recommendations. Ensuring accountability in such cases is essential to maintain confidence in AI-driven educational tools. The analysis in the work [15] highlights the importance of assessing AI literacy in higher education. The mentioned study offers a validated assessment tool and valuable insights into current student knowledge levels, emphasizing the need for broader-reaching AI education and adaptable teaching approaches.

I.1. Job Displacement

I.1.1. Stable and Known Educational Situations

In stable areas, AI can automate routine tasks, freeing educators to focus on more complex teaching activities, thereby enhancing the overall educational experience. The investigation work [16] explores the potential for Artificial Intelligence (AI) to significantly automate human tasks and displace workers, a possibility largely overlooked in previous research. Practitioners expect automation to increase steadily: 22% of tasks currently performed by humans could be automated with existing AI. This figure is projected to rise to 40% in 5 years and 60% in 10 years. Median forecasts suggest a 50% chance of AI automating 90% of jobs within 25 years and 99% within 50 years. Interestingly, attendees of the Human-level AI Conference offered even shorter timelines for these extreme scenarios (10 and 15 years respectively, with a 10% probability). The findings suggest a need for future research to consider the possibility of extreme labor displacement by AI more seriously. These high-likelihood scenarios should be factored into discussions about the future of work and potential impacts for students.

I.1.2. Unknown with Large Uncertainty Educational Situations

There is a fear that AI might replace human educators in more complex, uncertain areas of transportation education. Ensuring that AI is viewed as a tool to augment human teaching rather than replace it is crucial to addressing these concerns. While digital technologies like AI are transforming many industries, including education, some fear they might completely replace human educators, especially in complex and uncertain areas like transportation education. The analysis in the study [17] sheds light on how AI can actually complement human instructors. The mentioned study explores the impact of digital tools (similar to AI) on employment in the manufacturing sector (China, 2011-2020). This research offers valuable insights applicable to the education field. The study [17] reveals that digital tools, like AI in education, can actually increase overall employment within an organization (manufacturing companies in this case). However, the impact is not uniform. Organizations with better management structures and competitive environments are more likely to utilize digital tools effectively to optimize their workforce structure. AI can support human educators in transportation education, potentially freeing them from routine tasks and allowing them to focus on complex areas that require human expertise and judgment. Similar to effective management in manufacturing, educators and institutions can utilize AI to optimize the educational experience for students in transportation education. This could involve personalized learning approaches or AI-powered tools supporting areas like assessment or data analysis.

J.1. Responsible AI Development

J.1.1. Stable *and Known Educational Situations*

Establishing ethical guidelines for using AI in well-understood areas of transportation education helps prevent misuse and ensures that AI is used responsibly. The research paper [18] explores the ethical and responsible use of AI chatbots (like ChatGPT) in education, particularly focusing on their potential to encourage students to analyze information critically and develop independent thought processes, support students in adapting their learning strategies and approaches to different situations and help students develop self-management skills to regulate their learning activities. By proposing a framework and practical examples, this analysis [18] emphasizes the importance of ethical considerations when developing and utilizing AI chatbots in education. These ethical guidelines can ensure AI chatbots support critical thinking, cognitive flexibility, and self-regulation in students, ultimately promoting a more responsible and effective use of AI in the classroom.

J.1.2. Unknown with Large Uncertainty Educational Situations

In emerging fields, continuously updating ethical guidelines to keep pace with AI advancements is necessary to ensure ethical use and to address new challenges that arise with technological progress. The investigation [19] explores the development and evaluation of a curriculum designed to educate students on the ethical use of Large Language Models (LLMs) like ChatGPT. The research acknowledges a lack of established educational resources that specifically focus on AI ethics principles and their integration into curriculum design. The study utilizes the Technology Acceptance Model to analyze factors influencing student attitudes towards ChatGPT: factors like perceived usefulness, justice and fairness, privacy, and data protection directly affect student acceptance of ChatGPT. Despite consenting to data use, students expressed discomfort with their personal information being used for training ChatGPT. Further research could explore how to tailor AI ethics education to different age groups and learning styles.

K.1. Integrating the Basic Hypothesis into Practical Applications

Every student represents a unique learning equation (challenge). The curriculum and teacher represent an arithmetic mean solution that does not fully satisfy the unique student learning equation. This assumption asserts that each student has individual learning needs and challenges that are not fully met by the standardized curriculum and teaching methods, which are designed to cater to the average student. The reasoning behind this assumption lies in the inherent diversity of students' learning styles, paces, and preferences. Standardized educational approaches aim to serve the majority but often fail to address the specific requirements of individual students, leading to gaps in learning effectiveness. In Stable and Known Educational Situations, AI can optimize the arithmetic mean solution by customizing content delivery and assessments to individual needs, improving overall learning outcomes. In Unknown with Large Uncertainty Educational Situations, AI can dynamically adapt teaching methods and resources to address the unique learning equations of each student, ensuring that educational strategies remain effective despite the unpredictability of the learning environment. In other words, integrating AI into transportation engineering education requires addressing both the historical paradoxes and ethical challenges of teaching, learning, and evaluation. By leveraging AI's capabilities to personalize education and adapt to dynamic conditions, educators can shift the center of gravity in the teaching-learning-evaluating process, ultimately enhancing the effectiveness and equity of educational outcomes.

K.1.1. Stable and Known Educational Situations

In stable and well-known situations, integrating AI into the curriculum requires careful planning to ensure alignment with educational objectives. The curriculum can be redesigned to leverage AI for automating routine tasks, providing consistent information, and supporting data-driven decision-making. This ensures that educational objectives are met with precision and reliability. The assumption here asserts that each student represents a unique learning equation, while the curriculum and teacher represent an arithmetic mean solution that does not fully satisfy the unique student learning equation. This assumption highlights the necessity of personalized education approaches. AI can optimize the arithmetic mean solution by customizing content delivery and assessments to individual needs, improving overall learning outcomes. Scholars [20] have identified three main approaches to curriculum design in universities: Curriculum as product (it focuses on clear learning objectives), Curriculum as process (it focuses on the dynamic interactions that occur during learning) and Curriculum as content (model highlights the knowledge and information that students acquire through their studies).

K.1.2. Unknown and with Large Uncertainty Educational Situations

In an unstable and uncertain environment, the curriculum needs to be flexible and adaptive. AI can analyze large datasets and offer predictive insights, helping to navigate unpredictability. However, this requires careful consideration of the interpretability and trustworthiness of AI-generated recommendations to ensure the curriculum remains robust and responsive to emerging challenges. According to the assumptions, each student has individual learning needs and challenges that are not fully met by the standardized curriculum and teaching methods, which are designed to cater to the average student. In such dynamic conditions, AI can dynamically adapt teaching methods and resources to address the unique learning equations of each student, ensuring that educational strategies remain effective despite the unpredictability of the learning environment.

The study [21] demonstrates that cultural values impact student privacy concerns in learning analytics. In high-uncertainty contexts, clear communication and culturally sensitive design are crucial. Learning analytics might indirectly affect learning styles and openness in the learning environment. Prioritizing privacy and adapting to cultural variations can improve the overall learning analytics experience for students. Integrating AI into transportation engineering education requires addressing challenges of teaching, learning, and evaluation. By leveraging AI's capabilities to personalize education and adapt to dynamic conditions, educators can shift the center of gravity in the teaching-learning-evaluating process, ultimately enhancing the effectiveness and equity of educational outcomes. Additionally, investigating effective strategies for building trust and addressing privacy concerns within the context of AI education is essential.

L.1. Teacher-Student Dynamics

L.1.1. Stable and Known Educational Situations

In stable situations, the relationship between teachers and students can benefit from AI by enhancing the delivery of content and automating assessments. AI can personalize content delivery based on a student's learning style and pace. This ensures students grasp concepts efficiently and avoid being held back by a standardized curriculum.

L.1.2. Unknown with Large Uncertainty Educational Situations

In Unknown with Large Uncertainty Educational Situations, the relationship between teachers and students must adapt to the challenges of unpredictability. AI can assist by providing real-time data analysis and adaptive learning pathways. Teachers must also be equipped to interpret AI recommendations and guide students through ambiguous scenarios, fostering a collaborative environment where critical thinking and exploration are encouraged. Uncertain environments necessitate fostering a collaborative learning environment where students develop critical thinking skills to navigate ambiguity and solve problems that fall outside the scope of a standardized curriculum. According to research [22] AI prompts in peer review improve feedback quality but students rely on them too much. Self-monitoring checklists help students regulate learning without AI. Combining both offers minimal benefits due to cognitive load. AI in education should balance support with student agency and encourage independent learning.

M.1. Teaching Methods

M.1.1. Stable and Known Educational Situations

In stable and known educational scenarios, traditional teaching methods can be augmented with artificial intelligence (AI) to optimize the "arithmetic mean solution." AI can efficiently deliver well-established knowledge by facilitating the standardization of instructional content, automating grading, and providing data-driven insights to enhance teaching effectiveness. By personalizing content delivery and assessments to meet individual needs, AI can improve overall learning outcomes, ensuring that the curriculum addresses the unique learning equations of each student more effectively.

M.1.2. Unknown with Large Uncertainty Educational Situations

In unstable and uncertain environments, teaching methods need to be dynamic and adaptable to address the unique learning equations of each student. AI can support this need by offering real-time insights and adaptive learning tools, which help manage uncertainty and ensure that educational strategies remain effective. Educators must be proficient in using these AI tools to foster a learning environment that encourages problem-solving and critical thinking, adapting to the diverse and evolving needs of students.

The study [23] explores pre-service teachers' perspectives on using ChatGPT, an AI tool, to support metacognitive self-regulated learning (MSRL) in education. ChatGPT can be a valuable tool in established curriculum by assisting pre-service teachers with lesson planning, content organization, and goal setting. This could enhance the quality, clarity, and alignment of learning materials with objectives. The effectiveness of AI tools in highly uncertain situations needs further exploration. Pre-service teachers might require additional training in AI competency and critical evaluation skills to navigate dynamic learning environments. ChatGPT's ability to personalize learning materials could facilitate dynamic knowledge transfer by catering to individual needs and adapting to changing environments. By promoting MSRL through increased self-awareness and planning skills, ChatGPT can contribute to a positive learning environment for both pre-service teachers and their future students. However, it’s crucial to ensure responsible AI integration to avoid overreliance and maintain a human-centered learning experience. The study [23] suggests AI tools have promise in enhancing MSRL and improving pedagogical practices in teacher training. However, further research is needed to explore their effectiveness in diverse educational contexts and ensure responsible integration for optimal learning outcomes.

N.1. Learning Strategies

N.1.1. Stable and Known Educational Situations

In stable educational environments, the assumption "Every student represents a unique learning equation (challenge). Curriculum and teacher is an arithmetic mean solution that does not fully satisfy the unique student learning equation" highlights the limitations of standardized teaching methods. These methods, designed for the average student, often fail to address the individual learning needs and challenges of each student. AI can play a crucial role in bridging this gap by offering personalized learning experiences. Through consistent feedback and data-driven study plans, AI can tailor content delivery and assessments to meet individual student needs. This personalized approach reinforces established knowledge, ensuring steady academic progress and optimizing learning outcomes.

N.1.2. Unknown with Large Uncertainty Educational Situations

In uncertain and dynamic educational environments, the need for flexible and adaptive learning strategies becomes paramount. According to the assumption, the standardized curriculum and teaching methods are insufficient to meet the unique learning requirements of each student, particularly in unpredictable scenarios. AI can assist by identifying emerging patterns and suggesting adaptive learning pathways. This capability allows AI to dynamically adjust teaching methods and resources, addressing the specific learning equations of individual students even in uncertain conditions. Additionally, students must develop resilience and critical thinking skills to effectively navigate unpredictability.

The research [24] investigates the effectiveness of a system that utilizes Internet of Things (IoT) data and Internet of Behavior (IoB) analysis to personalize learning experiences. The study demonstrates promise for using IoT and IoB to identify student weaknesses in well-defined learning areas (e.g., writing elaboration, participation). Personalized recommendations and targeted exercises can be delivered through learning management systems to address these weaknesses. The effectiveness of the system in highly dynamic or uncertain learning environments remains untested. Further research is needed to explore how the system adapts to changing learning goals or contexts. The system's ability to personalize learning materials based on student behavior has the potential to facilitate dynamic knowledge co-creation by catering to individual needs. However, the study doesn't address how the system adapts to changes in learning objectives or the curriculum itself. By identifying and addressing student weaknesses, the system could contribute to a positive learning environment where students receive targeted support. The study [24] demonstrates a significant improvement in student performance after receiving personalized support and is proposed as a method to help students understand the system's recommendations and improve transparency.

O.1. Measurement Inquiry in Education

O.1.1. Stable and Known Educational Situations

In a stable environment, AI can streamline the evaluation process by providing standardized assessments and immediate feedback. This ensures a consistent and objective measure of student performance. By leveraging AI, the arithmetic mean solution represented by traditional curriculum and teaching methods can be optimized to better address individual needs. AI's ability to analyze and adapt content delivery and assessments to each student's unique learning equation enhances overall learning outcomes.

O.1.2. Unknown with Large Uncertainty Educational Situations

In Unknown with Large Uncertainty Educational Situations, evaluation methods need to be more flexible and reflective of the dynamic learning environment. AI can assist by offering formative assessments and real-time analytics, allowing educators to consider the broader context and potential biases in AI-driven evaluations. This adaptability ensures that educational strategies remain effective despite the unpredictability of the learning environment. AI's capacity to dynamically adjust teaching methods and resources addresses the unique learning equations of each student, thus mitigating the shortcomings of a one-size-fits-all approach.

The issue [25] explored diverse perspectives on ChatGPT integration among Philippine Higher Education Institutions students and faculty. By employing Q-methodology, three distinct groups emerged: ethically-minded users, balanced pedagogy advocates, and convenience-focused adopters. Findings highlight the need for tailored strategies to optimize ChatGPT's use, emphasizing ethical considerations, cross-cultural nuances, and ongoing research.

P.1. Should universities consider replacing human teachers with technology?

The paper [26] discusses the potential to take over university teaching roles and scientific writing. AI offers exciting features like personalized learning and real-time feedback. The author concludes that ChatGPT is not currently suitable for scientific writing due to factual errors, lack of scientific expertise, and potential for misinformation spread, while acknowledging limitations in timeliness and understanding user intent.

AI cannot fully replace teachers. Human educators excel at fostering critical thinking and emotional support, making AI a valuable supplement, not a replacement. The future lies in collaboration, where AI and teachers work together to optimize student learning.

3. Results and Discussion

To evaluate the validity of the basic hypothesis (BH.0.0.), a dual-method approach was employed. First, existing published data were analyzed to assess the initial plausibility of the hypothesis within stable and known educational environments. This provided a foundational understanding based on previous research.

Second, hypotheses derived from BH.0.0. were scrutinized against available published data to determine their accuracy and predictive power within educational situations characterized by high uncertainty. This step aimed to identify any limitations or inconsistencies in the original hypothesis under these conditions.

Finally, the findings from both analyses were synthesized to form a comprehensive evaluation. By integrating the results from the literature review and testing analysis, a robust and nuanced understanding of basic hypothesis BH.0.0. was achieved across both types of educational contexts.

Stable and Known Educational Situations

This section examines the initial plausibility of the basic hypothesis (BH.0.0) presented in the "Introduction" section within stable and known educational environments. Data from [27], specifically tables 1-13, were analyzed to identify trends, correlations, and statistical significance to determine the hypothesis's validity or invalidity. The study [27] investigated factors influencing university students' attitudes toward ChatGPT adoption for educational purposes. By extending the value-based adoption model and employing various statistical techniques, the research identified personal innovativeness as the primary predictor of attitude, followed by self-efficacy and enjoyment.

Basic hypothesis BH.0.0. The level of uncertainty within an educational situation will have a significant impact on the effectiveness of knowledge transfer as a co-creation process, with stable and known educational situations leading to stronger co-creation and positive learning environments compared to educational situations with large uncertainty.

For reference, the following tables were used from source [27]: Table 1: Recent quantitative studies on VAM (Value-Added Models); Table 2: Demographic data; Table 3: Dataset summary; Table 4: Factor loadings (FL), variance inflation factors (VIF), composite reliability (CR), and average variance extracted (AVE) values; Table 5: Discriminant validity; Table 6: coefficient of determination R^2 and cross-validated redundancy Q^2 values ATT (Attitude); Table 7: Effect sizes; Table 8: Hypothesis test results; Table 9: Model validation results; Table 10: Importance of independent variables; Table 11: Comparison of Partial Least Squares (PLS), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN) models; Table 12: Prediction of attitude (ATT) by perceived usefulness (PU), perceived enjoyment (PE), perceived technicality (PT), perceived cost (PC), social influence (SI), self-efficacy (SE), and personal innovativeness (PI); Table 13: Prediction of intention to adopt AI by attitude (ATT).

In stable educational environments characterized by low variability, consistent outcomes, and reliable forecasts, the following was observed based on data from study [27]: Personal Innovativeness had the highest contribution to attitude. Mean scores for personal innovativeness (PI1 to PI5) ranged from 5.15 to 5.61 with low skewness and kurtosis, indicating positive attitudes and readiness to adopt new technologies among students. Self-Efficacy had a significant positive influence on attitude. Mean scores for self-efficacy (SE1 to SE4) ranged from 5.12 to 5.56, showing high confidence in using ChatGPT. Perceived Enjoyment and Usefulness had small but significant positive effects on attitude. Mean scores for perceived enjoyment (PE1 to PE4) ranged from 5.4 to 5.7 and perceived usefulness (PU1 to PU4) ranged from 5.43 to 5.75, reflecting overall positive perceptions. Social Influence had a significant positive effect but was smaller compared to other factors. Mean scores for social influence (SI1 to SI6) ranged from 4.07 to 4.7, suggesting moderate peer influence. Perceived

Technicality had a very small or no significant effect on attitude. Mean scores for perceived technicality (PT1 to PT4) ranged from 3.32 to 3.78, indicating some perceived difficulty. Perceived Cost had no significant effect on attitude. Mean scores for perceived cost (PC1 to PC3) ranged from 4.21 to 4.42, indicating neutral to slightly negative perceptions.

Correlation and regression analysis revealed strong model fit, indicated by high R^2 values of 0.626 for attitude and 0.652 for intention. Personal innovativeness and self-efficacy emerged as significant predictors. Effect sizes further emphasized the importance of self-efficacy (0.063) and personal innovativeness (0.068). Neural network analysis corroborated these findings, highlighting the substantial influence of personal innovativeness (24.48%) and self-efficacy (20.07%).

The findings from the study [27] align with the hypothesis that stable and known educational situations (characterized by positive attitudes towards ChatGPT and its perceived usefulness, enjoyment, social influence, self-efficacy, and personal innovativeness) lead to stronger co-creation and positive learning environments. Therefore, the hypothesis is confirmed by the data provided, indicating that reduced uncertainty and a positive perception of educational tools like ChatGPT enhance knowledge transfer effectiveness through co-creation of knowledge.

Educational Situations with Large Uncertainty: Initial Assessment of Basic Hypothesis

To assess the basic hypothesis's applicability in uncertain educational contexts, the hypothesis itself was tested against existing published data. This analysis aimed to uncover potential limitations or inconsistencies under these conditions.

The Spanish study [28] investigated factors influencing educational innovation between 2018 and 2021. Through in-depth interviews, eleven obstacles and eight facilitators were identified. The study [28] focuses on educational innovation, characterized by inherent uncertainty, aligns with the criteria for "Unknown and Uncertain Educational Situations". Its dynamic research design, encompassing diverse participants and a focus on emerging challenges, positions it as a suitable framework for exploring such contexts. The authors of the basic hypothesis consider innovation as a future-oriented concept, where unknown student responses, behaviors, and expectations represent forms of educational uncertainty to which the basic hypothesis was applied. The investigation's emphasis on innovation, inherently linked to unpredictability, further solidifies its relevance to these conditions.

For reference, the following tables were used from study [28]: Table 1: Characteristic Features of Grounded Theory; Table 2: Description of Research Cycles; Table 3: Summary Table of Participants in the Research; Table 4: Theoretical Coding Procedure; Table 5: Criteria of Quality and Scientific Rigor Followed in Research; Table 6: Results Categories Cycle of Innovation; Table 7: Results Categories Cycle of Experts in Innovation; Table 8: Results Categories Cycle of Management and Guidance; Table 9: Results Categories Cycle of Inspection and Administration; Table 10: Overall Results of the Study.

Based on the provided tables, educational situations were categorized into two groups: "Stable and Known Educational Situations," characterized by lower variability and stronger relationships, and "Educational Situations with Large Uncertainty," characterized by higher variability and weaker relationships. The percentages of different facilitators and obstacles across the cycles offered insights into the stability and uncertainty of educational environments. The distribution of these factors was compared to identify variability and the strength of relationships. For each cycle, variability was calculated and weaker relationships were identified by analyzing the spread and dominance of subcategories. In the Cycle of Innovation, variability was high with distribution spread across multiple subcategories, and the strongest facilitator was "Accompaniment" at 28.95%, indicating weaker relationships due to the lower dominance of a single factor. Similarly, obstacles showed high variability with "Obstructive administration" at 26.92%. In the Cycle of Experts in Innovation, variability was moderate with facilitators like "Management team support" at 27.27% showing some dominance, indicating moderate relationships. The obstacles also showed moderate variability with "Obstructive administration" at 36.11%. In the Cycle of Management and Guidance, high variability was observed in facilitators with "Management team support" at 27.78%, indicating weaker relationships. Obstacles also showed high variability with "Obstructive administration" at 27.27%. In the Cycle of Inspection and Administration, facilitators exhibited high variability with "Management team support" at 20.63%, indicating weaker relationships. Obstacles, characterized by "Family conflicts" at 18.60%, also showed high variability. Overall, facilitators exhibited moderate variability with "Management team support" being the highest at 22.35%, indicating some dominance by a few factors and thus moderate relationships. Obstacles showed high variability with "Obstructive administration" at 25.61%, indicating weaker relationships. Based on this analysis, stable and known educational situations were likely represented by cycles where variability was lower and relationships were stronger, such as the overall results for facilitators and obstacles. Unknown and uncertain educational situations were characterized by high variability and weaker relationships, as seen in the Cycle of Innovation, Cycle of Management and Guidance, and Cycle of Inspection and Administration.

The study [28] confirmed the Basic Hypothesis BH.0.0: "The level of uncertainty within an educational situation has a significant impact on the effectiveness of knowledge transfer as a co-creation process, with stable and known educational situations leading to stronger co-creation and positive learning environments compared to educational situations with large uncertainty." Cycles representing uncertain educational situations (Innovation, Management and Guidance, Inspection and Administration) demonstrated higher variability and weaker relationships among factors, indicative of a more dynamic and complex environment. The cycles with higher variability and weaker relationships showed poorer model fit, validating the hypothesis.

Educational Situations with Large Uncertainty: Second Assessment of Basic Hypothesis

To assess the hypotheses and determine if the basic hypothesis was accurate, the following educational situation was examined: the period of teaching from the onset of COVID-19. This period exemplified dealing with unexpected changes, significant uncertainty within educational settings, and the daily responses of all educational stakeholders to these challenges. The study [29] examined uncertainties articulated by high school students, their teacher and administration during COVID-19-induced educational disruption. By adopting a triadic perspective, the research differentiated between expectation-based and generative uncertainties, with the latter reflecting creative tension within the teaching and learning process. The paper [29] distinguishes between generative and non-generative uncertainties. Generative uncertainties, characterized by their potential to foster creative outcomes (e.g., innovative teaching methods, improved student engagement), are contrasted with other forms of uncertainty as non-generative outcomes (e.g., confusion, disengagement). To assess the impact of pandemic-induced uncertainties, the study examines whether they led to generative outcomes, such as innovative teaching methods or increased student engagement, or non-generative outcomes. The study [29] explored the relationship between these shifting expectations and the uncertainties inherent in the new educational environment.

The initial basic hypothesis, BH.0.0., was supported by previously published data [27-29] and can be considered valid within the analyzed conditions. The data suggests a positive correlation between the level of certainty and the effectiveness of knowledge transfer through co-creation. This supports the basic hypothesis that stable and known educational situations provide a stronger foundation for co-creation and a more positive learning environment. Furthermore, after reviewing existing research, the basic hypothesis can be rephrased.

Revised BH.0.0. The level of uncertainty in education significantly impacts knowledge transfer as a co-creation process. While stable educational contexts provide structure and facilitate easy cognition and learning, unforeseen challenges, can both hinder and enhance this process. When students assume responsibility in uncertain situations, it fosters innovation through creative tension. Conversely, excessive control or unrestricted freedom in learning can stifle this potential. University professors must confront their own fears regarding educational uncertainties to either create or encourage student agency, or risk losing their impact as teachers. Embracing uncertainty cultivates resilience and problem-solving skills in students, essential for success in complex professional environments.

Limitations and future research directions. Several limitations merit consideration. First, the data may not encompass the full spectrum of educational scenarios. Second, the inherent limitations of the data itself might restrict the understanding of the complexities of co-creation across diverse educational settings. Future research endeavors could address these limitations by investigating more thoroughly the interplay between educational uncertainties, co-creation styles, and learning outcomes within a broader range of educational contexts.

4. Conclusions

This study investigated the intricacies and dynamism inherent to higher education systems, particularly within the context of ITS. The research yielded several key findings and conclusions. The established structures and processes of the current higher education system were validated through their continued existence and functionality, confirming the effectiveness of the status quo in describing the present educational paradigm. However, further research is encouraged to explore potentially superior educational models. Traditional models focused solely on direct information transfer from instructor to student were found to be inadequate as they fail to account for individual learning styles and the dynamic nature of knowledge acquisition. This study proposes frameworks integrating scientific principles and mathematical models to enhance understanding and foster knowledge co-creation between educators and students. Mathematical models were employed to analyze learning processes in distinct educational contexts. The research underscores the necessity for personalized and adaptive teaching methods.

The FATE framework is crucial for the responsible development and use of AI in education. Further research is needed to bridge the gap between technical and descriptive definitions of FATE and foster collaboration between quantitative and qualitative methodologies. Traditional assessment methods were found to be insufficient in capturing the complexity and evolving nature of ITS knowledge. AI-powered assessments offer dynamic scenario-based evaluations and personalized learning experiences, catering to individual student needs and better preparing them for real-world challenges.

The study demonstrated that a student's individual knowledge grows in situations of educational uncertainty when real examples are provided by the university professor. The increase in students' knowledge, skills, and behavior begins with the courage applied by the university lecturer to overcome situations of wide educational uncertainty. Professional and everyday life often place us in situations of extensive uncertainty, where decisions must be made under time constraints and with limited knowledge from other sources. Teaching students to acquire knowledge under conditions of uncertainty is considered a productive approach in the pedagogy of engineering sciences. A reluctance to exert effort and a fear of uncertainty often hinder the intellectual growth of all participants in the educational process. Overreliance on prescribed curricula and textual sources can discourage critical thinking and decision-making, as teachers and students may be deterred from independent thought and action. Fostering reason and removing educational barriers is essential to cultivate the self-reliance of students.

This research advocates for a paradigm shift from traditional, one-size-fits-all educational models towards more dynamic, personalized, and adaptive learning approaches. By leveraging AI and adhering to ethical principles, educators can create more effective and equitable learning environments that cater to the unique needs of each student while responding to the evolving knowledge demands within the field of Intelligent Transportation Systems.

The present article has explored the limitations of traditional pedagogical methods in the university setting. As long as educators adhere strictly to the curriculum and navigate all constraints without critical examination, the teaching-learning-evaluation process will be placed in a false perspective, leading to potentially detrimental consequences. The findings presented in the actual article underscore the need for university teachers to embrace a more experimental pedagogical approach, venturing beyond established methodologies. By actively engaging with unconventional methods, educators can foster deeper student engagement and cultivate a more dynamic learning environment. This aligns with the evolving needs of a contemporary student body and paves the way for a more effective and impactful educational experience. In doing so, university teachers can contribute to a pedagogical evolution that empowers students to become not just learners, but active participants in the construction of knowledge, fostering a lifelong love of learning and ensure their continued existence.

Conflicts of Interest. The author declares no conflict of interest.

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Citation: Nantoi, V.; Nantoi, D.; Ceban, D. Challenges and solutions for integrating artificial intelligence into transportation engineering education. *Journal of Social Sciences* 2024, 7 (4), pp. 64-95. https://doi.org/10.52326/jss.utm.2024.7(4).06.

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