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A digital learning model with artificial intelligence to increase the flexibility and accessibility of education

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Abstract

This study aims to address the challenges of unstructured learning and information overload in digital education by developing and analyzing a digital learning model integrated with artificial intelligence (AI) to enhance the flexibility and accessibility of education. The methodology is based on system analysis and simulation modeling. A mathematical model was created to describe the interaction between learners, the digital platform, and educational content, incorporating key parameters for flexibility, accessibility, and knowledge acquisition. This model was then modified to assess the impact of AI on platform adaptability, content interactivity, student motivation, and learning rate. The simulation was implemented in Python using the NumPy and Matplotlib libraries. The simulation results demonstrate that while AI tools for adaptability and interactivity increase system flexibility, their overall impact on effectiveness is limited by a plateau effect. The most significant improvements in overall effectiveness are driven by AI components that optimize knowledge acquisition (AIk) and student motivation (AIm). Accessibility remained constant throughout the simulations, indicating that it requires separate optimization strategies beyond the pedagogical scope of this model. The model provides practical recommendations for educational institutions, prioritizing investments in AI solutions for personalization and motivation to achieve the greatest impact on learning outcomes. The proposed framework can serve as a foundation for designing and implementing next-generation intelligent learning systems. This study confirms that the strategic integration of AI can significantly increase the flexibility and effectiveness of digital learning. The findings underscore the importance of focusing AI implementation not just on technological features but on core pedagogical drivers like student motivation and optimized knowledge acquisition.

Keywords: Adaptive learning, Artificial intelligence, Digital learning, Educational model, E-learning, Education accessibility, Personalized learning, Simulation modeling.

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1. Introduction

Digital educational resources are becoming an integral part of the learning process, providing new opportunities for learning and development. Like any innovative solution, they have their advantages and disadvantages. One such disadvantage is the increasing number of digital educational resources. On the one hand, the abundance of digital educational resources offers unlimited opportunities for learning and self-development, but on the other hand, it requires students to possess critical thinking skills, self-organization, and a responsible attitude toward selecting educational materials. As the number of available resources grows, it becomes more challenging to assess their reliability and quality, and students must spend time filtering out unreliable or poor-quality sources. An uncontrolled multitude of resources can lead to unstructured or fragmented learning, especially if there is no clear curriculum or mentoring. Additionally, not all students have equal access to technology and the internet, which exacerbates educational inequality. A comprehensive approach to the use of digital resources through the development of a digital learning model could address these issues. For example, the study Ingavélez-Guerra et al. [1] proposes a methodology for the automatic adaptation of educational resources to enhance their accessibility, particularly for students with disabilities. Furthermore, the study identified the real needs of students, including the necessity for high-quality image descriptions (alternative text), accurate subtitles for videos, and audio-to-text conversion.

The next article, Kaouni et al. [2] proposes the design and model of an intelligent, dynamic, and adaptive learning system based on artificial intelligence to create a personalized learning environment. The result of the work is the proposed system model itself, the main goal of which is to identify the individual needs of the student and provide them with learning materials and processes tailored to them. The study Suryanarayana et al. [3] examines how artificial intelligence (AI) and machine learning can improve digital learning in education management systems. The use of AI has been proven to assess student performance, predict their personal qualities to recommend suitable courses, and improve administrative processes, such as automatic equipment maintenance planning. It is noted that AI is generally capable of improving student outcomes and their learning experience. Article Saborío-Taylor and Rojas-Ramírez [4] explores the intersection of Universal Design for Learning (UDL) and artificial intelligence (AI) principles and their combined impact on creating an inclusive and autonomous learning environment. It demonstrates how the synergy of UDL and AI can transform education.

2. Literature Review

An analysis of scientific literature shows that, despite the enormous and widely recognized potential of artificial intelligence (AI) in transforming education, its practical integration faces a number of systemic and as yet unresolved problems. For clarity, we have grouped existing research into three key areas: the use of AI to create adaptive learning environments, the main problems and ethical challenges of its implementation, and the need to create holistic models to overcome technological fragmentation. Previous studies have also highlighted both the opportunities and potential risks of AI in education and underscored the need for a strategic and pedagogically sound approach [5].

2.1. AI For Personalization and Adaptive Learning

One of the most actively researched areas is the use of AI to create personalized and adaptive learning systems. Such systems are designed to adapt to the unique needs of each student. For example, Kaouni et al. [2] propose a model of an intelligent and dynamic learning system, the main goal of which is to identify the individual needs of students and provide them with tailored materials. Study Tapalova and Zhiyenbayeva [6] also offers a conceptual framework for the application of AI in education (AIEd) with the aim of creating personalized learning trajectories..

Numerous studies confirm the effectiveness of this approach. A systematic review of the literature [7] shows that AI and machine learning (ML) can optimize educational trajectories, increase student engagement, and improve academic performance, which in some cases is confirmed by higher test scores. Similarly, a study by Sajja et al. [8] notes that AI improves learning efficiency by allowing students to learn at their own pace and receive individualized feedback through intelligent learning systems. Specialized platforms are being created to solve specific problems, such as AIIA, an AI-based intelligent assistant for personalized learning in higher education [9].

Despite the obvious advantages, the authors note that the practical implementation of such systems remains a challenging task. Articles by Hashim et al. [9] and Chandramma et al. [10] emphasize that, despite the proposed architectures and concepts, their implementation and overcoming the accompanying difficulties remain tasks for the future, especially in regions with low levels of implementation and support for these technologies.

2.2. Implementation Issues and Ethical Aspects

In parallel with the development of new technologies, researchers are actively studying the barriers to their widespread implementation. One of the main problems is the high cost and technical limitations. For example, Ghosh and Ravichandran [11] discuss AI technologies for improving the accessibility of e-learning for students with disabilities, but note that their potential is limited by high implementation costs and current technical limitations. Practical implementation challenges, including high costs and the need to train teachers, are also identified as key issues in Vistorte et al. [12].

Data privacy is another serious obstacle pointed out by many authors [7, 11, 13]. When creating personalized systems, it is necessary to collect and analyze large amounts of data about students, which creates risks of misuse.

Finally, social and ethical issues cannot be ignored. The work of Kamalov et al. [14] emphasizes that, although AI contributes to the creation of personalized experiences and the reduction of educational inequality, ethical considerations related to its implementation must be taken into account. The study Tapalova and Zhiyenbayeva [6] also acknowledges that AI can give rise to serious social and ethical problems for humanity, which need to be addressed as education becomes increasingly digitized. Moreover, AI will lead to a radical transformation of the labor market, which poses a complex challenge for the education system to completely overhaul curricula and teaching methods to prepare people for the new reality [15, 16].

2.3. The Need for Holistic Models and Overcoming Fragmentation

Many studies point to the fragmentation of existing technological solutions. Analysis Whalley et al. [17] notes the convergence of technologies (mobility, interactivity, AI), but emphasizes that their use in education remains fragmented. The authors point to the urgent need to integrate and unify existing approaches into a single, student-centered pedagogical framework [18]. Similarly, article Strielkowski et al. [19] states that, despite the possibility of creating personalized learning environments using mobile devices, the question of how existing university structures should change for their successful integration remains unresolved.

Various conceptual models are proposed to address this issue. For example, the article Almaiah et al. [20] proposes a new paradigmatic model to help identify the most important factors for improving e-learning using cloud technologies. However, the practical implementation and testing of such models remain tasks for the future [20, 21]. Further research is needed on how higher education institutions can make sense of digital transformation and adapt effectively to meet the demands of the new industrial revolution [22]. In hybrid education, AI has the potential to increase student engagement, but optimal implementation approaches still require further research and validation [23].

Thus, a review of the literature reveals a key contradiction: on the one hand, there are many studies devoted to individual AI tools and their potential, and on the other hand, there is an acute shortage of comprehensive, holistic models that describe the systemic impact of AI on the flexibility, accessibility, and effectiveness of digital learning as a whole. Existing approaches are fragmented, and their practical implementation faces serious technical, economic, and ethical barriers. This study aims to fill this gap by developing and analyzing a holistic model that not only integrates technological tools but also proposes a strategy for their effective application.

3. Materials and Methods

The methodology employed is based on system analysis and simulation modeling. The theoretical framework incorporates prior research on adaptive learning [18] and artificial intelligence in education [5]. The study was carried out in three sequential stages.

The first stage involved model development, where equations were derived according to the balance of components, and coefficients (γ, δ, ε, η) were determined empirically; for instance, γ was assigned a value of 0.5. The second stage consisted of simulation, implemented using Python with the NumPy and Matplotlib libraries. Parameters were varied incrementally by 0.01 across 100 points, while other parameters remained fixed at baseline values, such as Ts equal to 0.7 and Qc equal to 0.85. The third stage entailed analysis, which included the construction and interpretation of dependency graphs, focusing on the growth and plateau phases of E'.

This methodological approach ensures reproducibility; however, limitations include the exclusion of stochastic factors.

The model describes a digital educational system as the interaction of three subsystems: learners (S), the digital platform (P), and educational content (C). The baseline model without artificial intelligence (AI) is defined by the following equations:

Flexibility is defined as the weighted sum of normalized parameters:

$$F = w_1 T_s + w_2 A_p + w_3 I_c \quad (1)$$

where T_s represents the normalized time allocated by the student ($0 \leq T_s \leq 1$), A_p is the platform's adaptability ($0 \leq A_p \leq 1$), I_c is the interactivity of the content ($0 \leq I_c \leq 1$), and w_1, w_2, w_3 are weights satisfying $w_1+w_2+w_3=1$.

Accessibility is expressed as:

$$A = \min(1, \frac{D_p R_c}{C_p}) \quad (2)$$

where D_p is the technical accessibility of the platform ($0 \leq D_p \leq 1$), R_c is the content accessibility ($0 \leq R_c \leq 1$), and C_p is the platform cost ($0 < C_p \leq 1$), normalized relative to minimum costs.

Knowledge Acquisition is given by:

$$K = M_s\, Q_c(1 - e^{-aT_s}), \qquad (3)$$

where M_s is the student's motivation ($0 \leq M_s \leq 1$), Q_c is the quality of the content ($0 \leq Q_c \leq 1$), and α is the learning rate coefficient ($0 < \alpha \leq 1$), reflecting the speed of learning.

Effectiveness is calculated as:

$$E = \beta_1 F + \beta_2 A + \beta_3 K, \qquad (4)$$

where β_1, β_2, β_3 satisfy $\beta_1 + \beta_2 + \beta_3 = 1$.
Integration of AI modifies the model parameters:

$$A_p{}' = \min\,(1, A_p(1 + \gamma AI_a)) \qquad (5)$$

$$I_c' = \min\,(1, I_c(1 + \delta AI_c)) \qquad (6)$$

$$M_s' = \min\,(1, M_s(1 + \varepsilon AI_m)) \qquad (7)$$

$$\alpha' = a(1 + \eta AI_k) \qquad (8)$$

where $A_p{}'$ – platform adaptability, $I_c{}'$ – content interactivity, $M_s{}'$ – student motivation, α' – learning rate coefficient.

The updated indicators F' and K' (using A_p', I_c', M_s' and α') are incorporated into E'. The model includes additional parameters to account for costs as:

$$C_p \geq C_{min} + kAI_{cost} \qquad (9)$$

where κ is the cost dependence coefficient on AI, and $AI_{cost} \in [0,1]$ represents AI-related expenses. All parameters are normalized to ensure universality.

4. Results

The simulation in Python shows the dependence of key indicators of the digital learning model (F' - flexibility, A - accessibility, K' - knowledge acquisition, E' - overall effectiveness) on one variable parameter in the range [0, 1]. The interpretation takes into account the mathematical model: F' - depends on adaptability and interactivity, K' - on motivation, content quality, and time, A - on infrastructure and cost (remains constant, as it does not depend on the variable parameters), E' - the weighted sum of F', A, and K'. The graphs show how changes in AI parameters or other factors affect the effectiveness of education.

Figure 1 shows that increasing AI's role in platform adaptability (AI_a) leads to a significant rise in system flexibility (F') from approximately 0.7 to 0.8, before stabilizing. This confirms that AI-driven personalization directly enhances the variety of learning paths available to students. However, the effect reaches a plateau, suggesting that adaptability alone has diminishing returns on overall effectiveness (E'), which shows only a modest increment from ~0.65 to ~0.7. Accessibility (A) and Knowledge Acquisition (K') remain constant, indicating that AI adaptability operates independently of these factors within the model's framework. This implies that while AI_a is beneficial, its impact is limited without corresponding improvements in other areas.

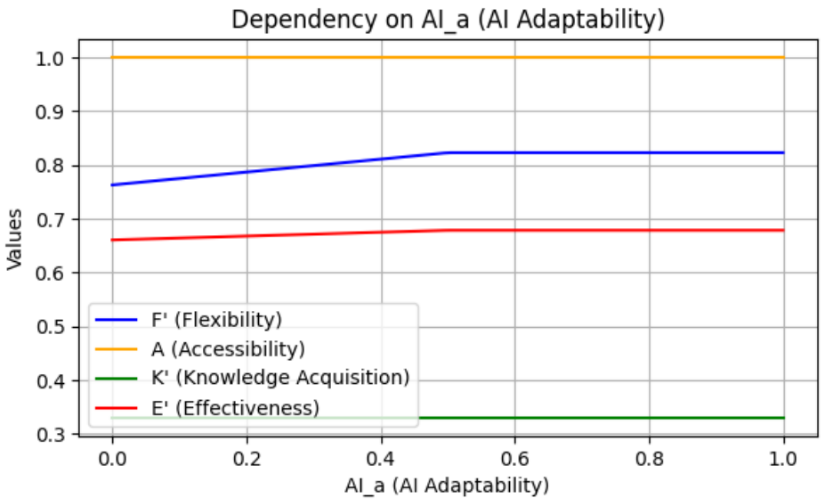

Figure 1.
Dependency on AI_a (AI Adaptability).

Figure 2 demonstrates that enhancing content interactivity through AI (AI_c) produces a similar effect to improving adaptability. It leads to a linear increase in system Flexibility (F') from approximately 0.7 to approximately 0.85, as more interactive content provides a richer, more varied learning experience. However, this improvement in flexibility only translates into a slight increase in overall Effectiveness (E'), while Knowledge Acquisition (K') remains unaffected. This result suggests that while interactivity is a valuable feature for user engagement, its direct impact on core learning outcomes is limited within the model, highlighting the need to combine it with other AI-driven pedagogical strategies.

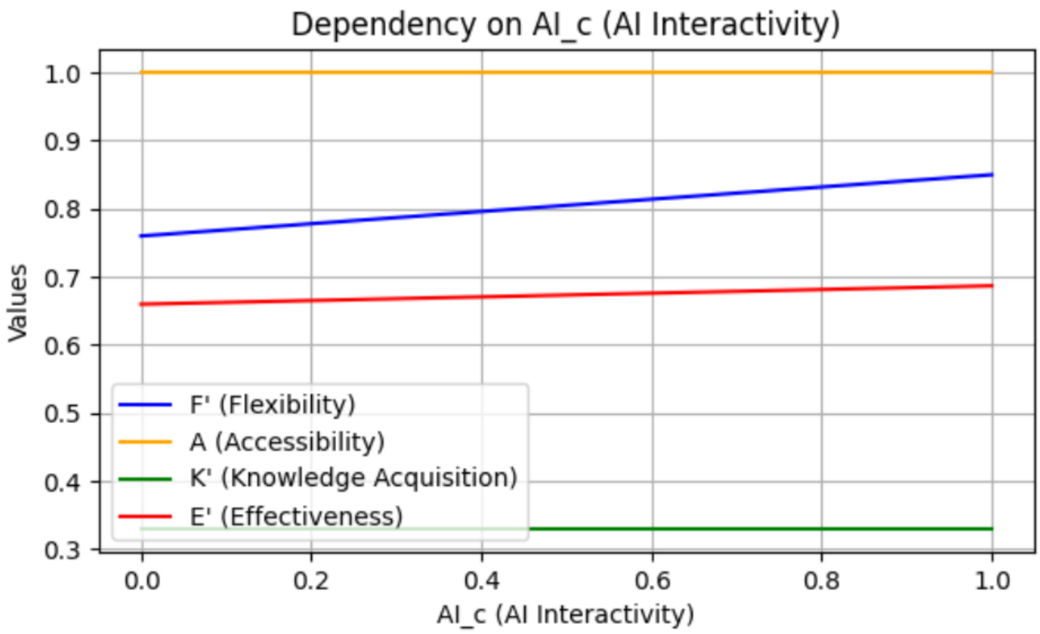

Figure 2.
Dependency on AI_c (AI Interactivity).

The dependency on AI-driven motivation (AI_m), shown in Figure 3, reveals a critical insight into the model. While Flexibility (F') and Accessibility (A) remain constant, Knowledge Acquisition (K') exhibits a significant linear increase from approximately 0.25 to approximately 0.35. This directly boosts overall Effectiveness (E') from approximately 0.65 to approximately 0.7 without reaching a plateau. This finding underscores the profound impact of psychological factors, suggesting that AI tools designed to enhance student motivation are a powerful lever for improving educational outcomes, even without altering the platform's technical features.

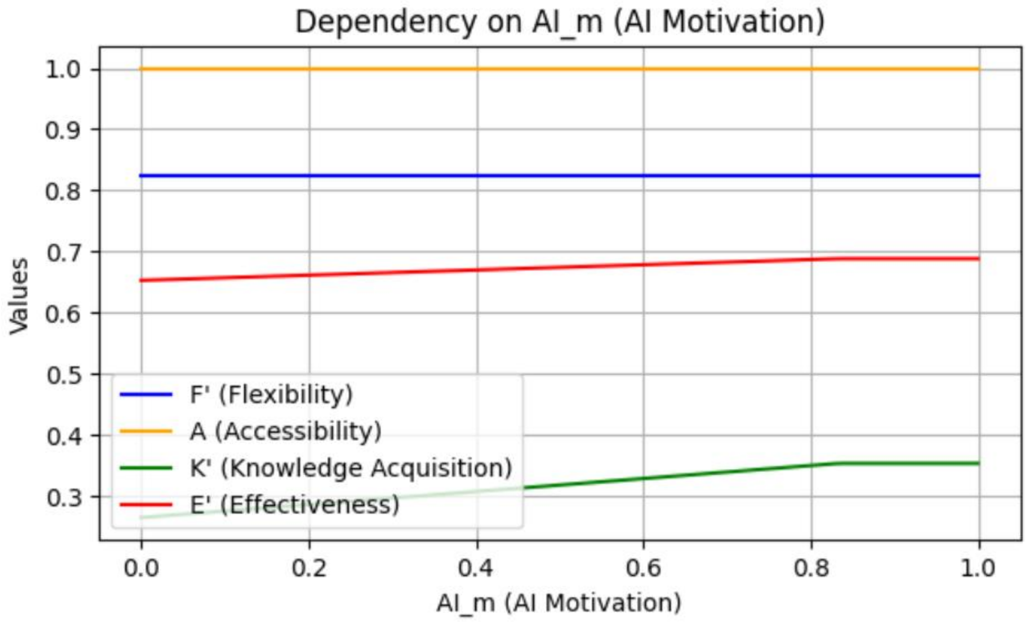

Figure 3.
Dependency on AI_m (AI Motivation).

Figure 4 illustrates the powerful influence of AI dedicated to optimizing the learning process (AI_k). As AI_k increases, there is a sharp, non-linear rise in Knowledge Acquisition (K') from approximately 0.2 to approximately 0.4. This is the most direct and significant improvement in learning observed in the simulations, which in turn drives substantial growth in overall Effectiveness (E') from approximately 0.6 to approximately 0.7. The non-linear nature of the growth suggests that initial investments in AI tools that accelerate learning yield the highest returns. This positions AI_k as a primary factor for enhancing the core educational function of a digital platform.

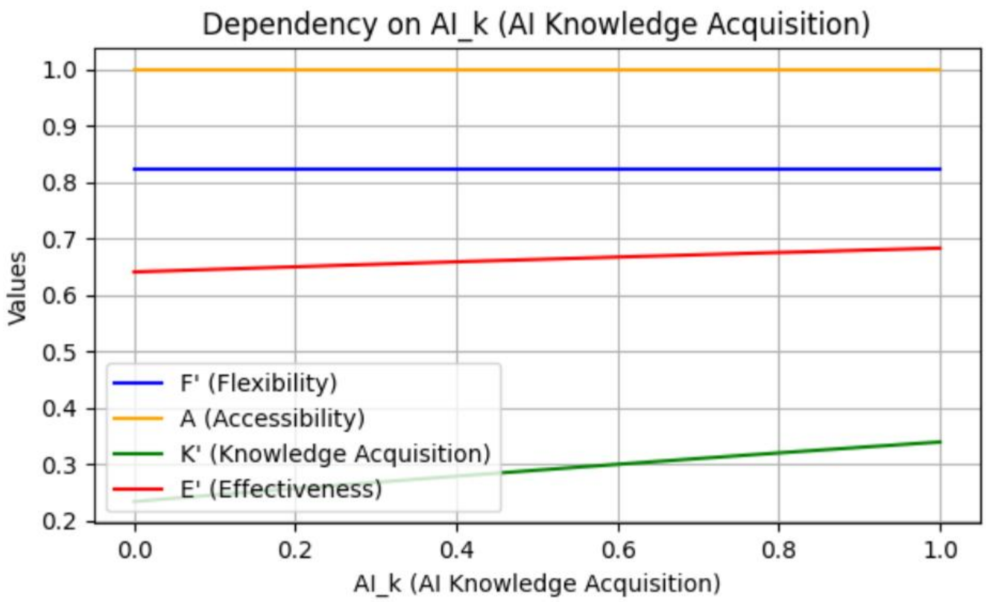

Figure 4.
Dependency on AI_k (AI Knowledge Acquisition).

The model's dependency on student time (Ts), depicted in Figure 5, highlights the importance of a fundamental, non-AI factor. Increasing the time a student allocates to learning simultaneously boosts Flexibility (F') linearly and Knowledge Acquisition (K') non-linearly. Consequently, Effectiveness (E') shows strong growth from approximately 0.4 to approximately 0.75. However, the curve for knowledge acquisition begins to flatten, demonstrating the principle of diminishing returns: after a certain point, simply spending more time becomes less efficient without high-quality content and strong motivation. This reinforces that time is a necessary but not sufficient condition for effective learning.

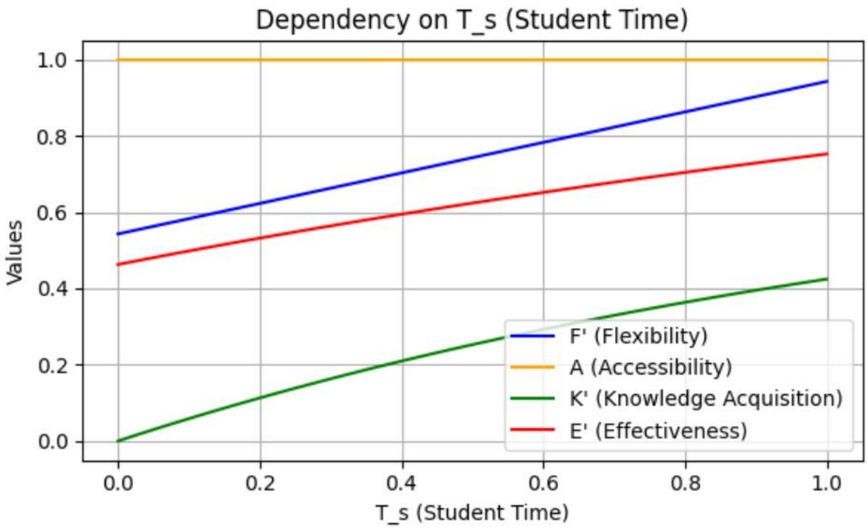

Figure 5.
Dependency on T_s (Student Time).

Figure 6 analyzes the impact of content quality (Q_c), another foundational element of the educational process. The graph shows that Flexibility (F') and Accessibility (A) are independent of content quality. However, there is a direct and linear relationship between Q_c and both Knowledge Acquisition (K') and overall Effectiveness (E'). This result is highly intuitive and crucial: it demonstrates that no amount of AI-driven personalization or interactivity can compensate for poor-quality educational materials. High-quality content acts as a direct multiplier for learning effectiveness, making it a critical prerequisite for a successful digital learning system.

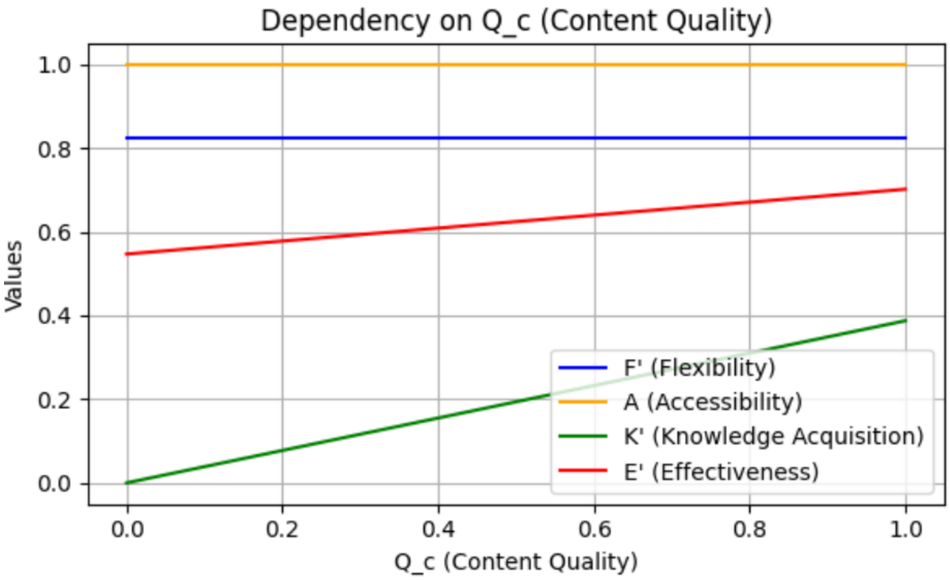

Figure 6.
Dependency on Q_c (Content Quality).

The collective analysis of the graphs affirms that AI parameters (AI_a, AI_c, AI_m, AI_k) alongside T_s and Q_c augment Effectiveness (E') through improvements in flexibility or knowledge acquisition, while Accessibility (A) necessitates separate optimization, potentially through reducing C_p. The most pronounced influence emanates from AI_k and T_s, advocating for a strategic emphasis on accelerating knowledge acquisition and optimizing student time allocation to enhance both flexibility and accessibility within educational frameworks.

5. Discussion

The simulation results effectively demonstrate how integrating artificial intelligence (AI) can enhance key indicators of digital learning, confirming our initial hypothesis. The dependencies of flexibility (F'), knowledge acquisition (K'), and overall effectiveness (E') on various AI parameters, as well as on student time (T_s) and content quality (Q_c), not only validate the model's logic but also offer insights that resonate with the unresolved challenges identified in the current literature.

The increase in flexibility (F') driven by AI adaptability (AI_a) and interactivity (AI_c) directly addresses the issue of technological fragmentation highlighted in the study [10]. That work points to an urgent need for a unified, student-centered pedagogical framework. Our model shows that AI can serve as the integrating force, creating a more cohesive and personalized learning environment. However, the observed plateau effect, where effectiveness (E') ceases to grow despite further increases in AI^a or AI_c, suggests that technology alone is not a panacea. This finding aligns with the broader academic discourse emphasizing that successful integration requires systemic changes in university structures and pedagogy, not just technological upgrades [18].

The most profound impact is observed in knowledge acquisition (K'), which is significantly boosted by AI-driven motivation (AI_m) and learning optimization (AI_k). The enhancement of student motivation offers a direct solution to the persistent challenge of maintaining student engagement, a key unresolved issue in hybrid learning environments identified in the study [22]. Furthermore, the optimization of the learning rate via AI_k provides a practical mechanism for creating adaptive systems and personalized learning pathways called for in numerous studies [6, 14, 17]. While our model proves the concept, it also implicitly touches upon the complexity of AI/ML systems, a concern raised in the literature [6].

The dependencies on student time (T_s) and content quality (Q_c) reinforce a critical point: AI complements, not replaces, fundamental educational elements. This finding supports the argument that technology's role is to amplify good pedagogy, a theme echoed in studies discussing the need for teacher training and strategic resource allocation [8]. Even a perfectly optimized AI system, as our model suggests, cannot overcome the limitations of poor-quality content or insufficient student time allocation, highlighting the continued importance of "human factors" in the digital age.

Finally, the limitations of our model correspond to some of the most pressing unresolved issues in the field. The treatment of accessibility (A) as a constant parameter underscores that our simulation focuses on pedagogical effectiveness, leaving aside the critical real-world barriers of high implementation costs, data privacy, and the digital divide—major concerns cited repeatedly in the literature [5, 6, 8, 19]. This simplification highlights that achieving true accessibility requires policy and infrastructure solutions beyond the scope of a purely mathematical model. Moreover, the model's deterministic nature does not account for complex socio-economic factors and calls for empirical validation on real-world educational platforms. This is a necessary next step to bridge the gap between theoretical frameworks and practical implementation, a challenge noted by multiple researchers [9, 13, 15].

6. Conclusion

The proposed mathematical model of digital learning with AI integration successfully demonstrates the potential for significantly increasing the flexibility and effectiveness of education. Our key finding is that the greatest improvements in effectiveness are driven not merely by enhancing technological features like adaptability and interactivity, but by leveraging AI to directly support core pedagogical goals: optimizing knowledge acquisition (AI_k) and strengthening student motivation (AI_m). This insight confirms the central hypothesis that AI's primary value lies in its capacity for deep personalization and motivational support. The model also reinforces the foundational importance of human factors, showing that sufficient student time (T_s) and high-quality content (Q_c) are indispensable for achieving learning outcomes, regardless of technological sophistication.

From these findings emerge practical recommendations: for the greatest impact, educational institutions should prioritize investments in AI systems that personalize the learning process and actively foster student motivation. While enhancing platform flexibility is valuable, it yields diminishing returns if not paired with a focus on knowledge acquisition. To improve accessibility, efforts should be directed at reducing platform costs (C_p) and improving technical infrastructure (D_p), areas where AI-driven content automation could offer future solutions.

The limitations of this model, including its deterministic nature and fixed accessibility parameter, highlight avenues for future research. The next logical steps include integrating machine learning algorithms for dynamic optimization and validating the model's predictions through empirical testing on real-world educational platforms. Overall, this study contributes a valuable framework for designing more effective and responsive digital education, paving the way for the development of next-generation, AI-oriented learning systems.

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