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A Mathematical Curricular Complexity Analysis of U.S. Data Science and Data Engineering Bachelor's Degree Programs

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Abstract: The exponential growth of information stored within computing systems has led to a call for U.S. professional data scientists and data engineers towards writing the requisite algorithms needed to extract scientific trends from seemingly boundless, unstructured data sets. Data science and data engineering are inherently interdisciplinary academic disciplines braided together by conventional mathematics, statistics, engineering, and computer science departmental faculty. Despite the job market expansion in this computational area, a limited number of U.S. undergraduate degree programs in data science and data engineering have burgeoned due in part to the breadth of the required knowledge base and advanced undergraduate mathematical subject entanglements. Curricular analytics techniques, a graph theory framework for quantifying curricular tortuosity in the form of prerequisites and laboratory corequisite courses, provides a quantitative measurement of subject matter entanglements. Using curricular analytics techniques on a discrete set of U.S. bachelor's degree programs in data science and data engineering, the breadth and depth of integration of formal mathematical concepts was evaluated quantitatively through a novel variable entitled the mathematical curricular complexity involving ancillary mathematics course sequence progression requirements. Mathematical curricular complexity was observed to have very little or no statistical correlation with either elementary linear algebra course centrality, overall national or world university ranking, or public versus private university type. The mathematical curricular complexity values for U.S. undergraduate data science and data engineering degree programs were compared to mature bachelor's degree programs throughout the undergraduate mathematics and engineering landscape. Curricular analytics modeling was used to predict the future equilibrium number of U.S. bachelor's degree graduates expected for data science and data engineering as a function of mathemtical curricular complexity. Despite their very bright labor force outlook within several key U.S. industrial sectors, the number of bachelor's degree graduates in data science and data engineering remains modest to date due to the somewhat daunting requisite curricular combination of advanced undergraduate mathematics and concomitant intricate computational techniques.

Keywords: Curricular analytics, Mathematical curricular complexity, Data science undergraduate major, Data engineering undergraduate major, Bachelor's degree graduates

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Introduction

The Emerging Professional Fields of Data Science, Data Engineering, and Artificial Intelligence

Data science and data engineering are most certainly rapidly emerging professional fields within the United States of America (U.S.) as well as globally at this particular time. The rapid explosion in published data worldwide has led to a call for U.S. professional data scientists and data engineers toward writing algorithms in order to extract scientific trends from seemingly boundless, unstructured data sets (Cao, 2017). Data scientists and data engineers are absolutely vital for the proper handling, manipulation, mining, visualization, and storage techniques involved with large data sets in addition to machine learning for optimal information extraction in order to facilitate decision-making in complex systems (Van der Aalst, 2016). Many laymen are just not familiar with the vogue terminology and highly descriptive nomenclature which data science and data engineering professionals routinely iterate such as logistic regression, navigating decision trees, random forests, and neural networks making the field appear somewhat abstract to laymen within the general public. Nevertheless, data science and data engineering require a *multi*-faceted skill set in theoretical (pure) mathematics, applied mathematics, probability theory, statistics, computer science, information science, and engineering as well as proficiency with a plethora of novel data science specific computational applications. Using state-of-the-art tools including: (1) Python® coding language for data structures, (2) R® for statistical computing and data visualization as well as (3) Structured Query Language (SQL®) for database management in order to analyze relational databases, text, and image data. At present, U.S. data science and data engineering professionals are primarily graduate degree recipients with mathematics, statistics, computer science, or industrial engineering undergraduate training; relatively young, take on tremendous professional responsibility, and accordingly command relatively high annual monetary salaries.

Interrelation between Data Science, Data Engineering, and Artificial Intelligence as well as Operations Research

Data science and data engineering are interrelated with the artificial intelligence (AI) field. Artificial intelligence (AI), data science, and data engineering remain three of the most influential fields within today's technology landscape as these fields, when braided together, have the potential to significantly enhance decision-making, operational efficiency, and overall productivity within a wide variety of U.S. industrial sectors including manufacturing, health care, and finance in addition to their profound influence on scientific engineering research and development. AI is routinely used in data science for automating data management. Data science primarily focuses on the extraction of insights from data using machine learning, databases, and information theory to aid organizations in generating actionable insights and informed decision-making. Data engineering, although directly related to data science, uniquely focuses primarily on transforming raw data into an accessible and structured format by designing and constructing efficient computational systems which allow facile collection, storage, processing, and retrieval of data for further analysis. Artificial Intelligence (AI) develops machines capable of identifying data trends and patterns, translating texts, and ultimately making informed decisions from machine learning using algorithms routinely trained on substantial data sets. While data science focuses on extracting insights from existing data, AI focuses on building intelligent systems that can perform tasks which have conventionally required human intelligence and insight. Hence, AI, data science, and data engineering are inherently interconnected wherein all three seemingly play important roles within modern computational technology for attaining the most efficient business and engineering metrics, fundamental scientific research and development benchmarks as well as vital medical breakthroughs.

Data science is actually part of a significantly broader computational professional entity entitled operations research. In addition to data science, operations research also incorporates elements of game theory, graph theory, probability theory, statistics, simulations, and stochastic processes (Vasegaard, 2021). Unique components of the data science field, namely database management, data mining, machine learning, and critical path analyses toward systems engineering, add directly to the holistic operations research sphere (Vasegaard, 2021). Operations research had its historical origin in the 17th century in game-theoretic approaches toward expectation values and regained substantial mathematical importance during the second world war for military powers to solve significant logistic and supply chain problems. Operations research is an overarching, applied science which uses both mathematical and analytical computational methods to aid a wide variety of organizations, ranging from military operations to industrial manufacturing, in order to make optimal decisions and significantly improve efficiency using simulations, statistics, and machine learning. With the aid of aspects specific to data science, operations research is currently used for supply chain management, logistics and inventory management, pathfinding and routing problems, predictive maintenance, assignment and scheduling problems, systems engineering, forecasting, and multiple-criteria decision analysis in complex evaluation problems using linear algebra vector maximization techniques (Vasegaard, 2021).

Professional Development Type U.S. Undergraduate Education toward Return on Investment

Professional development type U.S. undergraduate education is most certainly different from classical liberal arts higher education. Many U.S. students have traditionally elected undergraduate majors in mature fields within liberal arts categories such as mathematics, the physical sciences (chemistry and physics), natural sciences (biology), humanities, social sciences, or the arts (visual and performing). Nevertheless, U.S. undergraduate students can elect to pursue a professional development (applied) major such as health (nursing), business management, engineering, computational science, or a relatively wide variety of specified, examination credentialed programs ranging from actuarial science to merchant mariner licensed maritime transportation bachelor's degrees. U.S. students being counseled in high school are absolutely inundated with a plethora of prospects concerning prospective undergraduate majors wherein each individual student must relate predictions concerning labor statistics with their own abilities and educational desires toward long-term career. Internet, broadcast, and print media directed toward prospective U.S. college students and their parents has increasingly focused keenly on monetary return on investment (ROI) strategies relating the modern choice of a U.S. college major to a purely economic decision (Wood, 2025; Morris *et al.*, 2025).

Many professional development undergraduate majors have become increasingly popular within the U.S. due to their inherently more applied nature and direct connection to expanding, lucrative, modern job markets. Professional development undergraduate majors are conventionally considered to be intense and densely packed with information in order to optimally prepare students for credentialing examinations as well as to directly enter the professional job market *post*-college already possessing both theoretical knowledge, *pre*-professional technical expertise from mastery of both rigorous lecture and laboratory coursework, and *multi*-tasking capability for optimal and immediate impact toward catalyzing rapid career advancement. Data science and data engineering undergraduate majors appear to be archetypical professional development degree examples using state-of-the-art computer application programs, built-in curricular professional-level capstone projects, and internships/co-operative industrial work experiences as well as their *multi*-disciplinary nature increasingly mimicking the requirements of industrial professional workplaces.

U.S. Bachelor of Science Degrees in Data Science and Data Engineering

The present state of U.S. Bachelor of Science (B.S.) degrees in the data science and data engineering fields is intriguing with respect to the overall steady growth of these particular professional fields. Although U.S. graduate programs have persisted for some time (*i.e.* more than ten years) within this area, an abundance of undergraduate data science and data engineering majors have recently burgeoned in a plethora of U.S. universities within the last five years. Data science and data engineering are inherently *multi*-faceted, interdisciplinary academic disciplines braided together by faculty and courses from conventional mathematics, statistics, computer science, information science, and engineering departments. A relatively large variance is observed in the breadth and depth, required knowledge base, learning intensity, and advanced undergraduate mathematical subject matter entanglements for U.S. data science and data engineering undergraduate programs at this particular time.

The Multidisciplinary Nature of Data Science and Data Engineering and Their Associated NCES CIP Codes

U.S. undergraduate data science and data engineering programs are required by the federal government to be listed by each university under a single National Center for Education Statistics' (NCES) Classification of Instructional Programs (CIP) six-digit taxonomic code (University of Wisconsin-Madison, 2025). In contrast to mature fields such as mathematics, physics, chemistry, and engineering disciplines, there appears to be no unique, single CIP code for undergraduate data science major programs used by U.S. universities at present. Oppositely, a variety of CIP codes have been utilized by U.S. universities to date for the B.S. Data Science degree and B.S. Data Engineering degree. In addition, there appears to be no single curricular standard, credentialing agency, or distinctive U.S. accreditation agency for newly formed U.S. undergraduate degree programs in both data science and data engineering. The CIP codes used to date by U.S. universities for data science and data engineering majors include Data Science (30.7001) [724 B.S. graduates in 2022], Data Analytics (30.7101) [135 B.S. graduates in 2022], Data Modeling and Database Management (11.0802) [486 B.S. graduates in 2022], Computational Science (30.3001) [245 B.S. graduates in 2022], Computational Mathematics (27.0303) [343 B.S. graduates in 2022], and Computational and Applied Mathematics (27.0304) [291 B.S. graduates in 2022] (National Center for Education Statistics' (NCES) Postsecondary Education Data System (IPEDS), 2023). Considering the heterogeneous nature of the above categories, there appeared to be less than or equal to 2224 B.S. undergraduate degrees granted in the fields of data science and data engineering within the U.S. in 2022. Furthermore, the Georgetown University Center on Education and the Workforce (CEW) in Washington, D.C. links data science directly to the field of statistics as well as under the more general heading of decision sciences (Morris *et al.*, 2025).

The Mathematical Track for B.S. Data Science Degree Programs

Many different academic undergraduate data science tracks have been created by U.S. universities to date. Example undergraduate academic track titles include applied mathematics-numerical analysis, software analytics, computational biology, statistical theory, geographic information systems, and business intelligence. Some U.S. universities are beginning to offer a variety of dual majors incorporating data science, thereby allowing students to integrate vital technical skills combining computer science, information science, mathematics, statistics, and probability theory into an integrated curriculum designed to prepare modern B.S. graduates for either immediate entry-level career positions or graduate school encompassing computational data analytical studies. Optimally, graduates with either a B.S. Data Science or B.S. Data Engineering education can not only develop theoretical models but also solve complex, applied problems within the industrial world from day one on the job. The mathematical B.S. data science track is essentially an applied mathematics degree with a very significant computational component. Herein, we conducted curricular analytics calculations on the *most mathematically oriented* data science degree track offered by each university studied.

The Central Role of Linear Algebra as The Key Mathematical Component within The B.S. Data Science Curricula

Mathematical techniques to solve both ordinary and partial differential equations lie at the heart of many engineering processes (*i.e.* fluid mechanics, mass transfer, heat transfer, process control-sensors, structural analysis, aerodynamics, reactor design, *etc.*) and are, in fact, inherently central to many engineering disciplines including mechanical, electrical, civil, aerospace, nuclear, and chemical engineering. In contrast, linear algebra mathematical concepts and matrix calculations lie at the heart of data science and data engineering. Linear algebra is a foundational mathematical discipline for data science and data engineering, which plays a critical and underlying role in both data analytics and machine learning. Linear algebra provides matrix tools to represent, manipulate, and analyze large data sets most efficiently, thereby making linear algebra an indispensable fundamental mathematical tool for data scientists and the continued development of their increasingly intricate computational applications. Hence, herein we concentrate on the curricular analytics centrality metric for the elementary linear algebra course as a potential marker for the B.S. Data Science and B.S. Data Engineering curricula as a whole compared to the overarching mathematical curricular complexity for the entire degree curriculum.

University Ranking for B.S. Data Science Programs at U.S. Universities

Ranking of universities is directly linked to the institution of higher learning's inherent prestige. The prestige of a university is a public perception based on many historical factors including academic rigor, research output, alumni success, and perceived educational effectiveness. Academic rigor and excellence encompass the university's robust lecture and laboratory curricula with challenging, advanced state-of-the-art, in-depth coursework taught by well-respected faculty members. Student research opportunities and advanced research facilities tend to add significant prestige to universities with cutting-edge laboratories and resources including their library's breadth, depth, and overall holding size. Admissions selectivity and a lower acceptance rate metric also tend to correlate with university prestige. Many students seeking admission can indicate to the public an overall desirability and increased prestige of the university. Highly selective universities tend to be the undergraduate college of choice for students who have both previously excelled academically and who are avidly seeking the opportunity to be at the forefront of academic research. The impact of alumni success in the professional world is ofttimes where universities take pride in producing successful graduates in scientific and engineering research and development, business executives, successful entrepreneurs, and highly acclaimed artists. The overall monetary endowment is also often connected with university prestige and higher ranking. University rankings such as the QS World Rankings (Quacquarelli Symonds, 2025) and U.S. News and World Report's National University Rankings (USNWR A, 2025) attempt to accurately quantify public perception of prestige on an annual basis. Herein, we concentrate on the university ranking as a potential marker for the holistic B.S. Data Science curriculum compared to the mathematical curricular complexity linked to the university's specific course curriculum. Does a more prestigious (i.e. higher ranked) university with perceived increasingly robust academic coursework, in fact, consistently produce a more mathematically integrated B.S. Data Science curriculum?

Methods

Curricular Analytics Metrics Quantifying Prerequisites, Laboratory Corequisites, and Subject Matter Entanglements

Curricular Analytics is a graph theory framework for quantifying curricular tortuosity and provides a quantitative measurement of subject matter entanglements (Heileman *et al.*, 2018; Wigdahl *et al.*, 2014). Herein, curricula were garnered from the most recent (2025-2026 if possible) official version of each university's catalog. A Microsoft Excel® workbook in comma-separated values (*.csv*) format was prepared for each university's most mathematically integrated data science or data engineering curriculum organized sequentially by academic term (eight total semesters or twelve total quarters) including its National Center for Education Statistics' (NCES) Classification of Instructional Program (CIP) code. The departmental course abbreviation (*e.g.* MATH, STAT, DATASCI, DAEN), course number, academic prerequisite courses, academic corequisite (laboratory) courses, and number of academic credit hours (weighting factor) were included for each curricular course in sequential order beginning from initial course of the first academic term within the curriculum to graduation.

Key curricular analytics metrics included the blocking factor (A), which measured the extent to which the course of interest blocks, until mastered or passed, the ability to take other courses within the curriculum. The delay factor (B) encompassed the length of the longest path within the corresponding curriculum graph, which merely contained the course of interest. Science, technology, engineering, and mathematics (STEM) type curricula routinely contain courses which must be completed in sequential order (*i.e.* prerequisites and laboratory corequisites) wherein the ability to navigate these pathways are absolutely critical for student success towards curricular completion (graduation). The course complexity (C) metric represented the arithmetic sum of the blocking factor (A) and delay factor (B) for the course of interest. The mathematical curricular complexity (a novel metric) was the arithmetic sum complexity ($\Sigma_i C_i$) for all $\{i\}$ number of required and elective mathematics courses within the curriculum.

For each university curriculum studied, applicable mathematics courses were chosen as upper division electives wherever appropriate. Nevertheless, the mathematical curricular complexity ($\Sigma_i C_i$) did not include statistics courses. The course centrality metric (D) represented the arithmetic sum of all the unique curricular pathways incorporating the particular course of interest. Centrality (D) incorporates the number of required foundational prerequisite courses connected to the course of interest in addition to the number of discipline-specific courses to which the course of interest serves as a prerequisite while moving forward within the curriculum. Each Microsoft Excel® curricular workbook in comma-separated values (*.csv*) format containing a unique university's Bachelors of Science (B.S.) Data Science or B.S. Data Engineering curricular degree program course was analyzed for course blocking factor (A), delay factor (B), complexity (C), and centrality (D) for each class using the curricularanalytics.org (Curricular Analytics, 2025) site. The mathematical curricular complexity ($\Sigma_i C_i$) for each curriculum was calculated merely by manually arithmetically adding the complexities (C_i) of all $\{i\}$ number of mathematics courses.

Mathematical Curricular Complexity and Multi-Disciplinary Computing Applications

The mathematical curricular complexity, involving ancillary mathematics course sequence progression requirements, was introduced previously as a novel metric within the International Society for Technology, Engineering and Science's (ISTES) International Conference on Education in Mathematics, Science and Technology (ICEMST) 2025 conference proceedings (Aronson *et al.*, 2025) and used to analyze forty-two (42)

Texas A&M University undergraduate major curricula across the university landscape. Modeling the number of graduates in each particular academic discipline (y-axis, ordinate) (National Center for Education Statistics (NCES), 2021) versus the mathematical curricular complexity (x-axis, abscissa) for that major at Texas A&M University produced a smooth, continuously differentiable function (no breaks, angles, or cusps) across the entire university landscape. Texas A&M University, the largest comprehensive public university in the U.S. by enrollment, was previously used as a model (Aronson *et al.*, 2025; List of United States public university campuses by enrollment, 2025). Using curricular analytics techniques on a discrete set of U.S. bachelor's degree program curricula in data science and data engineering herein, the breadth and depth of integration of formal mathematical concepts, including linear algebra techniques, was evaluated quantitatively. A single data science curriculum from each of thirty-one (31) universities (25 public and 6 private) across the U.S. were chosen in addition to the Texas A&M University's (public) B.S. degree in Data Engineering curriculum. The mathematical curricular complexity values for U.S. undergraduate B.S. Data Science and B.S. Data Engineering degree programs were compared herein to modeling for bachelor's degree programs within mature disciplines throughout the undergraduate mathematics, science, and engineering landscape (Aronson *et al.*, 2025) in order to predict the expected number of graduates for data science and data engineering given time enough to establish a state of graduation rate equilibrium in the future for these two particular fields.

Results and Discussion

Mathematical Curricular Complexity for B.S. Programs at U.S. Universities

The mathematical curricular complexity ($\Sigma_i\ C_i$), involving all $\{i\}$ ancillary mathematics course sequence progression requirements, was introduced previously at the ISTES ICEMST 2025 (Aronson *et al.*, 2025) and used to analyze forty-two (42) Texas A&M University undergraduate major curricula across the academic university landscape. As an example of an undergraduate data science curricula, the mathematical curricular complexity graph for the B.S. Data Science degree curriculum from Stanford University's (California) School of Humanities and Sciences (Stanford University, 2025) is shown in Figure 1 below wherein the liberal arts core courses have been suppressed.

Previous curricular analytics modeling (Aronson *et al.*, 2025) produced a continuously differentiable function across the university landscape for the number of baccalaureate graduates (y-axis, ordinate) versus the mathematical curricular complexity (x-axis, abscissa). Using curricular analytics techniques on a discrete set of thirty-two (32) U.S. bachelor's degree program curricula from individual universities in both data science and data engineering, the breadth and depth of integration of formal mathematical concepts, including linear algebra techniques, was evaluated quantitatively. The mathematical curricular complexity values for the U.S. undergraduate data science and data engineering degree programs were compared herein to modeling for mature bachelor's degree program areas throughout the undergraduate mathematics, science, and engineering landscape (Aronson *et al.*, 2025).

The single most mathematically oriented undergraduate data science curriculum was chosen for each of the thirty-one (31) universities (25 public and 6 private) across the U.S. in addition to the Texas A&M University (public) B.S. Data Engineering degree curriculum. For each curriculum, the lecture/laboratory sequence of engineering physics I (mechanics) with a calculus I course prerequisite and engineering physics II (electricity and magnetism) with a calculus II course prerequisite were specified as the science core curriculum courses of choice. Furthermore, advanced undergraduate mathematics classes were chosen as upper division elective courses wherever appropriate.

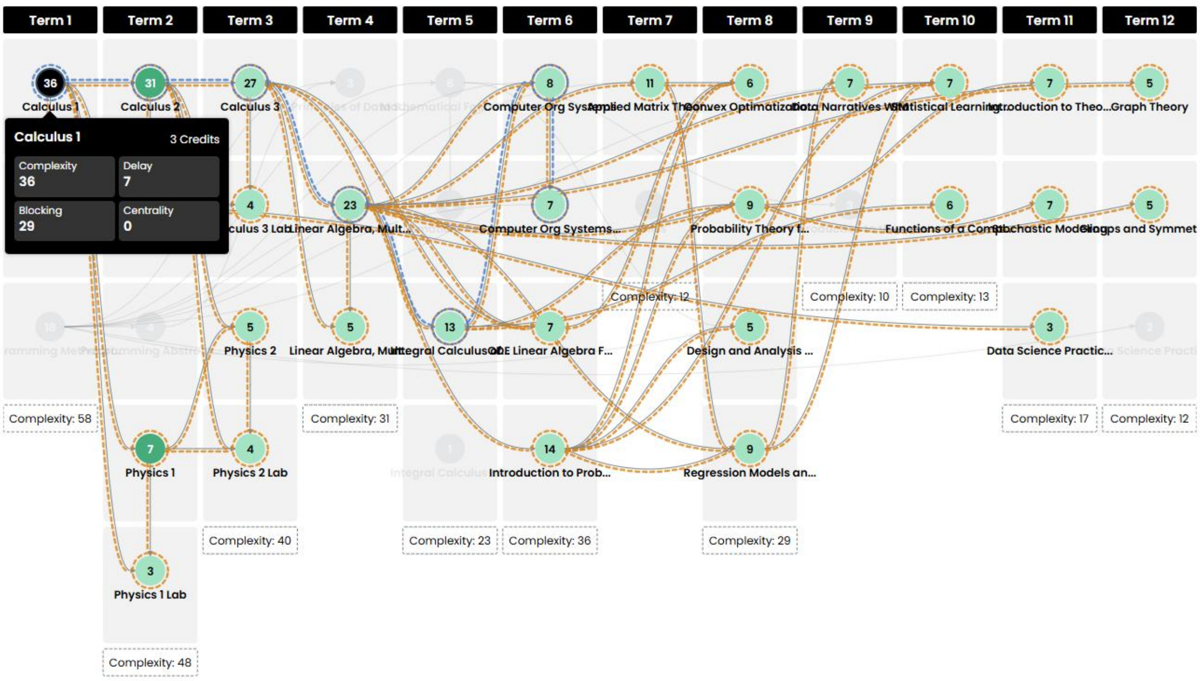

Figure 1. The Mathematical Complexity Graph for The Stanford University B.S. Data Science Degree Curricula wherein The Liberal Arts Core Courses Have Been Suppressed

Correlation of Linear Algebra Centrality for B.S. Data Science Programs at U.S. Universities

Linear algebra concepts and matrix calculations are absolutely central to data science and data engineering. The elementary linear algebra course was a requisite foundational mathematics discipline course for each B.S. data science and B.S. data engineering curricula studied herein toward subsequent discipline-specific data analytics and machine learning courses. Linear algebra provides the matrix tools to most efficiently analyze large data sets, thereby making it both a vital and indispensable mathematical tool for data scientists within their computational work.

In addition, many B.S. Data Science curricula required an advanced linear algebra course as well. Hence, we hypothesized herein that the curricular analytics graph theory centrality of the elementary linear algebra course alone would statistically correlate with the overall mathematical curricular complexity for B.S. Data Science and B.S. Data Engineering curricular degree programs. A linear algebra course centrality graph for the B.S. Data Science degree curriculum for Florida International University's Knight Foundation School of Computing and

Information Sciences (Florida International University, 2025) is shown in Figure 2 below wherein the liberal arts core courses have been suppressed.

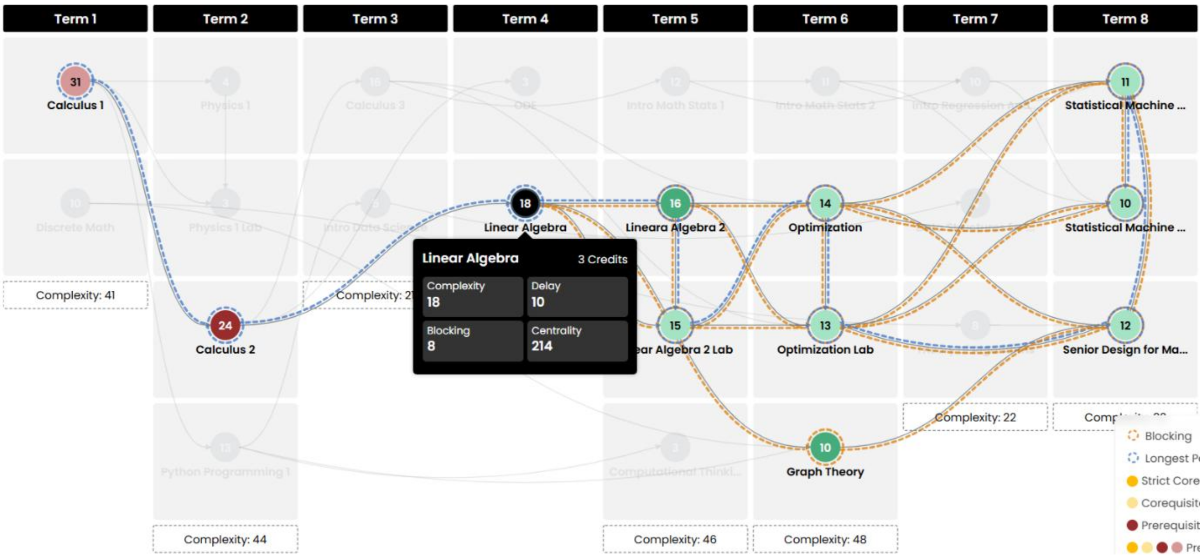

Figure 2. A Linear Algebra Course Centrality Graph for The B.S. Data Science Degree Curricula for Florida International University's Knight Foundation School of Computing and Information Sciences (Florida International University, 2025) wherein The Liberal Arts Core Courses Have Been Suppressed

Correlation of QS World University Ranking and U.S. News and World Report National University Ranking with The Mathematical Curricular Complexity for B.S. Data Science Programs at U.S. Universities

QS World University Ranking (Quacquarelli Symonds, 2025) methodology (QS World University Rankings, 2025) is based on academic reputation (40% of the overall score), faculty to student ratio (15%), faculty research publication citations (15%), alumni reputation to employers (15%), university internationalization (10%), and a combination of international research network partnerships, student employment outcomes, and university sustainability (5%). U.S. News and World Report National University Ranking (USNWR A, 2025) methodology is *multi*-faceted (USNWR B, 2025) and based first upon outcomes (52% of the overall ranking) in terms of graduation rates and retention rates (21%) with regard to the proportion of each entering class earning a degree in six years or less (16%), and the proportion of first-year entering students who returned for classes the following fall semester (5%). Next, U.S. News and World Report's National University Rankings are based on graduation rate performance (10%) in terms of actual six-year graduation rates compared with predictions, and social mobility (11%) with regard to exactly how well the university's graduates received U.S. federal Pell Grants (6%) in addition to the graduation rates and performance of first-generation students (5%). Graduate financial indebtedness (5%) calculated as the average accumulated U.S. federal loan debt by student borrowers at the university was also a factor.

Additional factors for ranking included the proportion of university graduates earning potential (5%) or the number of university graduates with federal loans four years after graduating earning more than a typical U.S.

high school graduate. Other university performance markers included university faculty resources (11%), faculty salaries (6%), student to faculty ratio (3%), and the proportion of faculty who work for the university on a full-time basis (2%). Expert opinion (20%) by university presidents, provosts, and admission deans rate the academic quality of their peer institutions. Financial resources (8%) are measured as the average *per*-student spending on instruction, research, student services, and related educational expenditures. Student selectivity (5%) as measured by the standardized test scores of admitted students and the proportion of admitted students in the upper percentiles of their high school graduating class. Finally, the contribution of faculty research (4%) as quantified by the citations to literature papers and research attributed directly to university faculty. Herein, we hypothesized that the QS World Ranking (Quacquarelli Symonds, 2025) and U.S. News and World Report National University Ranking (USNWR A, 2025) would statistically correlate with the mathematical curricular complexity. Would a higher ranked (*i.e.* more prestigious) university, in fact, consistently produce an increasingly more mathematically integrated B.S. Data Science curriculum?

Mathematical curricular complexity, graph theory centrality for the elementary linear algebra course, 2025 QS World Ranking (Quacquarelli Symonds, 2025), and 2025 U.S. News & World Report National University Ranking (USNWR A) for thirty-one (31) B.S. Data Science and one (1) B.S. Data Engineering degree programs from U.S. universities are shown in Table 1 hereinbelow wherein private universities have been italicized. Programs are listed in decreasing order of mathematical curricular complexity (column 2).

Table 1. Mathematical Curricular Complexity, Linear Algebra Centrality, 2025 QS World Ranking, and 2025 U.S. News and World Report Ranking for Each University wherein Private Universities Have Been *Italicized* Listed in Decreasing Order of Mathematical Curricular Complexity (column 2)

University Name	Mathematical Curricular Complexity	Linear Algebra Centrality	2025 QS World (USNWR) Ranking
Stanford University	194	103	6 (4)
Florida International University	180	214	574 (98)
University of Washington	178	25	81 (46)
University of California, Santa Barbara	160	202	178 (39)
University of Texas at Dallas	156	41	597 (109)
Virginia Tech University	155	46	389 (51)
University of California, Davis	150	123	130 (33)

University Name	Mathematical Curricular Complexity	Linear Algebra Centrality	2025 QS World (USNWR) Ranking
University of Houston	147	39	651 (144)
Arizona State University	134	37	200 (121)
San Jose State University (Regional U.)	132	18	1181
University of California, Irvine	132	42	293 (33)
Texas A&M University (B.S. Data Engineering)	126	59	154 (51)
Illinois Institute of Technology	125	18	601 (105)
Purdue University	124	31	89 (46)
University of Nebraska – Lincoln	123	42	701 (152)
University of Wisconsin – Madison	121	88	110(39)
University of Illinois Chicago	119	8	323 (80)
New York University	116	43	43 (30)
Washington University in St. Louis	115	18	171 (21)
Clemson University	109	12	951 (80)
Northeastern University	104	17	396 (54)
University of Utah	102	33	531 (136)
University of Texas at Austin	102	82	66 (30)
University of Maryland, College Park	101	23	218 (44)
University of Minnesota Twin Cities	99	44	203 (54)
San Diego State University	94	12	1001 (109)

University Name	Mathematical Curricular Complexity	Linear Algebra Centrality	2025 QS World (USNWR) Ranking
University of Massachusetts - Amherst	93	12	247 (58)
Iowa State University	82	17	470 (121)
University of Florida	76	22	215 (30)
Carnegie Mellon University	75	34	52 (21)
Pennsylvania State Univ.	71	0	89 (63)
South Dakota State University	65	8	1201 (266)

A large variation in mathematical curricular complexity was observed within the curricular requirements over the thirty-two (32) B.S. Data Science and B.S. Data Engineering undergraduate degree programs shown in Table 1 hereinabove ranging from close to 200 (greater than the mathematical curricular complexity calculated for the Texas A&M University's nuclear engineering major, aerospace engineering major, and electrical engineering major curricula) to under 70 (similar to the Texas A&M University's civil engineering major, meteorology major, and computer science major curricula) (Aronson *et al.*, 2025). The mathematical curricular complexity for the B.S. Data Engineering degree within the highly respected Texas A&M University College of Engineering was observed to lie merely towards the middle of the mathematical curricular complexity values (12^{th} highest out of 32 curricula) listed for B.S. Data Science programs within Table 1 hereinabove (Texas A&M University, 2025). The highest four linear algebra course centrality values for B.S. Data Science programs were observed for university data science programs within the top seven mathematical curricular complexity values as shown in Table 1. Nevertheless, statistical correlation between mathematical curricular complexity with the elementary linear algebra course centrality produced a coefficient of determination (R^2) equal to merely 0.3605 by linear least squares regression. Hence, despite the elementary linear algebra course being a key component within the B.S. Data Science degree program, little correlation was found between mathematical curricular complexity and the elementary linear algebra course centrality.

The statistical correlation between mathematical curricular complexity and QS World Ranking values listed in Table 1 produced a coefficient of determination (R^2) merely equal to 0.0006 by linear least squares regression. Hence, despite the hypothesis that a more prestigious (*i.e.* higher ranked) university would tend to offer a more academically robust and concomitantly increasingly mathematically integrated B.S. Data Science curricula, no correlation was found between the mathematical curricular complexity for B.S. Data Science programs and the QS 2025 World Ranking of universities (Quacquarelli Symonds, 2025). In a similar manner, a coefficient of determination (R^2) of merely 0.0284 was found between mathematical curricular complexity and U.S. News and World Report's 2025 National University Ranking (USNWR A, 2025) by linear least squares regression.

Hence, no correlation was found between the mathematical curricular complexity for B.S. Data Science programs and the U.S. News & World Report National University Ranking (USNWR A, 2025). More prestigious (*i.e.* higher ranked) U.S. universities simply did not necessarily tend to a produce more mathematically integrated B.S. Data Science curricula. The mathematical curricular complexity appeared to be simply a function of curricular decisions made independently by university faculty at each U.S. institution of higher learning studied herein. Furthermore, no statistical correlation was found between the mathematical curricular complexity of B.S. Data Science programs within the U.S. national university classification for public versus private institutional types as shown in Table 1 hereinabove. Nevertheless, B.S. Data Science at only six private institutions were studied as shown in Table 1.

Prediction of Future Equilibrium Number of B.S. Data Science and B.S. Data Engineering Graduates in the United States

Curricular analytics modeling results over the mature science and engineering fields (Aronson *et al.*, 2025) was used to predict the futuristic equilibrium number of bachelor's degree graduates in data science and data engineering. Over the entire university academic landscape, a continuous function was observed that was almost exactly a multiplicative inverse function or reciprocal relationship between the number of bachelor's degree graduates and the mathematical curricular complexity as shown in Equation [1] below (Aronson *et al.*, 2025):

$$\text{Number of Bachelor's Degree Graduates} = (667{,}481) \times (\text{Mathematical Curricular Complexity})^{-1.112} \qquad [1]$$

Equation [1] above was used to predict the number of B.S. Data Science graduates that would be expected for a discrete set of mathematical curricular complexity values theoretically given enough time to establish a B.S. Data Science and B.S. Data Engineering graduation rate equilibrium as shown in Table 2 hereinbelow.

Table 2. Number of Expected B.S. Data Science and B.S. Data Engineering Graduates as A Function of Mathematical Curricular Complexity Based on Equation [1] (Aronson *et al.*, 2025)

Mathematical Curricular Complexity	Expected Number of B.S. Data Science Graduates
65	6171
85	4567
105	3603
115	2963
125	2963

Mathematical Curricular Complexity	Expected Number of B.S. Data Science Graduates
150	2414
175	2031
200	1749

Thus, according to Equation [1] (Aronson *et al.*, 2025) the least mathematically integrated B.S. Data Science curriculum (mathematical curricular complexity value of around 65) would be predicted to produce more than 6000 graduates annually at equilibrium whereas the most mathematically integrated B.S. Data Science curriculum (mathematical curricular complexity value of close to 200) would be predicted to produce less than 2000 graduates annually as shown in Table 2 above. Less than or equal to 2200 U.S. undergraduate students are graduating in data science and data engineering nationwide to date (National Center for Education Statistics, 2023) according to NCES CIP code data before graduation rate equilibrium has been established within these two fields. Standardization of the B.S. Data Science curriculum by a U.S. academic accreditation agency would allow a significantly narrower range to be predicted for the equilibrium number of U.S. graduates. Nevertheless, an increase in the mathematical rigor for the B.S. Data Science degree would be predicted to rapidly decrease the number of U.S. graduates within the data science field as shown in Table 2.

B.S. Data Science Curricular Mathematical Course Variations

A unique undergraduate curricular variation involving a mathematical course sequence specifically tailored for data science students was implemented by the Academy of Data Science at Virginia Tech University for their B.S. Computational Modeling and Data Analytics (CMDA) degree program (Academy of Data Science, 2025). Mathematical courses entitled Integrated Quantitative Science I and Integrated Quantitative Science II were offered to students as a corequisite to the elementary linear algebra course during the second (sophomore) year of college beyond both the Calculus I and Calculus II courses (Academy of Data Science, 2025). The Integrated Quantitative Science I course encompasses probability and statistics, infinite series, multivariate calculus, and further linear algebra techniques for six academic credits while the Integrated Quantitative Science II course encompasses intermediate linear algebra techniques, regression, differential equations, and model validation for an additional six academic credits (Academy of Data Science, 2025). These two integrated quantitative science courses tailored specifically for the Virginia Tech University B.S. CMDA degree program are routinely taught within the Virginia Tech University Academy of Data Science and not within the Virginia Tech University Department of Mathematics and Virginia Tech University Department of Statistics as is customary.

The two integrated quantitative science courses effectively replace conventional courses in elementary/intermediate linear algebra techniques, multivariable calculus, and statistical methods as well as probability theory and distributions (Academy of Data Science, 2025). Substituting two (6 credit) integrated courses for five (3 credit) traditional courses in mathematics and statistics causes changes in both the overall mathematical curricular complexity and linear algebra course centrality. Changing from the traditional path to the integrated path caused a decrease in the mathematical curricular complexity for the Virginia Tech University B.S. Computational Modeling and Data Analytics (CMDA) degree program from a value of 155 (as shown in Table 1) to a value of 140 or a 10% decrease resulting from effectively streamlining the curriculum. A change in the elementary linear algebra course centrality from a value of 46 (as shown in Table 1) to a value 35 or a 24% decrease was also observed upon changing from the traditional path to the integrated course sequence regarding curricular analytics modeling of the Virginia Tech University B.S. Computational Modeling and Data Analytics (CMDA) degree program. Although the integrated quantitative science sequence is tailored specifically for the mathematics deemed absolutely essential for data science by the Virginia Tech University data science faculty (Academy of Data Science, 2025), the extra proofs, concepts, and techniques taught within the five-course traditional mathematics and statistics pathway may, in fact, provide both breadth and depth for a computational scientist towards fundamentally understanding, using, and ultimately creating future computational developments within the field of data science.

Conclusions

For the B.S. Data Science curriculum with the most integrated mathematics approaching a mathematical curricular complexity (a novel metric) value of 200, we would expect less than 2000 total graduates at equilibrium (Table 2) from U.S. undergraduate academic programs nationwide following our previous modelling across the university landscape (Aronson *et al.*, 2025). Nevertheless, graduates from these particular mathematically rigorous programs will be well grounded in fundamental mathematics and hence tend to make less erroneous extrapolations of results from computational applications allowing relatively rapid movement toward desirable professional independence within their workplace. No statistical correlation (coefficient of determination, $0 < R^2 < 0.36$) in linear regression was observed between the mathematical curricular complexity for B.S. Data Science programs and (1) public versus private U.S. universities, (2) linear algebra course centrality, or (3) university world or national ranking. At this time, no single curricular standard exists in terms of U.S. accreditation of B.S. Data Science programs similar to the B.S. Chemistry major from the American Chemical Society's (ACS) Committee on Professional Training (CPT) (American Chemical Society, 2023). In addition, no single, unique National Center for Education Statistics' (NCES) Classification of Instructional Program (CIP) code is currently utilized throughout the U.S. Hence, at present the B.S. Data Science degree curriculum is merely a function of faculty decisions as an autonomous academic group at each particular U.S. university wherein the corresponding mathematical curricular complexity (Table 1) shows a relative broad range of values.

As an intriguing example, the B.S. Data Science curriculum at San Jose State University (SJSU), a *regional* public university lying within the heart of Silicon Valley (Northern California), had a significant mathematical curricular complexity value of 132, comparable to programs at the top U.S. national research universities, as driven primarily by the San Jose State University faculty as well as the tremendous local professional employment opportunities for B.S. Data Science graduates and perceived concomitant industrial advisory board/alumni feedback (San Jose State University, 2025). Despite their very bright labor force outlook within several key U.S. industrial sectors, the number of U.S. bachelor's degree graduates in data science and data engineering remains very modest to date at less than or equal to 2200 or about 1% of the total U.S. baccalaureate degrees granted annually in 2022 (National Center for Education Statistics, 2023). The modest B.S. Data Science graduation rate is due somewhat to the daunting academic threshold regarding their requisite curricular combination of advanced undergraduate mathematical and statistical coursework mastery in addition to the concomitant intricate computational techniques required to be learned in just four (4) years alongside the liberal arts core curriculum portion.

The mathematical curricular complexity did not statistically correlate with elementary linear algebra course centrality, QS 2025 World University Ranking, or U.S. News & World Report 2025 National University Ranking by linear least squares regression. The lack of a singular accredited standardized curriculum for the B.S. Data Science degree within the U.S. at present caused a large range of values for the mathematical curricular complexity for the thirty-two programs analyzed herein. Hence, it appears that each U.S. university is simply creating one or more B.S. Data Science curricular tracks in the best manner in which their constituent faculty determine.

Variation of the mathematical requirements for the B.S. Data Science degree (Academy of Data Science, 2025) aimed at streamlining the curriculum by tailoring what is needed for this particular field may miss some fundamental mathematical problems, theorems, and proofs needed to lead a data science laboratory toward exciting, novel benchmarks and breakthroughs in the future. Although a bit narrower in academic scope compared to undergraduate mathematics, statistics, industrial engineering, computer science, electrical engineering, and computer engineering (braiding elements of computer science with electrical engineering) curricula, the B.S. degree in Data Science and the B.S. degree in Data Engineering encompass real professional-ready skills in the intricate utilization of state-of-the-art computational applications. Future research should include the rapidly growing number of U.S. universities with undergraduate data science program tracks in comparison with both worldwide (international) B.S. Data Science graduation rates as well as the newly formed artificial intelligence (AI) specific undergraduate major programs burgeoning at present within the U.S. (Florida International University, 2025). In order to more fully statistically analyze the mathematical curricular complexity difference in public versus private U.S. universities for B.S. Data Science curricula, a significantly increased number of curricula from private universities need to be calculated in the future.

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Comparative Analysis of AI Chatbots for Computer Program Generation

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Abstract: Artificial intelligence has rapidly advanced to perform complex tasks that traditionally required human expertise. This study examines the effectiveness of AI chatbots in generating computer programs and evaluates how much programming knowledge a user still requires using these tools effectively. Eight freely available AI services were tested using fifteen diverse prompts designed to assess their ability to handle a range of computer science problems, including algorithm development, file handling, and server interaction. Each output was analyzed based on successful execution, number of errors, code quality, runtime efficiency, and file size. The findings revealed that most AI-generated programs could run successfully and fulfill the given tasks, with only minor errors in certain cases. Smaller AI models tended to produce less reliable code, while larger models generated cleaner, more efficient programs. The study also found that users with little programming experience could successfully produce functional code, although advanced tasks still required a deeper understanding of programming concepts. This limitation highlights potential challenges and risks, particularly regarding security and implementation. Overall, larger AI chatbots demonstrated strong capabilities in reliable program generation, suggesting that while AI can assist in software development, human expertise remains essential for complex and secure applications.

Keywords: Artificial Intelligence, Code Generation, Chatbots.

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Introduction

With artificial intelligence (AI) advancing and becoming increasingly proficient at performing tasks that once required individuals with specialized skillsets, new questions emerge about the capabilities and limitations of these systems. One area of particular interest is the ability of AI chatbots to generate computer programs that function correctly and efficiently. As AI becomes more integrated into everyday problem-solving, understanding how well these models can create executable code and how much programming knowledge is needed to guide them effectively is essential.

Recent developments in large language models (LLMs) such as OpenAI's ChatGPT (OpenAI, 2023), Google's Gemini (Google, 2024), and Anthropic's Claude (Anthropic, 2023) have demonstrated remarkable progress in natural language understanding and code generation. These models are capable of producing complete programs, debugging existing code, and even explaining algorithmic concepts in human-like ways. However, despite these advances, concerns remain regarding code reliability, security vulnerabilities, and the user's ability to interpret or modify AI-generated outputs (Vaithilingam, 2022).

By systematically analyzing and comparing multiple AI chatbots, this research aims to assess their programming performance across a range of problem types. The study also seeks to evaluate how much prior experience is necessary for users to generate working computer programs effectively. This comparative approach provides insight into both the strengths and limitations of AI-driven code generation, offering a clearer understanding of the balance between automation and human expertise in modern programming practice.

The remainder of this paper is organized as follows: first, the Motivation and Objective section explain why the study was undertaken and what specific goals were set. Next, the Related Works section situates this research within the existing literature on AI code generation and programming education. Then, the Experimental Setup section describes the selection of chatbots, the prompt design and testing methodology, and the scoring system in detail. The Results section presents the empirical findings including tabulated performance data. The Discussion section interprets those findings, connects them to prior work, and highlights implications and limitations. Finally, the Conclusion section summarizes the key outcomes and suggests future work.

Motivation and Objective

As AI systems continue to evolve, their ability to perform tasks that once required human programmers has drawn increasing attention from both academia and industry. One motivating factor for this study is the need to understand how reliably these tools can produce working code and how much human oversight remains necessary. For novice users with minimal programming experience, the question is: can an AI chatbot serve as an effective facilitator for generating functioning programs, or is the expertise still a bottleneck? By exploring this question, developers and educators may identify areas for improvement in chatbot interface design, code quality, and user-friendliness.

The primary objective of this research is to:

1. Assess the capabilities of freely accessible AI chatbots in generating complete and functional computer programs across a range of difficulty levels.
2. Evaluate the extent to which users with little or no programming experience could use these tools to generate code that runs successfully, meets task requirements, and remains maintainable.
3. Compare different chatbots in terms of runtime efficiency, code quality, number of errors, storage

footprint, and language support to identify which services perform best and under what conditions.
4. Draw implications for both software development practice and computer science education, in terms of what tasks remain better suited to human programmers and where AI assistance is most effective.

Ultimately, this study seeks not only to benchmark tool performance but also to shed light on the evolving role of human expertise in an era of increasingly capable AI assistants.

Related Works

The field of AI-assisted programming has grown rapidly, with numerous studies evaluating code generation tools powered by large language models. OpenAI's GPT-4 (OpenAI, 2023), GitHub's Copilot (GitHub, 2024), and Google's Gemini (Google, 2024) have demonstrated strong capabilities in producing syntactically correct and logically coherent programs from natural-language prompts.

Research has shown that developers increasingly use AI-based tools to automate coding tasks and improve productivity. For example, (Vaithilingam, 2022) conducted a user study on AI-assisted programming, finding that while such tools enhance speed and creativity, they may also introduce logical and security-related errors that users often overlook. In (Svyatkovskiy, 2020) the authors examined AI models for code completion, emphasizing the potential of machine learning to reduce developer workload while noting that these tools are not infallible and require careful human verification.

Other studies have focused on educational implications. In (Finnie-Ansley, 2023) the authors found that students using ChatGPT to solve programming problems reported improved understanding of syntax and algorithm design, but they also demonstrated dependency on AI outputs. Another research (Becker, 2023) explored how AI coding assistants influenced learning motivation: while they reduced frustration, they also discouraged deep debugging practice.

Security considerations have also been addressed in several research. Authors in (Pearce, 2022) evaluated the security of code contributions generated by Copilot and emphasized that AI does not inherently understand secure programming practices. In (Zhuo, 2023), the authors benchmarked various LLMs on software engineering datasets and highlighted significant variation in the quality, runtime performance, and adherence to software-engineering principles across models. (Sobania, 2023) performed an empirical evaluation of ChatGPT's code-generation capabilities, concluding that although outputs were often correct, they occasionally contained hidden logic flaws. The authors in (Nijkamp, 2023) compared open and closed-source systems, noting that proprietary models consistently outperform smaller open models in runtime efficiency.

While these studies validate the capabilities of AI-generated code, few directly compare multiple freely available chatbots under uniform conditions. This research fills that gap by incorporating performance indicators such as file size and algorithmic complexity, offering a more granular understanding of efficiency and scalability across platforms.

Experimental Setup

AI Chatbots Overview

This study evaluated eight AI chatbots: ChatGPT (OpenAI), Copilot (GitHub), Gemini (Google DeepMind), Meta AI (Meta), Claude (Anthropic), ZZZ Code, CodeConvert, and Devv AI. Each chatbot offers distinct features:

- ChatGPT (OpenAI, 2023): Known for its conversational interface and broad programming language support, capable of debugging and explaining code.
- Copilot (GitHub, 2024): Integrated with Visual Studio Code, optimized for in-context code completion, with extensive multi-language support.
- Gemini (Google, 2024): Focuses on integrating reasoning and multi-modal capabilities.
- Meta AI (Meta, 2023): Built upon LLaMA architecture, emphasizing open accessibility.
- Claude (Anthropic, 2023): Prioritizes safety and interpretability, with human-aligned responses.
- ZZZ Code (ZZZTech, 2024): Tailored for educational code generation and cross-language conversion.
- CodeConvert (CodeConvertInc, 2023): Specializes in translating code across programming languages.
- Devv AI (DevvSystems, 2023): Designed for developer productivity with modular AI assistants.

The eight were chosen because they were free to use (at least in a limited version), had little to no limit on the amount of code generated, and used different underlying AI model architectures. This selection allowed for a better overview of the accessible AI chatbot capabilities.

Prompt Design and Rationale

Each chatbot was given fifteen different prompts covering a range of problems. The prompts were designed to escalate in difficulty and cover multiple key programming areas: basic operations, data structures, algorithms, file I/O, GUI, networking and web development. This enables a comprehensive assessment of the chatbot's capabilities across domains rather than a narrow focus.

Prompts Used in the Experiment:

Fifteen programming prompts were created to test each chatbot's capabilities. The prompts were designed to represent a range of fundamental and advanced computer science topics, ensuring both breadth and depth of evaluation. They included algorithmic problems (e.g., sorting, recursion), data structure operations (e.g., stacks, queues, linked lists), GUI development, networking, and web development. The inclusion of both basic and complex prompts allowed for assessing not only the ability to produce working code but also how well each chatbot adapts to higher-order programming challenges.

1. Create a program in Python that makes an array that takes 5 (int/float) inputs and displays the maximum and minimum value.
2. Create a program in Python that takes the user's string input and reverses the string before displaying it.
3. Create a program in Python that creates a queue to simulate a ticket counter.
4. Create a program in Python that evaluates post-fix terms using stack and linked list.
5. Create a program in Python that takes the string input of names and sorts them, with Quick Sort, alphabetically.
6. Create a program in (language) that takes a user int input and solves the Tower of Hanoi problem with the input number of rings.
7. Create a program in Python that simulates all classic sorting algorithms.
8. Create a program in Python that simulates factorials.
9. Create a program in Python that uses inheritance to simulate a Family Tree.
10. Create a program in Python that reads strings from a CSV file and sorts the words alphabetically.
11. Create a program in Python that simulates a web server.
12. Create a program in Python that simulates a client-server-messenger.
13. Create a program in Python that simulates a game of Tic-Tac-Toe.
14. Create a website with a home page, about page, content page, and navigation.
15. Create a program in Python that simulates a game of Tic-Tac-Toe with a GUI.

Prompts 1–2 test basic language and data-structure use; prompts 3–5 target queue, stack, linked list, and algorithmic complexity; prompt 6 introduces recursion and arbitrary language choice; prompts 7–10 test more advanced algorithmic, data I/O and object-oriented design; prompts 11–12 test networking, multi-file and server-client complexity; prompt 13 is a moderate GUI/game challenge; prompt 14 tests full web development (HTML/CSS/JavaScript); prompt 15 combines GUI and game logic to maximize complexity. Using this progression enables us to judge how each chatbot handles increasingly difficult tasks and how well they perform for novices. The tasks were selected to cover both breadth (different programming paradigms) and depth (increasing logical complexity). Runtime complexities such as $O(1)$, $O(n)$, $O(n \log n)$, and $O(2^n)$ were noted for each generated solution to reflect algorithmic efficiency. File sizes (in KB) were recorded to approximate code compactness and memory footprint.

Evaluation Criteria

Each chatbot's output was evaluated using several criteria:

- Runs Without Intervention (75 points total) – 5 points for each prompt that executed without human edits.
- Tasks Completed (75 points total) – 5 points for each task completed successfully. This is the basic

requirement for the chatbots.

- Runtime Efficiency (75 points total) – Based on performance during execution, each prompt rated in the range of 1–5.
- Code Quality (10 points total) – Evaluated on readability, logical structure, and commenting. Additionally, whether the code followed good coding practices.
- Number of Errors (5 points total) – Deductions for syntax or logical errors.
- Storage Space and Dependencies (6 points total) – Assessed for external libraries and space requirements.
- Explanation, Debugging, Refactoring, and Language Support (5 + 5 + 5 + 3 points) – Evaluated separately.

This yields a total of 251 possible points, with overall results normalized to a 1–5 scale for comparison.

Results

The results of the comparative analysis are summarized in Table 1 and Table 2, presenting the performance outcomes for each AI chatbot across all fifteen programming prompts. The evaluation focused on whether the generated programs executed successfully, the number of errors encountered, runtime efficiency, file size, and overall code quality. Additionally, metrics such as the total raw score (out of 251 points) and the corresponding normalized rating (out of 5) were included to provide a unified performance measure.

Table 1 reports each chatbot's task success rate, file size averages, and runtime complexities derived from the empirical testing. The majority of services successfully completed nearly all prompts, with minimal user intervention required. File sizes ranged from as low as 2 KB for compact models such as ChatGPT and Copilot to as high as 10 KB for Claude. Runtime complexities were also consistent with standard algorithmic expectations, ranging from $O(1)$ for constant operations to $O(2^n)$ for recursive tasks like the Tower of Hanoi. These results indicate that even free AI services can generate efficient and logically structured programs for a wide variety of programming problems.

Table 1. AI Chatbot Code Evaluation with File Size and Runtime Complexity

AI Chatbot	Runs w/o Intervention	Tasks Completed	Avg File Size (KB)	Avg Runtime Complexity	Errors
ChatGPT	15/15	15/15	2	$O(n \log n)$	None
Copilot	15/15	15/15	2	$O(n \log n)$	None
Gemini	15/15	15/15	5	$O(n \log n)$ – $O(2^n)$	None
Meta AI	15/15	15/15	3	$O(n \log n)$	None
Claude	14/15	15/15	10	$O(n \log n)$ –	Minimal

AI Chatbot	Runs w/o Intervention	Tasks Completed	Avg File Size (KB)	Avg Runtime Complexity	Errors
				$O(C \times M^2)$	
ZZZ Code	15/15	14/15	2	$O(n \log n)$	Minimal
CodeConvert	14/15	14/15	2	$O(n \log n)$	None
Devv AI	15/15	14/15	3	$O(n \log n)$	Minimal

As seen in Table 1, Copilot and ChatGPT both achieved perfect run and completion rates, while maintaining the smallest average file sizes, indicating compact and efficient code. Gemini and Meta AI also demonstrated strong performance but occasionally produced verbose programs. Claude, despite completing all tasks, required minor corrections and generated larger outputs, reducing its overall efficiency score. ZZZ Code and CodeConvert were reliable for simpler tasks but exhibited limitations when facing multi-file or web-based prompts.

Table 2 provides a higher-level comparison that includes language support, debugging capabilities, refactoring features, and explanation functionality. Each system's raw total (out of 251) is presented alongside its converted overall rating (out of 5). This view reveals that performance is influenced not only by code execution but also by auxiliary support features that enhance usability and learning potential.

Table 2. Overall Feature and Performance Comparison of AI Chatbots

AI Chatbot	# of Languages Supported	Debugging	Refactoring	Explanation Capability	Raw Score (/251)	Overall Score (/5)
ChatGPT	250	Yes	Yes	Yes	215	4
Copilot	312	Yes	Yes	Yes	240	5
Gemini	22	Yes	Yes	Yes	195	4
Meta AI	50+	Yes	Yes	Yes	200	4
Claude	60-70	Yes	Yes	Yes	125	2
ZZZ Code	17	Yes	Yes	Yes	130	2
CodeConvert	47	No	No	No	95	1
Devv AI	9+	Yes	Yes	Yes	175	3

The data in Table 2 reinforces the consistency of Copilot and ChatGPT as top performers, both offering comprehensive debugging and explanation tools that make them especially effective for educational and professional use. Gemini and Meta AI maintained respectable scores and runtime stability but produced larger files, indicating slightly higher computational overhead. In contrast, Claude's verbose code and limited efficiency lowered its normalized score to 2, despite strong language support and interpretability features. The smaller-scale chatbots, ZZZ Code, CodeConvert, and Devv AI, demonstrated that lighter models can still achieve high success rates but often at the cost of reduced versatility or greater reliance on user setup.

Taken together, these results show that AI chatbots can successfully generate, execute, and explain code across a wide range of programming tasks. However, model size, design purpose, and implementation approach significantly influence the trade-offs among runtime efficiency, file compactness, and ease of use. The following Discussion section interprets these findings in greater depth, relating the performance differences to model architectures, usability factors, and implications for future AI-assisted software development.

Discussion

The results shown in Tables 1 and 2 reveal clear differences in how AI chatbots generate, optimize, and present computer programs. The majority of models produced code that compiled and executed successfully, indicating that AI has become capable of producing structurally sound programs with minimal user intervention. The high completion rates observed across all fifteen prompts suggest that modern chatbots are no longer limited to simple scripts but can also create functional programs that incorporate advanced logic, recursion, and file handling.

Copilot and ChatGPT demonstrated the strongest performance, combining efficient code generation with clarity and readability. Their outputs consistently followed algorithmic conventions such as *O(n log n)* for sorting and *O(1)* for constant operations. These chatbots also provided meaningful explanations and comments that helped users understand how the code worked. This combination of accuracy and explanation shows that the top-tier models not only generate usable code but also act as effective educational tools. Users can learn programming concepts by analyzing the structure and logic of the generated programs, which aligns with findings by (Becker, 2023) and (Finnie-Ansley, 2023), who observed that LLMs enhance learning when combined with guided supervision.

Gemini and Meta AI produced well-organized programs but generated slightly larger files, reflecting a design preference for detailed explanations and additional documentation. While this increased memory footprint, it also improved interpretability for users who needed more context. Claude, in contrast, created verbose outputs that often contained redundant imports or unnecessary visualization code. Although this reduced efficiency, it also highlighted the system's safety-driven design, where explicit and transparent logic takes precedence over compactness. This trade-off mirrors the trends described by (Anthropic, 2023), where interpretability is prioritized to make AI reasoning more transparent.

The smaller models, such as ZZZ Code, CodeConvert, and Devv AI, displayed modest results. These systems proved capable in straightforward tasks but struggled when the prompts required multi-step or networked execution. CodeConvert, designed for cross-language translation, excelled when translating between programming languages but was less reliable for generating original programs. Devv AI demonstrated solid problem-solving ability but required external libraries for certain prompts, which could present obstacles for beginners. These limitations suggest that while smaller models are improving, they remain more suited for educational or conversion purposes rather than advanced development.

Another observation relates to the relationship between file size, efficiency, and user experience. Smaller programs were easier to execute, especially for beginners who might not understand complex dependencies. In contrast, larger files often included more guidance and context but were harder to run. This indicates that there is no single “best” model for every user. Efficiency-focused tools like Copilot are ideal for professional developers, while context-rich models like ChatGPT or Gemini serve learners better by offering interpretive clarity.

The presence of debugging and refactoring tools also contributed significantly to user-friendliness. As shown in Table 2, models with built-in debugging and explanation capabilities received higher overall scores. This implies that technical assistance and interpretive guidance are as important as raw code generation quality. A well-designed chatbot should therefore provide users with both functional outputs and instructional support, bridging the gap between automation and understanding.

Lastly, the results point to broader implications for programming education and professional software development. AI chatbots are increasingly functioning as interactive tutors that can guide users through code creation, testing, and correction. However, as noted by (Vaithilingam, 2022) and (Pearce, 2022), reliance on AI-generated code without understanding can introduce risks, especially in areas such as cybersecurity and system optimization. The data from this research suggest that as AI models evolve, their integration into classrooms and workplaces should be accompanied by structured guidelines that encourage active learning and critical evaluation rather than passive code generation.

Conclusion

This study compared eight AI chatbots including ChatGPT, Copilot, Gemini, Meta AI, Claude, ZZZ Code, CodeConvert, and Devv AI to evaluate their ability to generate computer programs accurately and efficiently. The research included fifteen programming prompts that tested a variety of problem types such as data structures, recursion, sorting algorithms, and client server systems. Each chatbot was assessed for correctness, runtime performance, code quality, file size, and user accessibility. The findings showed that most models could produce code that ran successfully with little or no user intervention, confirming the growing reliability of AI generated programming.

Copilot achieved the highest score with strong efficiency and minimal file sizes, while ChatGPT followed closely with readable, well-structured code and detailed explanations. Gemini and Meta AI also performed effectively, generating clear and functional programs, although their file sizes were larger and their performance slightly slower. Claude produced highly interpretable code but often included extra elements that reduced efficiency. The smaller chatbots, including ZZZ Code, CodeConvert, and Devv AI, showed promise in handling basic tasks but lacked versatility for more complex scenarios. These outcomes suggest that larger models are best suited for professional use, while smaller ones remain valuable for educational or lightweight applications.
The overall results demonstrate that AI chatbots are becoming effective programming assistants that can support

both learning and productivity. They can generate working code and provide explanations that help users understand the underlying logic. This makes them suitable for students, educators, and developers. However, challenges remain in dependency management, runtime optimization, and preventing overreliance on AI generated code without full comprehension. Human review continues to be necessary to ensure correctness, security, and ethical implementation in practice.

Future research should include more diverse AI systems and a broader range of programming challenges such as database, web, and mobile development tasks. It would also be valuable to involve users with different experience levels to measure learning impact and usability. Incorporating automated code quality and security checks could help establish consistent standards for evaluating AI generated code. As these tools continue to evolve, transparency, oversight, and responsible use will be essential for their safe and effective integration into education and software development. Collaboration among researchers, educators, and AI developers will further refine these systems to balance usability with safety. With thoughtful design and ethical guidance, AI assisted programming has the potential to enhance creativity, efficiency, and learning for the next generation of software development.

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Voice-First Accessibility: Rethinking Assistive Technology Use in Assisted Living via Smart Speakers

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Abstract: Smart speakers such as the Amazon Alexa have gained widespread popularity as everyday tools, primarily marketed for their convenience and entertainment value. However, their potential as assistive technologies within residential care environments remains underexplored. This paper argues that voice-activated smart speakers represent an underutilized yet potentially transformative accessibility tool for individuals with visual impairments, limited mobility, or cognitive disabilities - particularly within assisted living and long-term care facilities. By enabling hands-free interaction, these devices can facilitate greater autonomy, enhance safety, and foster social inclusion among residents who might otherwise experience barriers to communication and participation. This paper integrates socio-technical analysis and policy recommendations, offering a roadmap for structured integration of voice-first systems into assisted living care plans. Key recommendations include adopting inclusive design principles, engaging in participatory co-design with residents and caregivers, and rethinking prevailing approaches to privacy, surveillance, and control through a disability rights lens. Ultimately, this paper highlights the need to reimagine everyday technologies as tools for empowerment and equity in aging and disability care.

Keywords: Voice-First Interfaces, Smart Speakers, Assistive Technology, IoT, Human-Centered Design

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Introduction

The global shift toward smart living driven by advances in the Internet of Things (IoT), cloud computing, and edge intelligence has transformed nearly every sector of society, including healthcare, transportation, education, and urban infrastructure. These interconnected systems have redefined how people access services, manage resources, and maintain daily routines. Yet, despite this rapid diffusion of intelligent solutions, eldercare environments have been slow to capitalize on such innovations. Assistive technologies, which could benefit most from gains in ubiquity, automation, and personalization, remain underdeveloped or underutilized in institutional care settings (Pino, Mortillaro, & Rossi, 2020).

Voice-first interfaces such as Amazon Alexa, Google Assistant, and Apple Siri present significant but largely untapped potential to reimagine accessibility and autonomy for older adults in assisted living facilities. Although widely available in consumer markets, their role as formal assistive technologies has not been fully recognized. This oversight limits opportunities for enhanced independence, improved safety, and greater participation in social and cultural life within care environments (Pino, Mortillaro, & Rossi, 2020).

By leveraging natural language processing and ubiquitous connectivity, voice-first technologies enable intuitive, hands-free interaction with digital systems (O'Neill & Tedesco, 2024). For individuals with visual impairments, physical disabilities, or cognitive limitations, such functionality acts as a powerful equalizer allowing users to retrieve information, control environments, or access emergency services through simple speech commands. These devices extend beyond convenience to foster genuine empowerment, reducing reliance on caregivers and supporting institutional efficiency through increased resident engagement and reduced staff workload. Nevertheless, adoption in assisted living remains fragmented, often occurring informally through residents or families rather than through coordinated facility initiatives (Singh, Kropf, Hanke, & Holzinger, 2018).

This paper positions voice-activated smart speakers not merely as consumer electronics but as vital enablers of inclusive, dignified, and responsive care. Drawing on universal design principles (Steinfeld & Maisel, 2012) and insights from ambient assistive technology and disability justice frameworks (Tellioğlu, 2025) (Hemmings, 2025), we argue for a paradigm shift that centers accessibility, co-design, and ethical deployment in institutional contexts. Our analysis situates smart speakers within broader smart living goals while addressing persistent challenges of accessibility, autonomy, and institutional readiness advancing a socio-technical perspective on IoT-driven innovation that upholds dignity, independence, and inclusion for aging populations.

The Case for Smart Speakers in Assisted Living

The integration of smart speakers into assisted living facilities presents a compelling opportunity to transform the resident experience by enhancing autonomy, safety, and overall quality of life for older adults and individuals with disabilities (Chung, Winship, Falls, Parsons, & Bleich, 2021). Unlike traditional assistive devices, which often address narrow functional limitations, voice-first technologies offer a holistic platform that can adapt to a wide range of needs. Their conversational interfaces lower entry barriers to digital interaction, making them especially valuable for populations with declining vision, limited mobility, or other age-related impairments.

By leveraging the accessibility of natural language interaction, smart speakers can be reframed not simply as consumer gadgets but as personalized and adaptive assistive technologies. Their versatility allows them to respond dynamically to the unique challenges of aging and vision loss, providing tools for routine management, environmental control, emergency communication, and social engagement. When deployed intentionally, these devices can shift the balance of care toward greater independence, reducing reliance on caregivers for tasks that residents can manage with minimal technological support (Chung, Winship, Falls, Parsons, & Bleich, 2021).

Recognizing these capabilities, this paper identifies and explores five key dimensions that illustrate the transformative potential of smart speakers in assisted living contexts. These include their role in providing intuitive accessibility through voice-first interfaces, supporting independence via routine management, enhancing safety and comfort through environmental control, fostering social connectivity to combat loneliness, and delivering timely access to information for engagement and cognitive stimulation. Together, these dimensions demonstrate how voice-first systems can bridge critical gaps in current eldercare practices, while aligning with broader goals of inclusive and dignified smart living.

Voice-First Interface: Accessibility Through Simplicity

Unlike graphical user interfaces that rely heavily on visual cues and fine motor control, voice-first systems are inherently more accessible to individuals with limited or no functional vision (Oumard, Kreimeier, & Götzelmann, 2022). The ability to interact through spoken language removes the dependency on visual navigation, screen-based menus, or precise manual input, which are often insurmountable barriers for individuals with age-related or congenital vision impairments. In this way, smart speakers offer a more natural and inclusive mode of interaction that aligns closely with human communication patterns.

For older adults experiencing conditions such as age-related macular degeneration, glaucoma, diabetic retinopathy, or genetic disorders like cone-rod dystrophy, the tactile-free conversational nature of smart speakers provides a critical bridge to digital inclusion. Rather than being excluded from the digital ecosystem due to inaccessible interfaces, these users can rely on intuitive voice commands to access information, control their environment, or initiate communication. The removal of these barriers reduces frustration and creates opportunities for meaningful engagement with technology, often for the first time in years (Oumard, Kreimeier, & Götzelmann, 2022). This hands-free interface also carries broader implications for autonomy and quality of life. By enabling residents to bypass complex menus, remote controls, or assistive input devices, smart speakers reduce reliance on caregivers for basic tasks such as adjusting lights, checking the weather, or setting reminders. This independence not only preserves personal dignity but also lessens the strain on caregiving staff, who can redirect their attention to higher-level support needs. In doing so, voice-first systems can simultaneously improve resident satisfaction and optimize resource allocation within assisted living facilities.

Routine Management: Prompting Independence

Daily routines in assisted living facilities often center on time-sensitive, health-critical activities such as medication adherence, hydration, meal scheduling, and regular medical appointments. For many older adults, lapses in these routines can lead to serious health consequences from missed dosages that undermine chronic disease management to dehydration or nutritional deficiencies that contribute to frailty. While traditional reminder methods such as pillboxes or staff intervention remain useful, they often reinforce dependence on external cues rather than supporting personal autonomy. In this context, smart speakers offer an opportunity to embed proactive digital companionship into everyday life (Chang, Sheng, & Gu, 2024).

By issuing verbal prompts for medication, hydration, meals, and medical visits, smart speakers serve as accessible, adaptive aids for residents experiencing cognitive decline or memory loss. These spoken reminders reduce the cognitive burden of remembering complex routines while reinforcing essential health behaviors. Unlike static tools, voice-first systems can be personalized to individual schedules and updated dynamically, ensuring that notifications remain accurate and responsive to evolving medical or personal needs (Chang, Sheng, & Gu, 2024) (Marcuta, 2024). This adaptability distinguishes smart speakers from traditional assistive devices, positioning them as responsive, long-term supports in care environments.

Equally important is the ability for residents to create recurring or customized reminders using simple voice commands. This functionality empowers older adults to play an active role in managing their health routines rather than relying exclusively on caregivers. As a result, residents experience greater independence, while staff benefit from reduced oversight demands for repetitive daily tasks. Over time, this shared-responsibility model fosters self-reliance and consistency in care, underscoring the potential of smart speakers to promote sustainable autonomy within assisted living communities (Marcuta, 2024).

Environmental Control: Enhancing Comfort and Safety

The convergence of smart speakers with IoT-enabled appliances and home automation systems enables seamless, voice-based control of environmental features such as lighting, temperature, and window treatments (Torad & Bouallegue, 2022). In assisted living communities, this capability extends well beyond convenience as it redefines how residents interact with their surroundings to prioritize accessibility, safety, and independence. For individuals with mobility impairments, arthritis, or other conditions that limit fine motor control, issuing simple voice commands eliminates the need for physically demanding or complex manual adjustments. In doing so, smart speakers help residents maintain agency over their comfort while reducing the risk of strain or injury associated with navigating their environment in low-light or hard-to-reach spaces (Torad & Bouallegue, 2022).

With minimal setup requirements, smart speakers provide scalable and customizable solutions that adapt to individual needs within assisted living facilities. Personalized routines can automatically dim lights at bedtime, adjust thermostats for nighttime comfort, or raise window shades in the morning to align with circadian rhythms. These adaptive controls enhance both physical safety and emotional well-being, fostering environments that support autonomy and dignity. By reframing environmental control as a dimension of accessible design rather than convenience, smart speakers demonstrate how voice-first systems can contribute meaningfully to safer, more responsive living spaces for older adults.

Social Connectivity: Combating Loneliness and Isolation

Loneliness remains one of the most pressing issues in long-term care environments, functioning not only as an emotional burden but also as a critical determinant of resident health. Persistent isolation has been linked to depression, cognitive decline, and increased vulnerability to chronic conditions (Gardiner, Laud, Heaton, & Gott, 2020). Research further underscores that social disconnection negatively affects both physical and psychological well-being, reducing resilience and diminishing quality of life among older adults (Ong, 2022) (Boamah, Weldrick, Lee, & Taylor, 2021). Despite best efforts of caregivers, the structured nature of institutional care often limits opportunities for sustained, individualized social interaction, creating a need for complementary approaches that can extend human connection.

Voice-first systems such as smart speakers offer accessible and scalable tools to help fill this gap. Equipped with built-in communication features, they allow residents to make phone calls, send voice messages, or participate in virtual gatherings through simple speech commands bypassing the challenges of smartphones or tablets for those with visual or dexterity impairments (Gardiner, Laud, Heaton, & Gott, 2020). For older adults, this intuitive interaction reduces technological intimidation and restores a sense of agency, enabling them to maintain contact with loved ones and caregivers on their own terms (Ong, 2022).

Beyond facilitating communication, smart speakers can foster a sense of companionship that helps mitigate feelings of isolation. Their conversational nature enables responsive exchanges offering reminders, engaging in simple dialogue, and acknowledging user input in ways that simulate social presence. While such interactions cannot replace human connection, they can fill emotional gaps during periods of solitude, reducing the sense of abandonment often reported in care settings (Boamah, Weldrick, Lee, & Taylor, 2021). A recent case study found that elderly residents experienced two primary benefits from using smart speakers: greater agency in managing their environment and a perception of companionship, as if someone were present and attentive (Astell & Clayton, 2024). These findings suggest that smart speakers can serve as both communication aids and emotional supports, transforming “quiet moments” into opportunities for connection and enhancing overall well-being in assisted living facilities.

Information Access: Supporting Engagement and Cognitive Stimulation

Access to timely information and entertainment is essential for sustaining cognitive health and emotional well-being among older adults in long-term care (Astell & Clayton, 2024). Cognitive stimulation through music, news, and interactive content can slow cognitive decline, enhance memory retention, and stabilize mood. Yet many residents face barriers to these benefits due to visual impairments, mobility limitations, or the complexity of modern digital devices. Exclusion from such media not only limits engagement but can also deepen social isolation and reduce overall quality of life.

Smart speakers help overcome these challenges by offering immediate, voice-activated access to diverse informational and recreational content. With simple spoken commands, residents can retrieve weather updates, hear the latest news, listen to audiobooks, or enjoy personalized music playlists. Interactive features such as trivia games and guided meditation further enrich engagement, transforming smart speakers into adaptive, multipurpose companions. Their hands-free, screen-free operation represents a major improvement in usability for individuals with visual impairments, while personalization features such as selecting preferred news sources or revisiting familiar music from earlier decades reinforce autonomy and self-expression (Astell & Clayton, 2024). By aligning digital access with individual needs and preferences, smart speakers enable lifelong engagement and a more inclusive approach to cognitive and emotional wellness in assisted living settings.

Challenges and Ethical Considerations

While smart speakers offer promising opportunities to enhance accessibility, autonomy, and quality of life in assisted living settings, their adoption is not without significant challenges. The same features that make these devices appealing - seamless connectivity, always-on listening, and integration with personal routines - also introduce risks when placed in sensitive care environments. These risks are not trivial; they can directly impact residents' rights, institutional trust, and the overall safety of the technological ecosystem. A balanced perspective is therefore essential, one that acknowledges the benefits while rigorously examining the limitations.

As voice-first systems become embedded in the daily fabric of care facilities, they transition from optional consumer gadgets to infrastructure that shapes social and clinical practices. This shift amplifies the need to address technical vulnerabilities, ethical dilemmas, and organizational readiness. Left unaddressed, these factors may not only limit the effectiveness of smart speakers but also produce unintended harm, such as privacy violations, digital exclusion, or overburdened caregiving staff. In contexts where residents may already face heightened vulnerability due to age or disability, the margin for error is particularly slim.

To navigate these complexities, it is critical to identify and analyze the barriers that could undermine successful deployment. This paper highlights four core concerns - privacy and surveillance, digital literacy, accessibility gaps, and institutional constraints - that must be addressed to ensure effective integration of voice-first systems into assisted living environments (Yusif & Hafeez-Baiz, 2016) (Felber, Tian, Pageau, Elger, & Wangmo, 2023).

Each of these challenges reflects a different dimension of the problem. For instance, privacy concerns stem from persistent data collection and the "always listening" nature of these devices, while digital literacy issues highlight the difficulty some residents face in adopting new technologies (Chen, et al., 2023) (Mahmood, Wang, & Huang, 2024). Similarly, accessibility gaps remain due to limitations in voice recognition systems, particularly for users with atypical speech or cognitive decline [20].

Institutional readiness adds a further layer of complexity, as many facilities struggle with inadequate Wi-Fi infrastructure, limited IT support, or policy barriers that hinder adoption (Vrancic, Zadravec, & Orehovacki,

2024) (Lei, et al., 2017). Together, these issues represent the intersection of human, technical, and organizational factors, underscoring the need for collaborative approaches that involve residents, caregivers, developers, and policymakers alike. By critically engaging with these challenges, stakeholders can move toward solutions that maximize the benefits of smart speakers while safeguarding the dignity and rights of those they are designed to serve.

Privacy and Surveillance: Negotiating Consent in Shared Spaces

Perhaps the most pressing concern surrounding smart speakers is their persistent data collection and "always-on listening" design. Unlike traditional assistive devices that operate only when actively engaged, smart speakers are designed to remain in a constant state of passive audio surveillance, waiting for a wake word to activate. In private homes, users may find this trade-off acceptable; however, in communal or semi-private living arrangements such as assisted living facilities, the implications become far more complex. The continuous presence of such technology introduces new dynamics of power, oversight, and vulnerability that require scrutiny (Yusif & Hafeez-Baiz, 2016).

In environments where residents may share rooms, common areas, or visiting spaces, smart speakers can inadvertently capture the voices of individuals who have not consented to their use. Non-users may be exposed to ambient monitoring against their will, raising important ethical and legal questions about informed consent, data ownership, and individual autonomy. Compounding this concern is the lack of transparency in how voice data is processed, stored, or transmitted to cloud services, often beyond the control of the end-user or the care facility. Residents may not fully understand when and how their voices are being recorded, and even those who agree to use the devices may be unaware of the scope of data collection (Felber, Tian, Pageau, Elger, & Wangmo, 2023).

Without robust transparency, opt-in participation models, and granular controls over data collection, the presence of smart speakers risks normalizing surveillance under the guise of convenience. Such practices can erode trust within care communities, where residents already depend on institutions to safeguard their dignity and privacy. To avoid creating settings of digital surveillance, it is essential to establish privacy-by-design principles that clearly communicate how data will be used, empower residents to make informed choices, and provide easy-to-understand mechanisms for limiting or disabling monitoring in shared spaces. Only by embedding these protections can smart speakers be deployed responsibly in environments where personal autonomy and ethical care are paramount (Yusif & Hafeez-Baiz, 2016) (Felber, Tian, Pageau, Elger, & Wangmo, 2023).

Digital Literacy: Bridging the Usability Divide

While voice interfaces remove many of the barriers associated with traditional screens or tactile controls, they do not fully eliminate the challenges posed by limited digital literacy. For many older adults particularly those with minimal prior exposure to technology even basic tasks such as setting up devices, linking accounts, or managing Wi-Fi connectivity can be intimidating. This often results in heavy reliance on family members or staff, undermining the goal of fostering independence through voice-first systems (Chen, et al., 2023). Without adequate guidance, residents may hesitate to explore features or personalize their devices, leaving them dependent on others to mediate interactions.

Confidence, rather than capability, frequently becomes the determining factor in long-term adoption. Residents who did not grow up in digital environments may fear “breaking” the device or issuing incorrect commands, leading to avoidance or abandonment. To make smart speakers truly empowering, facilities must pair deployment with targeted digital literacy initiatives offering clear instructions, hands-on demonstrations, and ongoing support adapted to cognitive and sensory abilities of residents (Mahmood, Wang, & Huang, 2024). Such efforts bridge the gap between potential and practice, ensuring that the technology enhances rather than hinders resident autonomy.

Accessibility Gap: Limitation of Voice Recognition Systems

Although often marketed as universally accessible, current voice recognition technologies exhibit significant limitations when interacting with atypical speech patterns. Many older adults experience voice changes due to aging, while others may be affected by neurological conditions, disease, stroke, or dementia. These conditions can alter speech rhythm, clarity, or volume, leading to frequent misinterpretations or failed recognition attempts. Such breakdowns in communication can be discouraging, diminishing trust in the technology and reinforcing feelings of exclusion rather than empowerment (Kim, 2021). These errors can quickly erode trust, reinforcing frustration and feelings of exclusion among residents who most need reliable assistance. Compounding this challenge is the structured nature of many voice commands, which often require users to remember specific phrasing or syntax. For residents experiencing cognitive decline or memory lapses, recalling the difference between similar commands such as setting a timer versus an alarm can become a recurring source of confusion in using these devices (Chen, et al., 2023) (Mahmood, Wang, & Huang, 2024).

Addressing these shortcomings demands more than incremental technical refinement; it requires genuinely inclusive design. Developers should involve older adults with diverse speech patterns, cognitive profiles, and accessibility needs in the co-design, testing, and evaluation of voice-first tools. By incorporating feedback from these populations, systems can become more adaptive, forgiving, and responsive to real-world variation. In doing so, voice recognition can evolve from a source of frustration into a cornerstone of accessibility, fulfilling its promise as a truly inclusive interface (Kim, 2021).

Institutional Constraints: Policy and Infrastructure

The successful implementation of smart speakers in assisted living facilities depends not only on the technology itself but also on the readiness of institutions to support their adoption. Many care homes continue to face fundamental infrastructure gaps, including limited Wi-Fi coverage, inadequate network bandwidth, or outdated hardware that is incompatible with modern IoT devices. Without reliable connectivity and technical support, smart speakers cannot function consistently, undermining both user trust and staff willingness to incorporate them into daily care practices. These infrastructural shortcomings highlight the need for facilities to view smart living technologies as long-term investments rather than ad hoc additions (Vrancic, Zadravec, & Orehovacki, 2024).

Beyond infrastructure, organizational culture and policy frameworks play a decisive role in shaping adoption. Concerns about device security, liability, and the management of sensitive resident data often result in blanket prohibitions or cautious, small-scale experimentation rather than strategic integration. Administrators may fear reputational or legal risks associated with potential breaches or misuse of data, particularly given heightened awareness of cybersecurity threats in healthcare contexts (Lei, et al., 2017). Without clear guidelines or regulatory assurances, institutions may default to avoiding these technologies altogether, even when their potential benefits for residents are well-documented.

Financial considerations further complicate adoption decisions. Facility administrators must weigh the perceived cost-benefit ratio of deploying and maintaining smart speakers at scale, including not only the devices themselves but also staff training, technical support, and ongoing updates. Some may worry that introducing these technologies will add to the workload of caregivers, rather than alleviating it, creating resistance among frontline staff. Overcoming these barriers requires cross-sector collaboration between care providers, policymakers, and technology developers to establish standards of use, develop funding models, and demonstrate the tangible impact of smart speakers on resident well-being. Evidence-based studies that document improvements in autonomy, safety, and quality of life will be crucial in building institutional trust and fostering broad uptake across assisted living facilities (Vrancic, Zadravec, & Orehovacki, 2024) (Lei, et al., 2017).

Position Statement: Towards Integration of Voice-First Accessibility

We assert that smart speakers should be formally recognized and deployed as assistive technologies in assisted living settings, particularly for residents with visual impairments and related functional limitations. Their voice-first, hands-free functionality directly addresses critical accessibility needs by enabling users to perform tasks that would otherwise require visual acuity, fine motor skills, or caregiver assistance. However, despite their accessibility potential, smart speakers are still classified primarily as consumer devices, a categorization that restricts their structured integration into formal care planning and limits access to funding streams typically reserved for recognized assistive technologies (Chen, et al., 2023).

Reframing smart speakers as legitimate, regulated tools within the continuum of eldercare and disability support is essential to realizing their full potential. This requires moving beyond ad hoc, individual-driven adoption toward a systemic approach that embeds these devices into institutional practices. By positioning smart speakers alongside screen readers, mobility aids, and other established technologies, care environments can ensure that residents benefit from a consistent and reliable infrastructure that supports independence and dignity. Such recognition would also strengthen accountability among developers and providers, encouraging the creation of devices that meet healthcare-grade standards of security, reliability, and accessibility (Edwards, Jones, Shenton, & Page, 2021).

This paradigm shift will not occur without coordinated action across multiple stakeholders. Care facilities must invest in the necessary infrastructure and staff training to support sustainable use; technology developers must adopt inclusive design principles and co-create features with input from residents and caregivers; and policymakers must establish frameworks that provide regulatory clarity and financial support. Guided by principles of inclusive design and ethical governance, these efforts would transform smart speakers from optional consumer gadgets into indispensable components of modern assistive ecosystems. In doing so, we can bridge the current divide between consumer innovation and institutional care, ensuring that voice-first technologies are leveraged to their fullest capacity for the populations that need them most (Chen, et al., 2023) (Edwards, Jones, Shenton, & Page, 2021).

Facility-Level Integration and Staff Training

Assisted living facilities must move beyond ad hoc or resident-initiated adoption of smart speakers toward a more standardized and institutionally supported approach. At present, many facilities allow residents or families to introduce devices informally, leading to inconsistent access, uneven support, and fragmented integration into daily care. This reliance on individual initiative risks reinforcing inequalities, as only residents with personal resources or technologically savvy families benefit from the potential advantages of voice-first systems. By contrast, a facility-wide strategy ensures that all residents - regardless of background - can access smart speakers as part of a consistent assistive infrastructure (Edwards, Jones, Shenton, & Page, 2021).

Approaches requires investment in the elements that make deployment sustainable. Robust wireless infrastructure is a prerequisite, as are reliable technical support systems to manage device setup, troubleshooting, and updates. Equally important are clear policies governing device provisioning, maintenance, and security. Without these institutional safeguards, devices risk being underutilized, abandoned, or even disabled due to concerns about malfunction or misuse. Formalizing these responsibilities ensures that smart speakers are not merely tolerated as consumer gadgets but instead recognized as integral tools in advancing accessibility and autonomy (Davitt & Brown, 2022).

Equally critical is the role of staff training in successful integration. Training should extend beyond basic device functionality to encompass strategies for supporting residents in using voice-first systems as part of their daily routines. Caregivers and administrators must learn to embed smart speaker use within individualized care plans, ensuring that the devices reinforce independence while complementing other forms of assistance. This positions frontline caregivers not as gatekeepers who manage access to technology, but as facilitators who empower residents to maximize its benefits. Treating smart speakers as core components of the assistive ecosystem rather than discretionary extras can ultimately reshape how technology and caregiving intersect in long-term care environments (Edwards, Jones, Shenton, & Page, 2021) (Davitt & Brown, 2022).

Inclusive Co-Design by Developers

Technology providers have a responsibility to center the lived experiences of visually impaired older adults in the design and refinement of voice interfaces. Too often, innovations in consumer technology are developed with younger, digitally fluent populations in mind, leaving older adults and individuals with disabilities to adapt tools that were not designed for their needs. This retrofitting approach can exacerbate barriers to adoption, as features intended for convenience may fail to align with the accessibility requirements of vulnerable populations. By prioritizing inclusive design from the outset, technology developers can ensure that smart speakers are not only functional but also empowering tools that address the realities of aging and disability (Chen, et al., 2021).

Co-design processes are critical to achieving this goal. By involving end users, geriatric care specialists, and accessibility experts in every stage of development, technology providers can capture diverse perspectives that enrich feature development, interaction models, and feedback mechanisms. For example, individuals with speech impairments can provide insights into error-handling protocols, while caregivers may highlight the need for multi-user profiles that accommodate shared living spaces. Accessibility experts can also help identify potential compliance issues with legal standards, ensuring that devices align with broader disability rights frameworks. Such participatory design practices transform users from passive recipients into active collaborators, resulting in more responsive and equitable technologies (Chen, et al., 2021).

When co-design principles are implemented, smart speakers can be proactively crafted to accommodate the full spectrum of sensory, cognitive, and physical abilities found in assisted living communities. This proactive approach reduces the risk of exclusion by addressing limitations before they reach residents, rather than retroactively attempting to correct usability failures. Moreover, it positions smart speakers as intentionally inclusive assistive technologies rather than generalized consumer devices adapted after the fact. In this way, inclusive co-design fosters trust, usability, and long-term adoption - ensuring that voice-first systems evolve as meaningful accessibility tools within institutional care environments.

Policy Recognition and Funding Reform

To implement smart speakers as formal assistive technologies, existing funding frameworks must evolve to reflect their accessibility potential. At present, many public and private insurance schemes exclude commercially available devices such as smart speakers from reimbursement categories, largely because they are marketed as consumer electronics rather than medical or assistive tools. This classification creates a structural barrier to adoption, as facilities and residents are often required to cover costs out of pocket. For individuals with limited financial resources, this effectively places voice-first systems out of reach, even when the devices could significantly improve autonomy and quality of life (Medical coverage policy: Speech generating devices, 2018).

The exclusion of smart speakers from reimbursement schemes also sends a broader message that their role in accessibility is peripheral rather than essential. This lack of formal recognition undermines their legitimacy as tools for eldercare and disability support, leaving facilities hesitant to invest in deployment at scale. Policymakers can address this gap by updating eligibility criteria within assistive technology funding programs to explicitly cover voice-first systems when prescribed for visual, cognitive, or mobility impairments. By aligning funding mechanisms with the realities of contemporary assistive technology, governments and insurers can legitimize smart speakers as critical infrastructure rather than discretionary conveniences (Reimbursement knowledge guide for medical devices, 2024).

Recognizing smart speakers within reimbursement frameworks would yield multiple benefits. It would lower cost barriers for both residents and institutions, enabling broader adoption across socio-economic groups. It would validate their critical relevance in eldercare, providing facilities with a financial incentive to integrate them into care planning. Expanded funding support would encourage technology developers to design devices that meet healthcare-grade standards, knowing that reimbursement policies now encompass such tools. Together, these changes would create a virtuous cycle in which policy recognition, financial accessibility, and institutional adoption reinforce one another, accelerating the integration of smart speakers into assisted living environments (Medical coverage policy: Speech generating devices, 2018).

Privacy by Design and Resident Consent

As with any data-enabled technology introduced into healthcare and assisted living settings, the ethical deployment of smart speakers hinges on the implementation of robust privacy safeguards (Yusif & Hafeez-Baiz, 2016). These devices operate by continuously listening for activation cues and transmitting data to external servers, raising legitimate concerns about surveillance, consent, and misuse. In environments where vulnerable populations reside, the stakes are particularly high: a breach of trust in how data is collected and processed can compromise not only individual privacy but also institutional credibility. To mitigate these risks, facilities must adopt proactive strategies that embed privacy protection into the very design and governance of smart speaker use.

Central to these strategies is the principle of resident autonomy. Smart speaker integration must follow opt-in models that empower residents to make informed choices about their participation. Clear, accessible explanations of how data is collected, stored, and shared should accompany every deployment, ensuring that residents understand what is at stake. Importantly, this process must be ongoing rather than one-time, allowing residents to revisit and adjust their consent as their comfort levels or living arrangements change. Facilities also bear responsibility for establishing clear boundaries regarding device functionality in shared spaces, where non-consenting individuals may otherwise be inadvertently exposed to passive monitoring.

Equally important is the need for user-friendly privacy settings that allow residents and staff to easily control device behavior. Too often, privacy controls are buried within complex menus or couched in technical jargon that excludes non-experts. By offering straightforward, transparent options - such as muting microphones, limiting data retention, or restricting third-party access - facilities can empower users to exercise meaningful control over their digital environments. Upholding these principles is not simply a matter of regulatory compliance with healthcare privacy standards; it is essential to maintaining the trust, dignity, and psychological safety of residents, staff, and visitors alike. Without such protection, the promise of voice-first accessibility risks being overshadowed by fears of surveillance and misuse (Yusif & Hafeez-Baiz, 2016).

Conclusion

The rapid rise of smart living technologies offers an important opportunity to enhance accessibility, autonomy, and quality of life in assisted living facilities. While healthcare monitoring, telemedicine, and home automation have received significant attention, the potential of voice-first smart speakers remains underexplored. Yet these devices can bridge critical accessibility gaps, enabling residents with visual, mobility, or cognitive limitations to engage with their environment and maintain independence. Smart speakers provide more than functional support; they foster social connection, agency, and cognitive stimulation. By simplifying interaction with digital services and embedding themselves into daily routines, they emerge as holistic assistive tools rather than convenience gadgets.

To realize this potential, voice-first systems must be formally recognized as assistive technologies and integrated into care through coordinated action. Facilities should strengthen infrastructure and staff training, developers should prioritize inclusive co-design, policymakers must expand funding frameworks, and privacy protections must center on resident consent. Only through such collaboration can smart speakers move from consumer devices to trusted components of institutional care. This reframing underscores a larger principle: accessibility and dignity must be central to innovation in eldercare. Recognizing smart speakers as legitimate assistive technologies provides a model for inclusive innovation across the broader smart health ecosystem.

By positioning devices like Amazon Alexa as critical tools for accessible aging, we move toward a vision of smart living that is both technologically advanced and deeply human-centered - where innovation empowers, dignifies, and includes the most vulnerable members of society.

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From Environmental Burden to Net Benefit: Making AI a True Ally for Health and the Environment

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Abstract: Artificial intelligence has become both a catalyst for discovery and a source of environmental burden. As computational infrastructures expand, their energy and water demands rise sharply while their potential to enhance public-health insight remains underused. This paper examines how high-resource computation can evolve into a sustainable research partner. Using recent evidence from environmental assessments and data-center policy along with a thought experiment integrating Bayesian Kernel Machine Regression (BKMR) and laboratory experimentation, we outline how digital modeling can reduce experimental redundancy and strengthen hypothesis development. The paper argues that responsible computational design and human oversight can transform digital systems from extractive technologies into instruments of environmental and public-health benefit.

Keywords: Artificial Intelligence; Environmental Health; BKMR; Sustainability; Cat's Claw; Nitrate Exposure

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Introduction and Background

Artificial intelligence (AI) has become a defining feature of twenty-first-century research and development. It now influences nearly every scientific and educational discipline, from atmospheric modeling to clinical diagnostics to pedagogical practice. Yet its rapid growth has created a paradox. On one hand, computational systems have accelerated discovery; on the other, they have imposed measurable environmental burdens through their demand for electricity, water, and rare-earth materials (International Energy Agency 2024; EESI 2023).

The global scale of this demand is striking. The IEA projects that data-center electricity consumption will more than double by 2030, reaching approximately 945 terawatt-hours per year which is roughly equivalent to the annual electricity use of Japan (IEA 2024). Large-language-model training alone has been estimated to emit hundreds of tons of CO_2 and consume millions of liters of water for cooling (MIT News 2025; Veolia 2023).

Beyond climate effects, local communities experience the constant low-frequency hum of server farms and land-use change associated with data-center sprawl (Larson Davis 2022; TechTarget 2023).

Despite these costs, AI offers transformative potential for environmental and public health research. When paired with robust statistical tools, it can model complex multi-exposure systems, forecast disease risk, and identify interventions that conventional methods might overlook and do so on a personnel and budgetary scale that could benefit small health departments immensely if properly used (Bobb et al. 2015). The challenge is not whether to use computational tools but **how** to use them responsibly and how to make them more environmentally sustainable.

This paper explores the balance between burden and benefit. It proposes that AI can become a constructive research collaborator when integrated with transparent modeling frameworks such as Bayesian Kernel Machine Regression (BKMR) or other statistical models and guided by sustainability principles. The analysis builds on published environmental impact assessments, emerging policy frameworks for greener data centers, and empirical work examining AI-assisted experimental design. This discussion demonstrates that computational science and environmental stewardship are not mutually exclusive; they can be mutually reinforcing.

The following sections first describe the methodological approach used to gather and evaluate recent literature and data. Subsequent sections quantify the environmental burdens of computation, summarize current mitigation efforts, and examine how underuse of AI in research, both primary and applied, wastes both intellectual and material resources. The thought experiment of applying AI to model a multiple exposure scenario in regard to immune responses to nitrate driven nitric oxide expression and Cat's Claw (*Uncaria tomentosa*) impacts on lymphocyte inflammatory markers, illustrates how a deliberately structured dialogue between human investigators and computational modeling can generate efficient, testable hypotheses that support sustainable scientific practice. A dialogue approach which can be utilized to model any of many multiple exposure scenarios that may present themselves in the environmental public health research laboratory or in communities experiencing multiple exposures to various environmental factors.

Methodology

A structured literature search was completed in 2025 to identify recent publications addressing the intersection of artificial intelligence, environmental sustainability, and public-health modeling. The search targeted work published from 2022 to 2025 to capture the most current analyses of computational energy use, policy responses, and methodological advances incorporating multivariate statistical techniques such as Bayesian Kernel Machine Regression (BKMR). Searches were performed in PubMed, ScienceDirect, and arXiv, supplemented by grey literature from governmental and industry sources, including the International Energy Agency, U.S. Environmental Protection Agency, and the Environmental and Energy Study Institute.

Key search terms and Boolean combinations included ***AI energy consumption***, ***data-center water use***, ***Bayesian mixture modeling***, ***BKMR health risk***, ***sustainable data centers***, **and** ***environmental health forecasting***. Results were filtered to include peer-reviewed studies, official reports, or policy briefs containing quantitative data or methodological innovation. Opinion pieces and non-documented blog content were excluded.

For each retained source, publication type, analytical scope, and relevance to sustainable computation were coded. Cross-validation was performed by comparing findings among the major databases. Additional backward searches of reference lists were conducted to ensure inclusion of foundational works in Bayesian computation and mixture-model development (Smith and Roberts 1993; Higgins and Spiegelhalter 2002).

The data from this search informed both the environmental burden assessment and the conceptual synthesis presented later in this paper. Table 1 summarizes the thematic categories, search terms, and inclusion criteria that structured the review.

Table 1. Search categories and inclusion criteria

Category	**Search terms**	**Inclusion criteria**
Environmental impact	AI energy use, data center water footprint, emissions	Peer-reviewed or official reports 2022–2025
Health modeling	BKMR, multi-chemical exposure, cytokine studies	Quantitative or experimental methods
Sustainability policy	Responsible technology, green data centers	Empirical or policy-based research

This framework provided a transparent and replicable foundation for evaluating how computational research can evolve from a high burden (environmentally, sustainability) to a net-benefit model.

Environmental Burdens of Artificial Intelligence

The environmental footprint of large scale computation has become impossible to overlook. Training and operating generative and analytical models require continuous energy input, extensive cooling water, and specialized infrastructure, all of which contribute to climate and community impacts (International Energy Agency 2024; EESI 2023; MIT News 2025). Data-center operations already account for roughly one to two percent of global electricity demand, and the International Energy Agency projects this share could double by 2030 as artificial-intelligence workloads expand (IEA 2024).

Energy Demand and Carbon Emissions

Energy consumption remains the most immediate burden. Each large language model training cycle can require thousands of megawatt-hours of power, translating to hundreds of tons of carbon emissions (Zhuang et al.

2025). Most of this energy still derives from non-renewable sources, despite growing commitments to carbon neutrality. Regional clustering of data centers can also strain electrical grids and displace renewable-energy access from surrounding communities (OECD 2024).

Water Consumption and Cooling Requirements

Cooling systems represent another critical concern. The Environmental and Energy Study Institute (2023) reports that single large model training events may consume more than two million liters of water, while Veolia (2023) documents continuous daily withdrawals of hundreds of thousands of gallons at large commercial sites. These withdrawals often occur in regions already vulnerable to drought. As shown in Table 2, typical AI-model development now demands both significant electricity and water, producing emissions comparable to many industrial operations.

Table 2. Estimated energy, carbon and water footprint of AI systems

Parameter	Estimated value	Source	Notes
Energy use	945 TWh by 2030	IEA (2024)	Approx. 0.24 Wh per prompt
CO_2 emissions	≈ 493 metric tons per training cycle	MIT News (2025)	Derived from LLM development phase
Water use	≈ 2.7 million liters per training event	EESI (2023)	Cooling demand for data-center operations

Noise and Land-Use Impacts

Environmental pressures extend beyond energy and water. Noise levels inside data centers frequently exceed 70 decibels, creating continuous background exposure for nearby neighborhoods (Larson Davis 2022; Omar et al. 2016). Construction of sprawling server complexes also transforms land cover and increases impervious surfaces, contributing to heat-island effects and altering local hydrology (TechTarget 2023). These cumulative burdens make clear that the ecological costs of computation must be considered alongside its analytical benefits. The next section reviews emerging technical and policy solutions designed to reduce these burdens and transition computational infrastructure toward net environmental benefit.

Sustainable Data Center Innovations and Regulatory Context

While the environmental costs of computation are substantial, rapid innovation in data-center design and governance offers credible pathways toward mitigation. Many of the most visible technology companies have adopted integrated sustainability strategies that target both energy and water use, and several governments are developing new frameworks to regulate these facilities more effectively (Clean Air Task Force 2025; Reed

Smith 2025). These responses demonstrate that environmental responsibility and computational expansion can progress together if corporate responsibility and public policy reflect a commitment to society and future generations.

Technological Innovations

Multiple corporations have begun to invest in closed-loop or low-impact cooling systems that dramatically reduce water withdrawal. Microsoft's zero-water cooling design in its Arizona and Washington facilities has eliminated freshwater use for thermal control, relying instead on advanced phase-change systems that circulate internally treated water (Microsoft 2024). Amazon Web Services operates more than twenty data centers using reclaimed wastewater for cooling, lowering its demand on municipal supplies (Datacenter Dynamics 2024).

European research centers such as ETH Zurich's *Aquasar* and Germany's *iDataCool* have pioneered hot water cooling in which waste heat from servers is repurposed to warm buildings (Wikipedia 2023a; Wikipedia 2023b). These examples indicate that technological redesign can yield measurable reductions in both emissions and water use without compromising performance. Public policy incentives should call upon the best lessons of green manufacturing and pollution prevention to encourage further improvements and broad adoption of these approaches.

Policy and Regulatory Developments

Public-sector initiatives have emerged to complement these private-sector advances. In the United States, New York State Bill S6394A establishes phased reporting requirements and renewable energy targets for data centers, aiming for 100 percent renewable sourcing by 2050 (New York State Senate 2025). The Commonwealth of Virginia recently advanced the *Responsible Data Center Development Bill*, which mandates environmental impact assessments and community consultation prior to new construction (Virginia Conservation Network 2025).

Pennsylvania's proposed *RESET Board* would centralize oversight of energy intensive industries, including data center siting and permitting, to ensure coordinated land use planning (Reed Smith 2025). At the federal level, the White House (2025) has proposed streamlining infrastructure permitting while retaining environmental review safeguards. This should be done with the highest ethical standards maintained.

Outside of US government initiatives, the Clean Air Task Force, an environmental advocacy group headquartered in Boston, MA, (2025) advocates transparent siting policies for renewable energy infrastructure that serve data center clusters, emphasizing community engagement and fair distribution of economic benefits. Together, these efforts reflect a growing recognition that computational capacity must develop within clear environmental and equity boundaries.

Transition Toward Net Benefit

The convergence of technological and policy innovation signals a turning point. As the case examples illustrate, responsible data center design can transform previously extractive systems into contributors to environmental resilience. When research institutions and public health agencies partner with the private sector to implement similar principles, prioritizing energy efficiency, water reuse, and transparent reporting, the environmental cost of computation can be substantially reduced. The following sections examine how scientific practice itself must evolve to ensure that such hardware level advances are matched by smarter, more deliberate use of computational tools within research. It is in the more advanced applications of developed AI models that the greatest return on both environmental costs and human time are realized.

Shallow vs. Deep Use of Computational Systems in Research

Despite rapid advances in computational power, much current academic and industrial use of artificial-intelligence systems remains superficial. In most research environments, AI is treated as a convenience for searching literature, summarizing content, or producing code snippets rather than as a genuine analytical collaborator (Handa et al. 2025; McKinsey and Company 2025). This narrow engagement limits innovation, consumes unnecessary resources, and overlooks opportunities for complex modeling that could directly inform environmental and health protection.

The Problem of Under-Use

Empirical studies reveal that the majority of interactions with generative systems fall into augmentation rather than exploration. Handa et al. (2025) found that 57 percent of AI use was limited to human and AI text augmentation tasks, while only 43 percent approached automation or higher-order analytical reasoning. Such patterns reflect a comfort zone in which researchers and public health practitioners use digital tools to polish work rather than to question assumptions or identify new causal relations. This under-use also carries environmental consequences. Each redundant query, repeated computation, or shallow interaction draws on the same energy intensive infrastructure described earlier (OECD 2024). Thus, ineffective use translates directly into wasted energy.

Toward Deeper Integration

A deeper form of computational use situates AI within the scientific method itself. Rather than replacing analytical reasoning, the system becomes a partner in iterative hypothesis testing, data interpretation, and model validation. For instance, Bayesian frameworks such as BKMR can integrate AI assisted parameter exploration to evaluate nonlinear exposure effects in complex environmental mixtures or aid in the development of community public health needs assessment by modeling health outcomes from multiple exposures or risks (Bobb et al. 2015). When researchers employ computation at this level, every cycle of analysis yields refined data and stronger evidence rather than redundant output. The result is an overall reduction in computational waste and a simultaneous improvement in research/applied research quality.

Efficiency as a Form of Sustainability

Efficiency in research is often framed as a matter of time and cost, but in the context of environmental stewardship, it also represents an ethical responsibility. McKinsey and Company (2025) argue that well-designed "super-agency" workflows, balancing human creativity and digital automation, achieve higher productivity with lower environmental impact. When computation is focused on meaningful analytical work, the total number of energy consuming operations decreases. Deep integration therefore aligns scientific rigor with sustainability, ensuring that every watt of power used contributes to genuine discovery.

Thus, computational dialogue can function as a modern form of dialectic reasoning; a process through which hypotheses are refined by structured questioning rather than passive automation.

Artificial Intelligence as a Dialectic Partner in Discovery

The idea of using computational systems as dialectic partners arises from a very old intellectual tradition. In classical philosophy, dialectic referred to the disciplined exchange of questions and counter-arguments that revealed hidden assumptions and improved reasoning. When applied to contemporary research, this approach reframes artificial intelligence not as an oracle that provides answers but as a reflection that helps scholars examine the structure of their own thought (Brynjolfsson et al. 2023).

Dialogue and Hypothesis Formation

In practical scientific work, dialectic engagement occurs when the researcher uses a computational model to test competing explanations or boundary conditions for a phenomenon. Each iteration of model building and critique functions like a round of conversation, gradually converging on a clearer hypothesis. Bayesian reasoning naturally fits this process because it incorporates prior beliefs, evaluates evidence, and updates conclusions through sequential learning (Higgins and Spiegelhalter 2002). When artificial intelligence supports this reasoning by generating alternative scenarios, exploring parameter spaces, or identifying data gaps, the exchange becomes a genuine dialogue between human and machine that can be used to test realities in the laboratory or the daily work of environmental health specialists.

From Automation to Reflection

This perspective challenges the notion that the primary value of AI lies in automation. Automation reduces labor, but dialectic interaction improves understanding and requires a human creator. As Brynjolfsson and colleagues (2023) note, the most productive uses of generative systems occur when human insight and computational capacity reinforce each other. Such reflective collaboration guards against overconfidence and ensures that the conclusions drawn from models remain transparent and reproducible. It also creates an intellectual feedback loop that refines both the model and the investigator's conceptual framework. And, it requires that the human creator be well familiar with the issues being engaged and analyzed.

Ethical and Cognitive Dimensions

Engaging AI dialectically introduces an additional ethical dimension. It requires acknowledging that computational systems influence the framing of questions as much as their answers. The Organization for Economic Co-operation and Development (OECD 2024) emphasizes that responsible governance of artificial intelligence research should include mechanisms for transparency, interpretability, and accountability. Treating the system as a dialectic partner rather than a black-box decision maker aligns scientific practice with these values. The process cultivates humility, prompting researchers to ask whether the patterns detected by a model truly represent reality or merely reflect the data fed into it.

In the environmental health sciences, such reflexivity is essential. Mixture exposures, non-linear dose responses, and context specific interactions all demand interpretive depth that no single model can supply. Dialectic use of computation encourages multiple perspectives and continual verification, an approach that mirrors peer review itself.

The following section presents a concrete example of this principle through the integration of AI-assisted BKMR modeling with laboratory experimentation focused on nitrate exposure and the botanical supplement of Cat's Claw (*Uncaria tomentosa*). These are areas that the authors have worked in extensively already in a laboratory setting.

Illustrative Thought Experiment: Designing an AI-Informed Research Loop

To illustrate how a dialectic exchange between researcher and computational system might function in practice, imagine a study still in its planning stage rather than one already executed (**Figure 1**). The scenario uses nitrate exposure and the botanical supplement Cat's Claw (*Uncaria tomentosa*) as representative variables within a Bayesian Kernel Machine Regression (BKMR) framework. The goal is to show how reflective modeling could guide hypothesis formation and experimental design before any cell culture work begins (Bobb et al. 2015).
In this conceptual model, nitrate derived nitric oxide (NO) expression in lymphocytes serves as an environmental exposure of interest because it can both support and disrupt immune function depending on concentration. Cat's Claw, a plant extract with reported antioxidant and immunomodulatory effects, represents a potential moderating factor. Through BKMR simulation, a research team could explore how varying nitrate concentrations interact with hypothetical supplement levels to influence lymphocyte behavior in regard to the release of proinflammatory molecules. Posterior inclusion probabilities (PIPs) generated by the model would

highlight which exposure combinations most strongly affect predicted outcomes such as NO accumulation, cytokine expression, and cell viability.

Rather than providing definitive results, the exercise demonstrates how iterative modeling can inform the *next* round of laboratory inquiry and aid researchers in estimating multiple exposure impacts. Each computational cycle clarifies which dose ranges and biomarkers merit direct measurement, thereby conserving materials and energy once experiments move to the bench. The process embodies the dialectic principle: questions posed ***in silico*** refine the questions later asked ***in vitro***. Of course, this approach could be applied to a community health or environmental health needs assessment, also.

alt text: The schematic illustrates a continuous cycle of data → modelling → hypothesis → experiment → updated modelling. Each iteration deepens understanding and guides efficient study design without presuming outcomes.

Figure 1. Conceptual research loop linking modelling and experimentation

Results and Discussion

Although the nitrate and Cat's Claw scenario remains theoretical, analyzing it as a structured thought experiment reveals several important outcomes for research practice. The value lies not in empirical data but in what the process demonstrates about how reflective computational modeling can guide sustainable experimentation and broader public health inquiry.

Key Insights from the Conceptual Model

The iterative loop shown in **Figure 1** illustrates how modeling can precede and inform laboratory design. In this conceptual case, BKMR was used to explore possible interaction surfaces between nitrate concentration and supplement exposure. The model run by the author's produced qualitative predictions, moderation of cytokine responses and stabilization of variability, that can be tested by future work. A researcher could use past data or past consolidated data tables to also estimate possible response ranges. By identifying plausible dose ranges and outcome measures before any bench work occurs, the researcher gains a strategic blueprint for experimentation. The approach therefore transforms computation from a retrospective analytic tool into a proactive design instrument (Bobb et al. 2015; Brynjolfsson et al. 2023).

Anticipated Benefits for Laboratory Efficiency

Planning experiments through dialogue with a model offers several sustainability advantages. First, it reduces the number of trial-and-error exposures required to locate meaningful response ranges, conserving reagents and culture media. Second, it lowers instrument time and energy use associated with unnecessary assays. Third, it enables researchers to prioritize measurements that will yield the greatest interpretive return per sample analyzed. In effect, every computational refinement decreases the physical and environmental footprint of the eventual experiment (OECD 2024; Clean Air Task Force 2025).

Integrating Sustainability and Scientific Rigor

The thought experiment also underscores a philosophical shift in how environmental health research can be organized. Efficiency here is not just economic, it is ecological and analytical. When experimental design is informed by transparent modelling, fewer materials are consumed, and each data point holds greater explanatory power. This reframing connects scientific rigor with environmental stewardship, illustrating that methodological clarity and sustainability are complementary goals rather than competing priorities.

Implications for Future Empirical Work

Future laboratory studies will test whether the predicted moderating effect of Cat's Claw on nitrate induced inflammation holds true. Even if the empirical outcomes differ from the forecasts, the conceptual process retains value because it demonstrates how the modelling experiment feedback loop can evolve over time. Updated models would integrate new data, refine priors, and generate improved hypotheses, perpetuating the cycle depicted in **Figure 1**. Through this ongoing exchange, environmental health research becomes both adaptive and resource conscious. Prediction of complex exposure scenarios and complex public health challenges becomes a model of responsible innovation suited to the sustainability challenges of the twenty-first century.

Implications for Public Health and Environmental Practice

The conceptual research loop shown in **Figure 1** demonstrates a scalable approach to inquiry that extends well beyond the laboratory. If implemented broadly, the same reasoning cycle of data, modelling, hypothesis, experiment, updated modelling could improve how environmental and health institutions plan interventions, allocate resources, and evaluate risk.

Strategic Applications in Public Health

Public health agencies often face decisions about complex exposure mixtures without sufficient experimental evidence. Modelling frameworks such as BKMR, supported by iterative dialogue with computational tools, could narrow uncertainty ranges and guide field sampling strategies before costly data collection begins (Bobb et al. 2015). By integrating community level environmental data with health outcome indicators, these models can highlight which combinations of pollutants or social stressors warrant priority attention. When coupled with transparent communication of model assumptions, the approach supports evidence based policy while maintaining public trust (OECD 2024).

Policy Relevance and Cross-Sector Collaboration

At a policy level, the research loop aligns neatly with current sustainability initiatives in data center governance and green infrastructure planning (Clean Air Task Force 2025; Reed Smith 2025). Agencies developing environmental regulations increasingly require computational forecasting to evaluate cumulative impacts. Embedding iterative modeling within those frameworks would enable continuous policy refinement as new monitoring data emerge. Collaboration among environmental scientists, computational specialists, and policymakers can ensure that technological capacity translates into societal benefit rather than additional burden.

Educational and Institutional Implications

The same principles hold value in education and institutional practice. Training future scientists to engage computation dialectically by questioning its results and refining their own assumptions encourages critical thinking and environmental responsibility. University research programs could adopt reflective modeling exercises similar to the nitrate and Cat's Claw thought experiment as low-impact teaching tools. Such exercises illustrate that scientific creativity and sustainability can coexist as hypotheses are generated, critiqued, and improved without consuming physical resources.

Toward a Culture of Responsible Innovation

Finally, this framework promotes a broader cultural shift toward responsible innovation. Whether the context is cell culture, environmental modelling, or public-policy design, the same ethics apply wherein which computational power should serve thoughtful inquiry rather than replace it. Efficiency and integrity are intertwined. Each iteration of the research loop deepens understanding while minimizing environmental cost. In this sense, reflective modelling becomes both a scientific method and an ethical commitment to stewardship.

Conclusions and Future Directions

The conceptual framework developed here demonstrates that artificial intelligence, when applied reflectively and when held to high standards of environmental sustainability and stewardship, can become a constructive force in environmental and public-health research rather than an extractive one. By placing modelling at the start of the scientific or needs assessment process, researchers can generate hypotheses that are both targeted and resource efficient.

The iterative reasoning process presented in Figure 1 positions computation as an ally in the movement toward sustainable science. Instead of viewing large scale modelling as a drain on energy and water resources, the dialectic approach sees each cycle as an opportunity to refine purpose, reduce waste, and improve interpretive clarity. When combined with ongoing innovations in green infrastructure and policy reform, reflective use of AI can help align scientific discovery with environmental stewardship (Clean Air Task Force 2025; Microsoft 2024; OECD 2024).

Future work will extend the thought experiment described here into empirical verification. Laboratory testing of the nitrate and Cat's Claw interaction will evaluate whether the predicted moderating effects occur in practice and whether model-guided dose selection reduces redundancy. The results, whatever their direction, will contribute to refining both the computational model and the broader framework for sustainable experimental design.

Beyond this single example, the principles outlined here offer a general model for twenty-first-century research. Transparent, iterative dialogue between human reasoning and computational power can help scientists confront complex environmental problems while maintaining allegiance to ethical and ecological values. As the tools of artificial intelligence continue to evolve, the task for environmental health researchers is not simply to adopt them but to shape their use through critical reflection and responsible design. In doing so, the scientific community can transform a technology often criticized for its resource demands into one that actively advances both knowledge and planetary wellbeing.

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Artificial Intelligence and Education Career in Transition: Historical Parallels, Looking at the Past, and Present Perception

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Abstract: This study examines the historical and contemporary intersections of technological revolutions, specifically the Industrial Revolution and the current rise of artificial intelligence (AI), with a focus on education-related careers. By situating AI within a historical framework, the research highlights how societies have repeatedly navigated transformations in labor, social roles, and cultural practices during times of technological confusion. Literature on the Industrial Revolution illustrates the devaluation of physical labor, displacement of traditional manual jobs, and reconfiguration of gender roles as machinery surpassed human muscle. While these shifts generated both social dislocation and economic growth, they also catalyzed broader cultural changes, including challenges to male authority and the emergence of early feminist movements. Similarly, today's AI revolution signals a parallel disruption, threatening intellectual and creative labor, reshaping educational practices, and redefining professional identities. Some scholars position AI as a new stage of the industrial revolution, while others emphasize its capacity to model human intuition, underscoring the magnitude of its impact. By drawing from these historical parallels, the study asks whether AI is perceived as a revolutionary force, how it will affect education-related careers, and what challenges and opportunities educators should be ready for.

Keywords: artificial intelligence, Industrial Revolution, historical comparison, future of education, educators' careers

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Introduction

Imagine a 10-year-old girl standing in front of her laptop. After playing Paganini's 24th Caprice, she listens as her AI violin tutor responds: "… at this tempo, you need to relax your left-hand hypothenar muscle. This muscle, as you can see in this video …". The new AI violin tutor has synthesized insights from every book, article, and pedagogical guide ever written on violin playing and teaching. The tutor is sophisticated, intelligent, adaptive, and nearly cost-free. Once a futuristic dream, such scenarios are becoming increasingly plausible.

The rapid advancement of artificial intelligence (AI) has sparked extensive debate about its impact on society, education, and careers. Just as the Industrial Revolution reshaped economic and social structures through mechanization, the current AI revolution is transforming intellectual labor, cultural and artistic practices, and educational methods. Those planning a career and those who assist them are faced with enormous challenges at present (Lent, 2020).

The purpose of this literature review is to examine the similarities between the Industrial Revolution and the AI era to understand how educators and students should interpret the social and educational consequences of AI's impact. By centering this investigation in a historical context, the study seeks to highlight patterns and insights that can shed light on the contemporary situation and offer more grounded predictions of what will happen to educators' careers in the future.

Research Questions

- What parallels can be drawn between AI evolution today and the 19th-century Industrial Revolution regarding the education careers?
- What threats, challenges, and opportunities should educators anticipate for their future careers?
- How might the future of education be envisioned in the age of artificial intelligence?

Literature Review

"They are no longer science fiction". These are the closing words of Nobel prize-winning Geoffrey Hinton's speech at the 2024 Nobel prize ceremony, concerning the swift evolutions offered by Artificial Intelligence (AI). Scholars have debated how best to situate these developments within broader technological history. Taj and Jhanjhi (2022) and Arabatzis (2017) position the AI revolution as the fourth or even fifth stage of the Industrial Revolution. Yet contemporary evidence suggests that AI represents more than a mere continuation of industrial progress; it signals a transformation of unprecedented scope, with implications that are already visible. Rather than simply beginning the discussion now, many scholars argue that proactive, thoughtful action is urgently required to address the societal and educational shifts ahead. As Hinton (2024) articulates in his speech, "this new form of AI excels at modeling human intuition rather than human reasoning".

Human Transformations

Human history is marked by a series of transformative revolutions. Throughout primate evolution (about 60 million to two million years ago), increases in brain size were associated with the greater cognitive demands of complex feeding strategies (Robson & Kaplan, 2006). In this era, after accounting for their own consumption, women contribute only about 3% of the caloric intake available to offspring, whereas men provide the remaining 97% (Robson & Kaplan, 2006). This distribution of contributions may help explain the central role of men in sustaining the group, thereby influencing their social position within the community. Archaeological and anthropological evidence places the emergence of Homo sapiens around 300,000 years ago (Chu & Xu, 2024; Ezekiel, 1938).

For most of their history, humans lived as hunter-gatherers. The Neolithic Revolution, beginning roughly 12,000 years ago, marked the transition to agriculture and settled communities. Centuries later, the Industrial Revolution, which began in the mid-to-late 18th century, led to a transition from agrarian societies into industrialized economies. Each of these revolutions not only altered modes of production but also redefined societal structures, cultural practices, and human identity (Chu & Xu, 2024).

Devaluation of Muscle

The Industrial Revolution was the transition from human and animal labor technology into machinery (Kumar Mohajan, 2019). The Industrial Revolution brought forward machinery that surpassed the strength, stamina, and reliability of human muscles. As Mantoux (2013) notes, unlike human labor, machine power was "tractable, regular and indefatigable." This shift made physical strength less economically valuable, particularly in sectors where mechanization thrived. Foster and Clark (2018) and Berg (1991) highlight how industries like textiles increasingly relied on female labor due to the reduced need for physical strength, further underscoring the declining value of muscle as machines took over the tasks traditionally performed by men.

Threat to Manual Jobs

Mechanization did not merely supplement labor; it often displaced it. Henderson (1937) documents public concern that machinery enabled a small number of workers to replace many, especially during times of economic strain. While Henderson optimistically argued that increased productivity could lead to long-term prosperity and higher overall employment, the short-term reality was clear: machines threatened manual labor. The long-term view was later explained by the "cobweb model," as elaborated by Ezekiel (1938). This model suggests that any later increase in labor demand would be smaller than the original loss, expanding the impact of technological disruption.

Decay of the Male's Traditional Role

The reduction in demand for physical labor not only altered employment patterns but also destabilized traditional gender roles. Berg (1991), McNeil (1990), and Foster and Clark (2018) show that many of the most innovative and productive sectors during the Industrial Revolution were dominated by women and children, not men. Francis and Holloway (2002) describe a linguistic shift from male "authority" to "influence" within families, indicating a symbolic erosion of paternal dominance. Meanwhile, Ahmad Raina (2017) places the emergence of first-wave feminism in this same era, showing how socio-economic changes catalyzed shifts in gender expectations.

Increased Welfare

Despite its displacing effects, the Industrial Revolution led to greater material wealth. According to Henderson (1937), technological advancements lowered production costs, which in turn reduced consumer prices and increased real income. Over time, this could expand purchasing power across society. However, this benefit was not uniformly distributed; while the overall economy grew, gains were often captured by industrialists and capital owners, reinforcing social hierarchies (Francis & Holloway, 2002).

The IR is considered as the sustained but very slow economic growth based on constantly growing useful knowledge (Kumar Mohajan, 2019). There were many technological changes at that time; Those inventions improved the total factor of productivity (Khan, 2008). At the start of the IR, landowners and aristocrats had occupied the top position in society. But later, factory owners, merchants, and bankers grew wealthier than the landowners and aristocrats. A larger middle class, such as government employees, doctors, lawyers, and managers of factories, mines, and shops, had grown. They acquired a comfortable standard of living (Hall, 2013).

Methods and Procedures

Research Design

This study employs a qualitative design (Creswell, 2020) grounded in a historical framework and guided by analogical reasoning to draw comparisons between the Industrial Revolution and the current AI revolution. The data are collected from websites, books, previously published articles, theses, conference papers, case studies, and various research reports. The review first examines the impact of the Industrial Revolution on careers, education, and social structures, drawing from historical scholarship to identify recurring patterns. These patterns are then used as an analogical lens through which to interpret the ongoing transformations brought about by AI. By situating current debates within a comparative historical perspective, the review seeks to generate insights into the potential evolving directions of education and the future of educators' careers.

Analogical Reasoning

Utilizing analogical reasoning (Smaling, 2002) I am attempting to identify similarities between the current state of the AI revolution and the aftermath of the Industrial Revolution, drawing on a historical review of the literature. By identifying meaningful parallels, the goal is to better understand what educators should anticipate and prepare for. To this end, Smaling's (2002) six criteria for analogical reasoning provide a framework for assessing the strength of this comparison.

Applied to this study, the criteria highlight both strengths and limitations of the analogy. First, the relative degree of similarity is considerable: both revolutions disrupted labor structures, altered social roles, and reshaped cultural practices. While the Industrial Revolution primarily displaced physical labor and AI now challenges intellectual and creative work, the parallels remain more significant than the differences. Second, the similarities are directly relevant to the conclusion, since the analysis focuses on career transformations rather than outlying cultural shifts. Third, the analogy gains credibility through support from other similar cases, notably the Digital Revolution and the rise of the internet, which exhibit comparable patterns of disruption and adaptation. Fourth, this reasoning is reinforced by variation, as even revolutions of very different scope (agricultural, industrial, digital) generated similar paths of social change. Fifth, the conclusion that AI will significantly affect education and careers has independent plausibility, given current scholarly and public debates. Finally, the analogy is strengthened by empirical and theoretical support, drawing on historical studies of the Industrial Revolution, contemporary analyses of AI, and methodological guidance from Creswell (2020) and Smaling (2002).

Research Objectives

The objectives of the research are:

16. To explore perceived historical parallels between AI and the Industrial Revolution.
17. To identify perceived threats and challenges posed by AI to educators' careers.
18. To provide insights into how music educators can prepare for the evolving landscape of education.

Findings

The review of historical and contemporary literature reveals several key patterns relevant to understanding technological revolutions and their potential impact on education-related careers.

Transformations in labor and skill demand

The Industrial Revolution introduced machinery that surpassed human strength, reducing the economic value of physical labor. Industries such as textiles increasingly relied on children and female labor, highlighting the declining importance of muscle in production (Mantoux, 2013; Foster & Clark, 2018; Berg, 1991). Mechanization often displaced manual jobs, generating short-term labor threats despite long-term increases in productivity (Henderson, 1937; Ezekiel, 1938). These changes illustrate how technological advancements can shift the skills and competencies required for employment, a phenomenon that may also be relevant to knowledge-based occupations, such as education.

Shifts in social and gender roles

Technological changes during the Industrial Revolution disrupted traditional male roles in production. Women became more central to certain industrial sectors, while linguistic and symbolic shifts indicated erosion of paternal authority (Berg, 1991; McNeil, 1990; Foster & Clark, 2018; Francis & Holloway, 2002). Socioeconomic transformations contributed to the emergence of early feminist movements (Ahmad Raina, 2017). For education-related careers, these findings suggest that technological change can alter professional hierarchies, roles, and expectations, potentially reshaping who holds influence in educational settings.

Economic growth and inequality

Technological advancements during the Industrial Revolution increased material wealth and reduced production costs; however, benefits were unevenly distributed. Gains were often concentrated among industrialists and capital owners, reinforcing social hierarchies even as a larger middle class of professionals emerged (Henderson, 1937; Francis & Holloway, 2002; Hall, 2013). For educators, such patterns highlight the possibility that technological change may create inequalities in resources, opportunities, and access to advanced teaching tools.

Human cognitive evolution and contribution patterns

Anthropological evidence indicates that increases in brain size during primate evolution were linked to higher learning demands in complex environments (Robson & Kaplan, 2006). This suggests that societies adopt labor roles and professional responsibilities in response to cognitive and environmental demands, which has implications for evolving educational practices.

Technological innovation and productivity

Sustained technological change, as observed in the Industrial Revolution, increased total factor productivity and led to gradual but lasting economic growth. Innovations transformed production methods, social structures, and professional hierarchies, creating new career paths and redistributing social influence (Kumar Mohajan, 2019; Khan, 2008; Hall, 2013). For education-related careers, this suggests that technological shifts can redefine the skills, responsibilities, and societal value associated with educators' roles.

Implications for education-related careers

Taken together, these findings indicate that technological revolutions historically reshape labor, skills, social roles, and economic hierarchies. For contemporary education, this suggests that educators may experience changes in required competencies, professional authority, and career opportunities. Anticipating such changes and adapting to new technologies may become essential for sustaining professional relevance and influence in educational environments.

Discussion

The findings of this literature review suggest that technological revolutions consistently reshape labor demands, social structures, and professional identities. When considered alongside current developments in artificial intelligence, clear parallels and new challenges emerge for education-related careers.

Parallels with the Industrial Revolution

The Industrial Revolution marked a turning point in human history by displacing manual labor and reducing the economic value of physical strength. In a similar fashion, AI technologies appear in place to diminish the value of certain cognitive tasks that were once the exclusive domain of human educators, such as information delivery, assessment, and even aspects of creativity (Mohammadagha et al., 2025a). Just as machines redefined industrial production, AI is now redefining intellectual and pedagogical production, with implications for how educational labor is valued and structured (Mohammadagha et al., 2025b).

Just as the Industrial Revolution reduced the social and economic value of physical strength, the rise of artificial intelligence may diminish the relative importance of certain forms of human cognition. Tasks such as information recall, calculation, or even pattern recognition, once markers of human expertise, can now be performed more efficiently by machines. This raises the possibility that human cognitive capacities could, over time, be devalued or underutilized, leading to a form of "cognitive weakening." While the evidence for such weakening is not yet established, historical parallels caution that when core human abilities are displaced by technology, societies must adapt by redefining which skills are cultivated and valued. In the case of education, this adaptation may require emphasizing creativity, reasoning, and interpersonal guidance; domains less likely to be replaced by machines.

Threats and challenges for educators

The literature underscores that technological progress often leads to short-term job displacement, social disruption, and uneven benefits (Henderson, 1937; Ezekiel, 1938; Francis & Holloway, 2002). In the context of AI, educators may face similar disruptions as automated systems take over routine teaching and administrative tasks (Abe et al., 2025). This could lead to a reconfiguration of professional authority, mirroring the erosion of traditional roles observed during the Industrial Revolution (Maleki et al., 2024). Furthermore, unequal access to advanced AI tools may deepen disparities between institutions, reinforcing inequalities in educational outcomes (Rahimi et al., 2019).

Opportunities and adaptation

Despite these threats, history also demonstrates that technological revolutions open new opportunities. The Industrial Revolution, while destabilizing, eventually contributed to economic growth, professional diversification, and the emergence of a larger middle class (Hall, 2013; Kumar Mohajan, 2019). For educators, AI may offer opportunities to shift professional focus from repetitive tasks toward higher-order functions, such as more proficiently facilitating creativity and fostering critical thinking (Kouchesfahani, 2025). By adapting to these new demands, educators can preserve and even enhance their societal relevance, much as new professions and social roles emerged in the wake of earlier revolutions.

Visioning the future of education

The broader historical lesson is that societal adaptation depends on expanding cognitive and cultural capacities. As Robson and Kaplan (2006) argue in their evolutionary analysis, human survival has always depended on increasing the ability to learn and manage complexity. In the age of AI, this may translate into reimagining education not merely as the transmission of knowledge, but as the cultivation of adaptive, reflective, and ethical capacities that cannot be easily replicated by machines. In this sense, AI should not be seen only as a competitor, but also as a catalyst for rethinking the very purposes and practices of education.

Conclusion

This study sets out to examine historical patterns of technological change to better understand the potential impact of artificial intelligence on education-related careers. The literature review revealed that technological revolutions, from primate evolution to the Industrial Revolution, consistently reshape labor demands, professional hierarchies, and societal structures. The findings suggest that while such transformations often bring disruption and inequality in the short term, they also generate new opportunities and long-term growth.

Drawing parallels with the Industrial Revolution, the discussion highlighted that AI is likely to devalue certain cognitive tasks in much the same way that machinery reduced the value of physical strength. Educators, therefore, face both threats (such as job displacement and reconfigured authority) and opportunities (probable long-term growth) to redefine their roles toward mentoring, creativity, and ethical guidance. For educators, the central issue is not whether change will occur, but how careers in education can adapt to remain meaningful in a rapidly evolving landscape.

Implications for Research Questions

In relation to the research questions, several points emerge. With respect to RQ1, the analogy to the Industrial Revolution highlights how new technologies can redefine not only labor but also the value of core human capacities. Regarding RQ2, educators should anticipate both challenges, such as the potential devaluation of certain cognitive skills, and opportunities, including the chance to cultivate uniquely human capacities like creativity, reasoning, and interpersonal guidance. Finally, in addressing RQ3, the future of education in the age of AI may be envisioned as one in which educators move beyond transmitting information toward shaping adaptable, resilient learners who can thrive alongside intelligent machines.

Future Studies

Future research could employ quantitative methods to investigate educators' attitudes toward the future of their careers, with particular attention to the balance between optimistic and pessimistic perspectives. In addition, studies drawing on expert interviews across related scientific fields could provide valuable insights into strategies for preparing educators to navigate the uncertainties of an AI-driven future.

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Perceiving a Missing Fundamental Without Even Harmonics: An Auditory Illusion Experiment Using Additive Synthesis

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Abstract: This study investigates whether listeners can perceive a musical tone that is not physically present in a complex sound. Specifically, it examines the phenomenon in which the brain reconstructs a fundamental frequency from a set of higher-order harmonics, without the fundamental itself or its replications in higher octaves being played. Using a digital audio workstation, illusion-based tones (IBTs) were synthesized by layering the 3rd, 5th, 7th, 9th, 11th, and 13th harmonics. A total of 56 musically trained participants took part in a simple listening test involving ten systematically randomized tones: five were pure tones played with a simple sound generator and served as a control condition to assess participants' baseline pitch recognition accuracy, and five were IBTs of the same tones. Participants identified the pitch of each tone freely, with a piano available for voluntary pitch comparison. The goal was to test whether the illusional tones could reliably evoke the intended pitch in the listeners' judgements. A strong positive correlation (ρ = .863) was found between participants' performance on recognizing normal tones and IBTs. This suggests that listeners with pitch recognition skills similarly identified the IBTs. The findings demonstrate that the perception of an IBT is not accidental, but a repeatable psychoacoustic effect among trained listeners. The results support the use of spectral content alone to imply a pitch. It means that the perception of a specific pitch can be created by using certain harmonics even if the fundamental frequency or any even harmonics of that pitch aren't physically present.

Keywords: acoustics, auditory illusion, auditory perception, missing fundamental, psychoacoustics.

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Introduction

Human auditory perception extends beyond simple frequency detection (Shafiei & Hakam, 2025). The human brain does not recognize sounds as scientifically as mechanical instruments. Essien (2023) believes that human auditory perception is different from what happens physically:

> "Acoustics was conceived to explain auditory perception. Its success in other peripheral fields cannot compensate for its total failure to fulfil its original purpose. The failure did not take scientists by surprise because it was "always clear that the ear does not react like a simple Fourier frequency analyzer". The failure is a clear indication that principles of sound transmission do not apply in neurophysiological processes in auditory perception" (p. 2).

In psychoacoustics, a pure tone is a sound with a sinusoidal waveform; that is, a sine wave of constant frequency, phase shift, and amplitude (*Acoustical Terminology, ANSI S1.1-1994 (R2004)*, 2004). In contrast, there are complex sounds. The recognized tone in complex sounds is not the only frequency present in the signal (Kouchesfahani, 2025; Robertson, 2023).

The brain is capable of reconstructing tones based on their harmonic orders even when the fundamental frequency is missing (Knight & Setter, 2021; Viitanen, 2024). This phenomenon, known as the missing fundamental illusion, has long been observed in psychoacoustic research (Terhardt, 1974; Schouten et al., 1962). Missing fundamental is a well-known psychoacoustic phenomenon based on the perception of a pitch (i.e., the fundamental frequency) without the corresponding frequency actually being contained in the signal (Romoli et al., 2010). A missing fundamental happens when a weak or nonexistent fundamental frequency in a series of overtones is reconstructed by the hearing process (Vogt et al., 2023). Fundamental or fundamental frequency refers to the lowest frequency produced by any natural instrument, which is shown by f_0 (Evans et al., 2024). The missing fundamental phenomenon cannot happen in pure tones because they are built on only one frequency, the fundamental (Shofner, 2010).

Although the missing fundamental phenomenon is mentioned in many sources, all of them have only removed the fundamental tone from the signal, while the 2^{nd}, 4^{th}, 8^{th}, etc. harmonics of the fundamental tone are still available in the signal (Jahanpour, Ilbeigi, et al., 2016; Jahanpour, Porghoveh, et al., 2016). It means similar tones, but in higher octaves, can still be heard in the sound. But in this study, using additive synthesis instead of Harmonic termination (Mehraban et al., 2020), we have employed only odd-numbered harmonics to prevent the octaves of the fundamental or any other tones. Additive synthesis is a sound synthesis technique that creates timbre by adding sine waves together (Smith, 2011).

In musical contexts, this additive synthesis technique allows us to produce and play tones even when certain frequencies are absent due to any limitations, recording constraints, or spectral shaping in mixing (*Physics Tutorial*, n.d.). The present study seeks to actively recreate this illusion by constructing a harmonic complex that omits the fundamental tone of C, and all its duplications, yet produces its perception in non-amusic listeners. The experiment was implemented in FL Studio, a digital audio workstation (DAW), using the 3xOSC synthesizer as a pure tone generator and the Sytrus synthesizer for additive synthesis and generating overtones accurately.

This study investigates whether listeners perceive a musical tone when only its odd-numbered harmonics (excluding the fundamental) are played. We hypothesize that a harmonic complex composed of selected partials, including the 3rd to 13th odd harmonics, will produce the illusion of a C tone in musically trained listeners.

Methodology

This study employed a quantitative experimental design to test whether listeners could perceive specific pitches from illusion-based tones (IBTs) composed solely of odd-numbered harmonics, excluding the fundamental. The experiment involved a controlled listening test with musically trained participants, comparing responses to pure tones generated by a synthesizer, and IBTs to see if the participants can hear the fundamental while it is not being played.

Software and Sound Design

The IBTs were designed and executed in FL Studio, specifically, the Sytrus synthesizer. The 3xOsc was used to create reference pure tones for control. The Sytrus synthesizer was utilized to construct and layer six specific harmonics: 3rd, 5th, 7th, 9th, 11th, and 13th. Sytrus has the option to layer any harmonics of six different sounds, providing full control over their specifications.

Figure 1. The interface of the Sytrus synthesizer (Picture from the Image Line company website (Create Your Best Music | FL Studio, n.d.).)

Only odd-numbered harmonics were chosen to avoid redundant tonal reinforcement from even harmonics, which often replicate existing partials (e.g., 6th duplicates the 3rd, and 10th duplicates the 5th). The six harmonics were layered into a sustained tone, and amplitude levels were balanced from loud to soft to make a near-natural timbre. For example, an instrumental C_3 tone consists of a 131 Hz frequency (i.e., the Fundamental Frequency), a 262 Hz (131×2), a 393 Hz (131×3), etc. (In this article, we have used the scientific pitch notation (SPN) for numbering octaves.). For creating A C_3 IBT using the additive synthesis technique, passing the first and second harmonics, we started with the third harmonic, which is 131×3 = 393 Hz (G_4 tone). Then, passing all even harmonics, added 131×5 = 655 Hz (E_5), 131×7 = 917 Hz ($B\flat_5$), 131×9 = 1179 Hz (D_6), 131×11 = 1441 Hz (F^{+}_{6}), and 131×13 = 1703 Hz (A^{-}_{6}).

Table 1. The harmonics, frequencies, musical note equivalents, and their presence in Piano C3 and C3 IBT.

Harmonic	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Frequency (Hz)	131	262	393	524	655	786	917	1048	1179	1310	1441	1572	1703	1834
Musical Note	C_3	C_4	G_4	C_5	E_5	G_5	$B\flat_5$	C_6	D_6	E_6	F^{+}_{6}	G_6	A^{-}_{6}	$B\flat_6$
Piano C3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C3 IBT	-	-	✓	-	✓	-	✓	-	✓	-	✓	-	✓	-

Figure 2 illustrates the frequency analysis of the C_3 IBT. All C tone frequencies are absent in Figure 2. Figure 3 demonstrates the frequency analysis of the piano C_3 tone, in which all the overtones under 2000 Hz can be found. In Figure 4, you can see three periods of the C_3 IBT waveform shape (The audio file used in the example, constructing the C3 IBT, is available upon request for replication or further analysis).

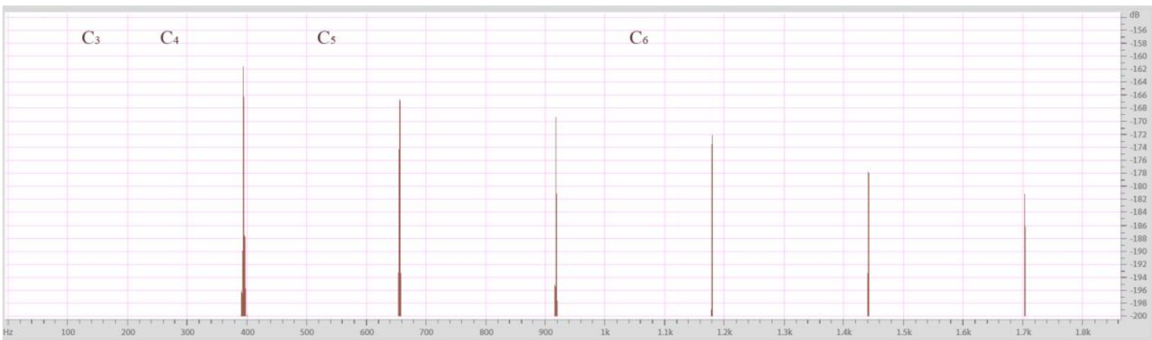

Figure 2. Frequency analysis of the C3 illusion-based tone.

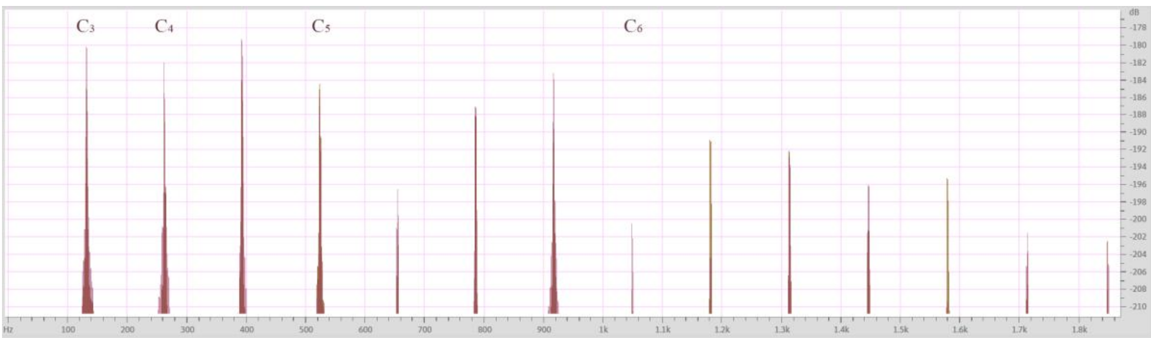

Figure 3. Frequency analysis of the piano C3 tone under 2000 Hz.

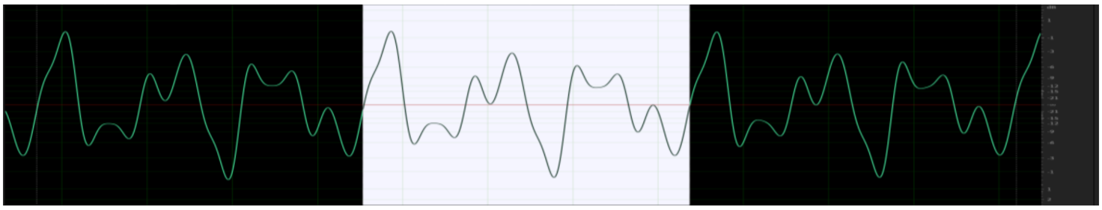

Figure 4. The waveform shape of the C3 IBT. A single period is highlighted.

Participants

A total of 56 individuals participated in the listening experiment. All had musical training and either advanced or basic auditory skills: 24 music teachers with extensive performance experience, and 32 music students who had previously passed the academy-level solfège proficiency examination. Each participant was asked to identify 10 different tones, presented in randomized order. Five of them were pure tones for control, and five were IBTs composed only of odd harmonics (3rd and above). This setup allowed for a controlled comparison between typical pitch recognition and IBT perception.

Listening Environment and Procedure

All sessions were conducted in a quiet classroom at Guildad Music Academy in Rasht, Iran. Participants listened using Beyerdynamic DT 990 Pro studio headphones to ensure trustworthiness and consistent audio reproduction. Each person sat individually and experienced the same experimental protocol. An audio file containing 10 tones (five normal, five IBTs) was rendered in randomized order and played for each participant. After each tone, participants wrote down the note name they perceived. The systematically randomized tones were C, E, A, F#, and D#. There were two versions of each note: one normal pure tone and one IBT.

Figure 5. The location of experiment at Guildad Music Academy.

For control tones, responses were categorized as true if the note was correctly identified, and false if it was incorrect. For IBTs, true meant that the participant perceived the fundamental tone of the intended illusional note, and false indicated that the illusion failed or was misidentified. A standard-tuned piano was provided in the room for pitch comparison if desired by participants. The goal of the test was not to assess listeners' musical ability but to determine whether participants could perceive the fundamental tone of the IBTs.

Figure 6. Beyerdynamic DT 990 Pro studio headphone (Picture from the Beyerdynamic website (Headphones & Microphones |beyerdynamic, n.d.).)

Results

The correlation test demonstrated a reliable result on pitch perception for the IBTs among musically trained participants. Participants who struggled to identify IBTs also tended to perform relatively poorly on normal tones. A Spearman's correlation analysis revealed a strong positive relationship between recognition on normal tones and IBTs: $\rho(56) = .863$, $p < .001$. This suggests that the illusion is effective primarily among individuals with strong pitch recognition skills, reinforcing that the misidentifications are accounted for by the lack of aural skills of the specific participant.

Table 2. Descriptive statistics of participants' performance on recognizing tones.

	N	Minimum	Maximum	Mean	Std. Deviation
IBT Scores Sum	56	4	5	4.95	.227
Control Scores Sum	56	3	5	4.91	.345
Valid N (listwise)	56				

Table 3. Spearman correlation test results.

	Control Sum	Test Sum

Spearman's rho	Control Scores Sum	Correlation Coefficient	1.000	.863
		Sig. (2-tailed)	.	<.001
		N	56	56
	IBT Scores Sum	Correlation Coefficient	.863	1.000
		Sig. (2-tailed)	<.001	.
		N	56	56

Discussion

The results of this study demonstrate that listeners with musical training are able to reliably perceive a fundamental pitch that is not physically present in the sound signal, provided that an auditory illusion is occurring. The illusion-based tones (IBTs), composed of the 3rd to 13th harmonics and excluding both the fundamental and all even harmonics, were perceived as the fundamental pitch by a majority of participants. The strong positive correlation between perceiving control tones and IBTs, $\rho(56) = .863$, $p < .001$, suggests that the failure to recognize the virtual pitch is closely linked to the listener's existing pitch recognition weakness. These findings support and extend the body of literature on the missing fundamental phenomenon (Schouten et al., 1962; Terhardt et al., 1974; Vogt et al., 2023) confirming that virtual pitch perception is not limited to signals that exclude only the fundamental frequency. This study provides empirical evidence that additive synthesis using odd harmonics alone is sufficient to evoke a stable pitch perception, even when the actual fundamental frequency and its octave multiples are entirely absent.

In contrast to many prior studies that left the second harmonic and other even-numbered harmonics intact, this experiment removed them completely. This methodological distinction allowed us to isolate the perceptual strength of odd harmonics and clarify their sufficiency in pitch reconstruction. The results suggest that harmonics are particularly important for establishing a strong tonal center, consistent with prior theories on spectral pitch processing (Essien, 2023; Judge, 2017; Matsui & Ohgushi, 2020).

Limitations

A key limitation of this study is that all participants were musically trained individuals, including music teachers and students with verified pitch recognition skills. While this ensured that participants were capable of identifying tones accurately and not affected by amusia, it limits the generalizability of the findings to the broader population. The illusion's effectiveness may differ among non-musicians or individuals with less developed auditory discrimination abilities.

Future Research

Future studies could build on this work by investigating the specific harmonic conditions under which the advanced missing fundamental illusion fails to occur, particularly by systematically altering or removing individual odd harmonics to determine the perceptual threshold at which the illusion collapses. Investigating whether certain harmonics (e.g., the 3rd or 5th) are more critical to the illusion than others may help refine models of virtual pitch perception. In addition, applying this phenomenon in real-world auditory contexts, such as sound design or hearing aid algorithms, could reveal practical benefits of using IBTs to recreate pitch percepts. Future research also should replicate this experiment with a non-musician control group to determine whether the illusion is equally perceivable without formal musical training.

Conclusion

This study demonstrates that the perception of pitch is not solely dependent on the physical presence of a fundamental frequency. Instead, listeners can reconstruct pitch from carefully constructed harmonic spectra, even when the signal lacks any even harmonics or octave equivalents. These results confirm the strength of the missing fundamental phenomenon and offer new insights into how the auditory system synthesizes pitch from partial information.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contribution

Soroush Shoja Talab Kouchesfahani designed the study, conducted the experiments, analyzed the data, and wrote the manuscript. Sadaf Jamalzadeh contributed to the data collection, literature review, and reviewed the manuscript drafts.

Ethical Approval

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Guildad Music Academy. Informed consent was obtained from each participant. All data were anonymized prior to analysis.

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