CHAPTER: 02

ARTIFICIAL INTELLIGENCE IN EDUCATION: EFFECTS ON DECISION-MAKING, HUMAN EFFORT, AND RISK MANAGEMENT

Dr. A.K. SINGH
Assistant Professor, Department of Applied Science,
RBS Engineering Technical Campus, Bichpuri, Agra (India)

Prof. B.K. SINGH
Director, RBS Engineering Technical Campus,
Bichpuri, Agra (India)

Prof. S.P. PANDEY
Professor & Dean, Department of Applied Science,
RBS Engineering Technical Campus, Bichpuri, Agra (India)

Ch.Id:-RBS/NSP/EB/ RAASTTSE/2024/Ch-02
DOI: https://doi.org/10.52458/9788197112492.nsp.2024.eb.ch-02

ABSTRACT

Artificial Intelligence (AI) is rapidly transforming educational environments by enhancing decision-making, automating tasks, and improving safety measures. While AI tools offer benefits such as streamlined administrative processes, personalized learning, and real-time risk management, they also present challenges. Increased reliance on AI for decision-making may lead to a reduction in human autonomy and critical thinking, as educators and students may become dependent on automated systems for guidance. Similarly, the ease provided by AI could foster reduced human effort and engagement, raising concerns about student motivation and active participation. However, AI's ability to monitor and predict potential risks adds a significant layer of safety, from preventing security breaches to ensuring safer learning environments. This study aims to explore the dual impacts of AI in education, examining both the positive advancements in efficiency and safety and the potential drawbacks in decision-making and human effort, to provide a balanced perspective on AI's evolving role in educational settings.

Keyword: *Artificial Intelligence, Education, Decision-Making, Human Effort, Risk Management, AI Dependency, Educational Technology, Student Engagement, Safety in Education.*

1. INTRODUCTION

Artificial Intelligence (AI) is reshaping the educational landscape by introducing powerful tools that enhance efficiency, personalize learning experiences, and reinforce safety protocols. As AI systems integrate into classrooms and administrative workflows, they offer substantial benefits in terms of streamlining decisions, supporting individualized instruction, and automating tasks that previously required significant human effort. However, this shift also brings challenges: the convenience of AI-assisted decision-making may inadvertently reduce human engagement and critical thinking, as educators and students rely increasingly on automated guidance. Additionally, as AI automates various processes, the effort exerted by students and teachers may decline, potentially impacting motivation and active learning. On the positive side, AI-driven risk management tools offer new levels of safety, enabling real-time monitoring and predictive insights to maintain secure learning environments. This introduction of AI into education prompts a nuanced examination of its effects on decision-making, human effort, and risk management, revealing both the promises and the limitations of an AI-enhanced educational system.

Starting from earlier studies, Thomas et al. (2013) conducted an experimental study examining how negotiation strategies influence knowledge-sharing intentions in buyer-supplier relationships. Their findings underscore the importance of strategic approaches to fostering effective communication, which is a foundational element in resilient supply chains. Building on the notion of agility in supply chain decisions, Tseng and Huang (2016) explored sustainable service provision, proposing agile rule induction as a way to enhance efficiency and adaptability within production systems. Further contributions by Wooster and Paul (2016) examined the positioning of leadership in U.S. firms investing in China, providing insights into strategic decision-making across international boundaries. In another context, Wessling et al. (2017) tackled issues of data integrity and misrepresentation, particularly in online research environments, shedding light on the importance of reliable data for accurate decision-making in business contexts. Topuz et al. (2018) advanced the conversation on decision-making models by proposing a Bayesian decision support model aimed at predicting kidney transplant outcomes. Their work highlights the applicability of advanced predictive models for decision-making in healthcare, which has parallels in optimizing supply chain processes through predictive analytics. In a more recent systematic review, Toorajipour et al. (2021) investigated the impact of artificial intelligence (AI) within supply chain management, identifying AI as a transformative force for improving efficiency and decision accuracy. In the domain of AI ethics and transparency, Zhdanov et al. (2022) emphasized the importance of incorporating fairness, accountability, and transparency (FAT) principles into AI-based business decision frameworks. They argued that ethical considerations are critical to maintaining stakeholder trust and effective decision-making. Yang et al. (2023) extended this research by developing an interpretable system to analyze the effects of COVID-19 interventions on stock market performance, demonstrating the role of explainable AI in evaluating complex real-world impacts. Yu et al. (2023) investigated employees' perceptions of AI transparency, suggesting that clear and open AI models can positively influence trust and engagement. Most recently, Sadeghi et al. (2024) focused on explainable AI within the context of supply chain cyber resilience. Their study offers insights into how explainable AI can support agile decision-making, enabling businesses to better navigate cyber risks and strengthen their resilience in an increasingly digitalized environment. In summary, the evolution of research from traditional strategic approaches to integrating AI and ethical considerations illustrates the growing complexity and technological advancements in supply chain decision-making. These studies collectively highlight the importance of adaptability, transparency, and ethical frameworks in enhancing resilience and trust within modern supply chains.

2. DECISION-MAKING LOSS

AI systems often automate or assist in decisions, potentially reducing human involvement. The level of decision-making loss (D) can be modeled as a function of AI dependency and human engagement in decision-making processes.

$$D(t) = \alpha\left(1 - \frac{H(t)}{H_0}\right) \quad (1)$$

where:

$D(t)$ is the decision-making loss over time ttt,

α represents the rate at which decision-making is influenced by AI

$H(t)$ denotes the level of human engagement in decision-making at time ttt,

H_0 is the initial human engagement level without AI influence.

3. LAZINESS (REDUCTION IN ACTIVE EFFORT)

AI may influence laziness (L), or the reduction in human active effort, especially as tasks become automated. The laziness index can be a function of task automation (A) and the level of reliance on AI tools.

$$L(t) = \beta . A(t) . \{1 - E(t)\} \quad (2)$$

where:

$L(t)$ is the laziness index at time t,

β is a coefficient reflecting the impact of automation on human effort,

$A(t)$ represents the degree of task automation by AI at time t,

$E(t)$ is the effort or engagement level by humans, reducing laziness when high.

4. SAFETY IN EDUCATION

AI enhances safety in education by providing tools for monitoring and predicting risks. A safety index (S) can model this impact, taking into account risk reduction provided by AI (R) and initial safety levels (R_0).

$$S(t) = S_0 + \gamma . R(t) \quad (3)$$

where:

$S(t)$ is the safety level in education at time ,

S_0 represents the baseline safety level without AI intervention,

γ is a scaling factor indicating the effectiveness of AI in enhancing safety,

$R(t)$ is the risk reduction achieved through AI monitoring and prediction tools.

5. COMBINED IMPACT MODEL

The combined model for the impact of AI on education could be represented as:

where:

$I(t)$ is the overall impact of AI in education at time t,

w_1, w_2, and w_3 are weights representing the importance of decision-making loss, laziness, and safety in the overall impact.

6. SOLUTION PROCESS

Assume that human engagement $H(t)$ decreases exponentially over time due to increasing reliance on AI, modeled as:

$$H(t) = H_0 e^{-\lambda t} \quad (4)$$

where λ is a positive constant representing the rate of reduction in human engagement.

Substituting $H(t)$ into the decision-making loss equation:

$$D(t) = \alpha\left(1 - \frac{H_0 e^{-\lambda t}}{H_0}\right) \Rightarrow D(t) = \alpha\left(1 - e^{-\lambda t}\right) \tag{5}$$

Assume the task automation level $A(t)$ increases over time and the human effort level $E(t)$ decreases exponentially. Let:

$$A = A_0(1 - e^{-\mu t}) \tag{6}$$

$$E = E_0 e^{-\nu t} \tag{7}$$

where A_0 is the maximum level of task automation, E0E_0E0 is the initial level of human effort, and μ and ν are constants representing the rates of change for automation and effort, respectively.

Substituting into the laziness equation:

$$L(t) = \beta A_0(1 - e^{-\mu t})(1 - E_0 e^{-\nu t}) = \beta A_0\left(1 - e^{-\mu t} - E_0 e^{-\nu t} + E_0 e^{-(\mu+\nu)t}\right) \tag{8}$$

Assume that the risk reduction $R(t)$ increases due to AI, following an exponential function:

$$R(t) = R_0(1 - e^{-\sigma t}) \tag{9}$$

where R_0 is the maximum achievable risk reduction level and σ represents the effectiveness rate of AI in risk management.

Substitute $R(t)$ into the safety equation: $S(t) = S_0 + \gamma R_0(1 - e^{-\sigma t})$ (10)

Using the analytic solutions from the individual components, we substitute $D(t)$, $L(t)$, and $S(t)$ into the combined impact model:

$$I(t) = \omega_1 D(t) + \omega_2 L(t) + \omega_3 S(t) \tag{11}$$

$$I(t) = \alpha\omega_1\left(1 - e^{-\lambda t}\right) + \omega_2\beta A_0\left(1 - e^{-\mu t} - E_0 e^{-\nu t} + E_0 e^{-(\mu+\nu)t}\right) + \omega_3 S_0 + \gamma R_0(1 - e^{-\sigma t}) \tag{12}$$

7. NUMERICAL SIMULATION

Let's define typical values for the parameters based on hypothetical scenarios where AI's influence grows over time in educational settings:

(i) Decision-Making Loss:

$\alpha = 0.8$: Moderate sensitivity to AI's effect on decision-making.

$\lambda = 0.3$: Gradual reduction in human decision-making engagement.

(ii) Laziness (Reduction in Active Effort):

$\beta = 0.6$: High impact of automation on human effort.

$A_0 = 1.0$: Maximum level of task automation.

$\mu = 0.25$: Growth rate of automation over time.

$E_0 = 0.7$: Initial human effort level.

$\nu = 0.2$: Gradual decrease in human effort.

(iii) Safety in Education:

$S_0 = 0.7$: Baseline safety level.

$\gamma = 0.5$: Moderate contribution of AI to safety.

$R_0 = 1.0$: Maximum achievable risk reduction.

$\sigma = 0.4$: Rate of safety enhancement by AI.

(iv) Weights:

$w_1 = 1.2$: High weight on decision-making loss.

$w_2 = 1.0$: Moderate weight on laziness.

$w_2 = 1.3$: High weight on safety.

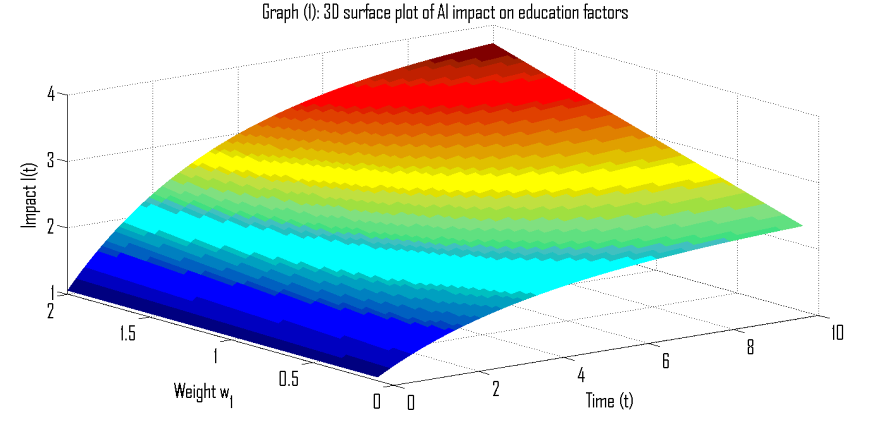
Table 1: Yearly Impact of AI on Education: Analysis of Decision-Making Loss, Laziness, Safety, and Overall Impact

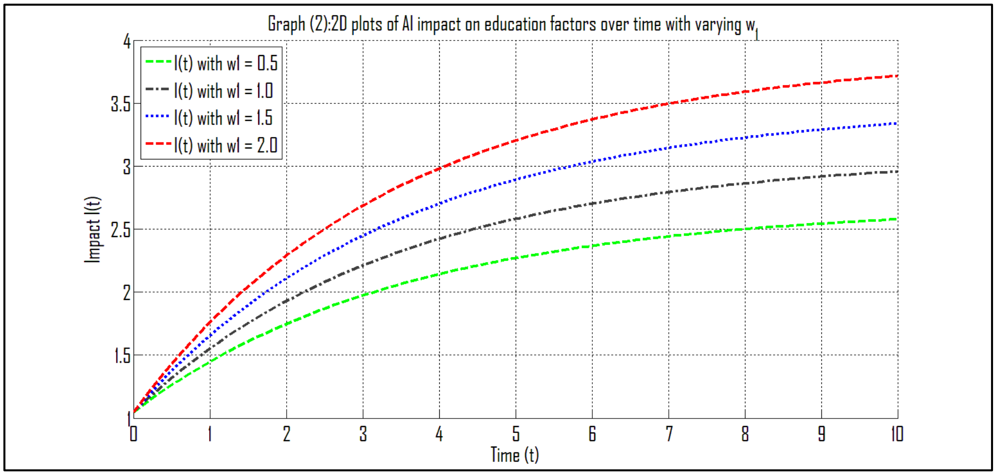
Year	Decision-Making Loss (D(t)	Laziness (L(t))	Safety (S(t))	Impact (I(t))
0	0	0	0.7	0.91
1	0.207345423	0.056656438	0.864839977	1.429762916
2	0.360950691	0.125306442	0.975335518	1.826383445
3	0.474744272	0.194960091	1.049402894	2.12887698
4	0.55904463	0.259979703	1.099051741	2.359600523
5	0.621495872	0.317855431	1.132332358	2.535682543
6	0.667760889	0.36784665	1.154641023	2.670193048
7	0.702034857	0.410162802	1.169594969	2.773078091
8	0.727425637	0.445478256	1.179618898	2.851893588
9	0.74623559	0.47465233	1.186338139	2.912374618
10	0.760170345	0.49857396	1.190842181	2.95887321

The table (1) summarizes how artificial intelligence (AI) affects various aspects of education over a 10-year period. Each column represents a different aspect: **Decision-Making Loss** $D(t)$, Laziness $L(t)$, Safety $S(t)$, **and** Impact $I(t)$. The table shows a steady increase in decision-making loss and laziness, suggesting a gradual decline in human engagement and effort as AI becomes more prominent in educational settings. The safety factor also improves over time, reflecting AI's role in enhancing monitoring and security measures. The final column, impact $I(t)$, is a cumulative measure that integrates these factors and shows a consistent upward trend. This increase in $I(t)$ over the years highlights the growing influence of AI on education, with both positive and negative implications on human roles and safety within the educational environment.

8. RESULTS AND DISCUSSION

Graph (I): 3D surface plot of AI impact on education factors





Graph (2):2D plots of AI impact on education factors over time with varying w_1

The 3D surface plot in graph (1) visualizes the impact of artificial intelligence (AI) on educational factors over time, with varying emphasis on decision-making loss (represented by weight w_1). The x-axis represents time, indicating how the impact evolves over a 10-year period. The y-axis represents weight w_1, showing different levels of importance placed on the decision-making component in the overall impact. The z-axis shows the total impact w_1, which combines effects on decision-making, human effort (laziness), and safety in education. The color gradient, ranging from blue at lower values to red at higher values, illustrates the magnitude of the impact. As both time and weight w_1 increase, the impact grows significantly, reaching higher values, which suggests that increased reliance on AI and higher weight on decision-making loss correlate with a stronger overall impact on education. This plot effectively demonstrates how the interaction between time and emphasis on decision-making influences the cumulative impact of AI on educational settings.

The 2D plot in graph (2) illustrates the impact of artificial intelligence (AI) on education over time, with various levels of emphasis on decision-making loss, represented by different values of weight w_1. The x-axis shows time, representing a 10-year period, while the y-axis shows the total impact $I(t)$, which combines effects on decision-making, human effort (laziness), and safety in education. Each curve corresponds to a different w_1 value: green for $w_1 = 0.5$, black for $w_1 = 1$, blue for $w_1 = 1.5$, and red for $w_1 = 2.0$. As w_1 increases, the impact $I(t)$ becomes larger over time, indicating that placing a greater emphasis on decision-making loss leads to a more pronounced overall impact of AI in education. This suggests that decision-making plays a critical role in the cumulative effect of AI, and higher weights accelerate this impact, showing steeper curves as w_1 increases. This visualization effectively demonstrates how varying the importance of decision-making influences the overall impact trajectory.

9. CONCLUDING REMARKS

In conclusion, artificial intelligence presents a transformative yet complex influence on the educational sector, offering clear benefits in decision-making support, efficiency, and safety, while also introducing new considerations for human involvement and autonomy. AI enhances learning experiences by tailoring instruction and automating routine tasks, allowing educators to focus on higher-level teaching activities. However, these advancements come with potential downsides, as dependence on AI systems can reduce human effort and critical engagement, potentially diminishing skills in decision-making and problem-solving over time. Additionally, while AI contributes to safer learning environments, the reliance on technology raises questions about maintaining a balance between automation and active human oversight. As AI continues to evolve, a balanced approach that harnesses its advantages while preserving human agency and engagement will be essential to fostering an educational environment that prepares students for a future in which technology and human capabilities work in harmony.

REFERENCES

1. *Sadeghi K., Ojha D., Kaur P., Mahto R.V., Dhir A. (2024): "Explainable artificial intelligence and agile decision-making in supply chain cyber resilience", Decision Support Syatem, 180:114194.*

2. *Thomas S.P., Thomas R.W., Manrodt K.B., Rutner S.M. (2013): "An experimental test of negotiation strategy effects on knowledge sharing intentions in buyer-supplier relationships",* Journal of Supply Chain Management*, 49(2):96–113.*

3. *Toorajipour R., Sohrabpour V., Nazarpour A., Oghazi P., Fischl M. (2021): "Artificial intelligence in supply chain management: A systematic literature review",* Journal of Business Research*, 122:502–517.*

4. *Topuz K., Zengul F.D., Dag A., Almehmi A., Yildirim M.B. (2018): "Predicting graft survival among kidney transplant recipients: A Bayesian decision support model",* Decision Support Systems*, 106:97–109.*

5. *Tseng T.-L.B., Huang C.-C. (2016): "Sustainable service and energy provision based on agile rule induction",* International Journal of Production Economics*, 181:273–288.*

6. *Wessling K.S., Huber J., Netzer O. (2017): "MTurk character misrepresentation: Assessment and solutions",* Journal of Consumer Research*, 44(1):211–230.*

7. *Wooster R.B., Paul D.L. (2016): "Leadership positioning among U.S. firms investing in China",* International Business Review*, 25(1):319–332.*

8. *Yang C., Abedin M.Z., Zhang H., Weng F., Hajek P. (2023): "An interpretable system for predicting the impact of COVID-19 government interventions on stock market sectors",* Annals of Operations Research*, 1–28.*

9. *Yu L., Li Y., Fan F. (2023): "Employees' appraisals and trust of artificial intelligences' transparency and opacity",* Behavioral Sciences*, 13(4):344.*

10. *Zhdanov D., Bhattacharjee S., Bragin M.A. (2022): "Incorporating FAT and privacy aware AI modeling approaches into business decision making frameworks",* Decision Support Systems*, 155:113715.*