

Transformative teaching in management statistics: Integrating real-world experiences and artificial intelligence

Kate Z. Williams¹  | Tatiana Rudchenko² 

¹Center for Teaching and Learning, Georgia Institute of Technology, Atlanta, Georgia, USA

²Scheller College of Business, Georgia Institute of Technology, Atlanta, Georgia, USA

Correspondence

Kate Z. Williams, Georgia Institute of Technology, Center for Teaching and Learning, Clough Commons Atlanta, GA 30332.
 Email: kate.williams@gatech.edu

Abstract

Traditional lecture-based teaching methods can fall short of preparing students for the complexities of modern workplaces. With the arrival of generative AI (GenAI) in both workplaces and academia, faculty must choose whether and how to introduce students to the powers of artificial intelligence. This teaching brief explores the implementation of a series of scaffolded lessons using GenAI in a quantitative, undergraduate operations management course. Leveraging Fink's theory of significant learning and Kuh's High Impact Practices (HIPs), the initiative integrates real-world applications of artificial intelligence to enhance student learning and career readiness. This brief explains how the teaching innovation allowed students to compare the practical value of Excel versus ChatGPT in conducting statistical analysis. Industry experts and a site visit provided insights into the use of generative AI in business contexts. Results indicate that these course enhancements elevate student interest in operations management and business analytics and offer a model for future improvements in business education.

KEYWORDS

Operations Management, Statistics, Experiential Learning, Pedagogical Approaches, Artificial Intelligence

1 | INTRODUCTION

Traditional lecture-based approaches often fail to engage students or prepare them adequately for the dynamic demands of contemporary workplaces. Innovative teaching methods, by contrast, (e.g., active learning, experiential learning, and the integration of advanced technologies) foster deeper understanding, critical thinking, and practical skills (Burch et al., 2014; Freeman et al., 2014). These methods make learning engaging and relevant and allow students to apply theoretical concepts to real-world scenarios.

Moreover, innovative teaching methods are essential for developing adaptable and resilient professionals. Employers seek individuals who not only possess specific technical skills (73%) but also candidates who can solve problems (88%), work in teams (81%) and communicate well (77%) (NACE, 2025). In analytics and data science careers specifically, job candidates need industry knowledge, skills with

modeling tools, and the ability to present analytical insights (Stanton & Stanton, 2020). This paper proposes that by employing modern pedagogical strategies, educators can better prepare students to meet employers' expectations. Methods such as industry collaboration and the use of generative artificial intelligence (GenAI) in the curriculum have the potential to enrich students' learning experiences and help them develop the critical, analytical, and problem-solving skills necessary for their future careers. This holistic approach to education benefits the students and contributes to the overall advancement of the educational system, better aligning it with the needs of the 21st-century economy.

This paper describes a teaching innovation within a quantitative course in an undergraduate management program. After a brief exploration of the literature, the paper explains key course enhancements and their impact on student perceptions of the field of operations management.

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2 | LITERATURE REVIEW

This project focused on enhancing the design of a management statistics course using two primary levers of change: (1) active and experiential learning in the classroom and (2) the incorporation of artificial intelligence in instructional materials and assignments. As such, the literature review first presents background information about course-based experiential learning, then provides a summary of the emerging literature on incorporating GenAI into classroom learning contexts.

The meta-analysis from Burch et al. (2014) reviews 40 years of literature on the impact of experiential learning on student learning outcomes. The authors define experiential learning as occurring when “students actively process an experience that leads to new knowledge, skills or insight” (p. 242). They found experiential learning activities had a positive effect on students’ understanding of social issues and on their cognitive development across the 89 studies included in the meta-analysis.

Kuh’s (2008) High-Impact Practices (HIPs) have been widely integrated into co-curricular learning opportunities through internships, undergraduate research, study abroad, and other programs, while classroom learning has been augmented by teaching techniques such as collaborative projects, writing across the curriculum, and ePortfolios. When integrated into the classroom setting, institutions can increase access to high-impact practices for students. In the context of an undergraduate business curriculum, Ammar et al. (2023) argue that incorporating high-impact practices can enhance traditional business analytics curricula and improve students’ career outcomes.

Fink’s theory of significant learning (2013) provides a framework to aid faculty in selecting and implementing HIPs to achieve student learning goals. This theory suggests that traditional higher education, focused on knowledge transfer and application, falls short of its potential to make lasting change for learners unless it purposefully incorporates human-focused learning elements. In addition to knowledge and application, Fink argues that significant learning should also explore the human impact of disciplines, consider student motivation in learning, teach students how to learn, and explicitly integrate these components. In courses redesigned using the significant learning theory, documented outcomes include (a) increases in academic performance and reductions in failure rate (Uribe Cantalejo & Pardo, 2020), (b) increases in students’ content mastery and application skills (Levine et al., 2008), and (c) increases in subject-matter interest, perceived importance, and self-rated knowledge (Krueger et al., 2011). For a comprehensive summary of outcomes associated with significant learning theory, see Huaman Vargas et al. (2024).

One established method for increasing student motivation for learning is to increase the perceived value of course material to students’ academic and career goals (Ambrose et al., 2010). Course-based experiential learning increases student access to opportunities not typically present in traditional lecture-style classrooms. Through guest speakers,

students learn about current applications of academic content in the workplace, gain information about industry culture and career paths, and use this information to enhance their academic work (Riebe et al., 2013). Industry site visits increase students’ motivation to learn by exposing them to the work environment and demonstrating the practical application of academic and technical skills (Burns & Chopra, 2017). According to Townsend and Urbanic (2013), industry tours that are aligned with course learning outcomes resulted in students’ observation of important career competencies and, important to the present paper, new technologies needed in the workplace.

Experiential learning is just one type of active learning, defined by Prince (2013) as “any instructional method that engages students in the learning process.” Decades of education literature provide evidence for the positive impact of active learning on student outcomes, including increased exam scores (Freeman et al., 2014), increased subject-related knowledge, professional skills, social skills, and communication skills (Hartikainen et al., 2019).

In contrast to the deep and broad educational literature that supports the effectiveness of active and experiential learning, research is just beginning to capture the use of generative AI in the classroom and to reveal its impact on student learning. Artificial intelligence became widely available in November 2022 when OpenAI released the first version of ChatGPT and access expanded in May 2023 with release of Google Bard. Both ChatGPT and Google Bard are large language models that can generate text, provide informative (though not always accurate) answers to questions, and adapt to user behavior (Labadze et al., 2023). GenAI tools like ChatGPT have been used in higher education to provide adaptive learning, personalize tutoring, generate feedback, and facilitate discussion and collaboration, among other forms of learning assistance (An et al., 2025). According to the 2025 Global AI Faculty Survey (Digital Education Council) of 1681 faculty respondents across 28 countries, just over 60% have used AI in their teaching. Of these, 50% reported teaching students to use and evaluate AI in class, as compared to 75% who used AI to create teaching material. Of the faculty who use AI in teaching, a small minority use AI extensively (9%) or as an integral part of their teaching (3%). A majority of faculty (66%) believe that incorporating AI into teaching will be an essential part of preparing students for the future workplace.

Student use and perception of GenAI is an important consideration in higher education, given the demonstrated impact of students’ perceptions of their learning environments—including digital learning resources—on their approach to learning (Biggs, 1999). According to Chan and Hu’s (2023) review of the emerging literature, most students agree that using GenAI in learning situations improves their attitude toward learning, increases their self-efficacy and motivation for learning, and helps them express themselves. Most students also believe GenAI will have a major impact on their future professions. Conversely, students reported being cautious about GenAI due to potential data breaches, ethical concerns, limited human interactions, and the potential for reduced job opportunities.

As large language models, one of the primary applications of GenAI in learning is the opportunity to interact via text-based questions and answers. There is relatively less evidence of GenAI being applied in quantitative analysis. For example, Schwarz (2025) identified only a handful of academic papers exploring the use of GenAI for statistical analysis, only one of which appears to translate the findings into a pedagogical intervention. In this same vein, Schwarz reports that a survey of German workers found only 21% of respondents use ChatGPT for data analysis.

While the education literature provides strong evidence for the integration of experiential learning into classroom settings to improve student learning outcomes, the literature is just beginning to explore the impact of GenAI on student learning.

3 | TRANSFORMING MANAGEMENT STATISTICS

The Transformative Teaching and Learning Initiative at Georgia Institute of Technology supports faculty efforts to embed High-Impact Practices into traditional course structures. Derived from the institution's strategic plan, the initiative provides support from the Center for Teaching and Learning in the form of faculty mini-grants, a cohort of faculty peers, and an embedded teaching expert to guide project development.

This paper presents results of a transformative teaching project in a management statistics course. This large (70-student) sophomore-level course is required for management majors and is generally accepted as a potential on-ramp to the operations management concentration due to the introduction to data-informed business decisions. This institution offers a single business major, a Bachelor of Science in Business Administration, that is complemented by students' enrollment in one of eight concentrations. Academic departments depend on student enrollment in their concentration to sustain faculty lines, to enhance student employability, and to maintain institutional reputation.

The primary goals of this project were to increase student interest in data analytics careers—particularly within the under-enrolled operations management concentration—and to improve career readiness by exposing students to real-world applications of quantitative methods and artificial intelligence in business contexts. To achieve this goal, two primary interventions were launched: the incorporation of a series of in-class lessons and assignments using ChatGPT and the addition of industry-based experiential learning via guest speakers and an industry site visit.

3.1 | Scaffolding lessons from Excel to ChatGPT

This required management statistics course is typically considered one of the more challenging introductory courses in the business major, particularly for students who have low self-efficacy for math-related subjects. To counteract

this learning challenge, the instructor teaches fundamental statistical methods using common technology tools like Microsoft Excel to build a solid subject matter foundation. This approach allows students to gain hands-on experience with data manipulation, analysis, and interpretation through easily accessible technology, which is crucial for their understanding of statistical concepts.

As generative artificial intelligence became widely available, the instructor quickly recognized the need to introduce students to ethical and effective uses of this new technology in business decisions. To that end, the instructor introduced methodological progression from Excel to GenAI to ensure that students are not only proficient in traditional statistical tools but are also adept at leveraging cutting-edge GenAI technology to solve complex business problems more efficiently. Specifically, students solved descriptive statistics and regression analysis problems from the course textbook and publisher-provided homework assignments using both Excel and ChatGPT-4, which offers significant quantitative functionality beyond its predecessors. For example, ChatGPT-4 can compute complex equations, analyze data, produce data visualization, and create synthetic data. According to the ChatGPT-4 technical report, the program scores in the 83rd percentile or above on a college-level standardized statistics exam, compared to the performance of ChatGPT-3.5, which scores in the 40th to 62nd percentile on the same exam (OpenAI, 2023).

As outlined in the section that follows, students learned—through a series of scaffolded lessons—how to display and analyze descriptive statistics and to conduct and interpret regression analysis.

Class 1: Introduction to descriptive statistics using Excel functions. In this lesson, students learned to compute basic descriptive statistics through Excel functions and interpreted the results for different types of data. Topics covered included: median, quartiles and percentiles, interquartile range, and range.

Class 2: Variability analysis using Excel functions. Students analyzed variability in datasets and computed the mean, variance, standard deviation, and coefficient of variation.

Class 3: Visual representation with histograms. Using Excel's Data Analysis Toolpak, students created histograms to visualize data distribution. They adjusted bin sizes and interpreted histogram shape (e.g., normal, skewed). Students also discussed how histograms represent data distribution and how outliers affect measures like mean and median. Through the practical exercises for this session, students created histograms with real world data and linked these to descriptive statistics and variability analysis.

Class 4: Advantages of ChatGPT-4. After students problem solved in Excel, ChatGPT-4 was introduced for the same analyses. Students solved similar problems using prompts in ChatGPT-4 to generate descriptive statistics and visualization. Students learned about the following features of GenAI:

1. Prompting: Students practiced crafting prompts that allowed ChatGPT-4 to quickly analyze datasets in the

desired volume and order, from summary statistics to variability assessments.

2. **Customization:** Students learned how to create and refine ChatGPT-4 prompts for specific needs, such as adjusting how the GenAI reports the results and asking follow-up questions.
3. **Automation:** Students experienced the superior processing speed of ChatGPT-4 and its ability to provide meaningful insights compared to manual Excel analysis for large data sets.

Class 5: Comparison and reflection. In this critical lesson, students compared the outputs from Excel and ChatGPT-4. During this discussion, students identified the following:

- **Speed:** ChatGPT-4 was faster at analyzing data compared to manually using Excel
- **Customization:** ChatGPT-4 provided tailored responses to follow-up questions
- **Interactivity:** Dynamic back-and-forth with AI boosted student engagement
- **Efficiency:** ChatGPT-4 handled repetitive tasks automatically, freeing time for complex analysis

Through this scaffolded series of class lessons, students learned the strengths of both Excel and ChatGPT-4. This approach prepared students for real-world situations where they may need to use both traditional software (like Excel) and emerging technology (like ChatGPT-4) to make data-driven decisions.

The value of GenAI for statistical analysis was demonstrated to students through exercises that utilized increasingly complex prompts. With simple prompts, students observed that ChatGPT-4 operated much like a calculator, producing a numerical summary, histogram, and measures of variability. With more complex prompts, however, ChatGPT-4 produced statistical analysis alongside interpretations of the results in relation to the original problem. The three learning objectives are listed below, along with the prompt that students provided to ChatGPT-4 and a summary of a typical response received for the descriptive statistics assignment. Appendix A includes the full descriptive statistics assignment with ChatGPT-4 output.

1. **Learning objective:** Simple prompts use GenAI as a “calculator.”

ChatGPT-4 prompt: “Compute descriptive statistics for dataset attached.”

Summary of ChatGPT-4 output: Count, mean, median, minimum, maximum, standard deviation, 25th percentile, 75th percentile.

2. **Learning objective:** By requesting specific analyses, results, and explanations, GenAI produces more sophisticated results.

ChatGPT-4 Prompt: “Create a histogram showing the distribution of file sizes (in MB) from the attached dataset. Additionally, provide an analysis of the variability of this data, including key statistics such as the mean, standard deviation, and range.”

Summary of ChatGPT-4 Output: Response included histogram, variability analysis, and defined and calculated the range, interquartile range, variance, and standard deviation.

3. **Learning objective:** Complex prompts reveal potential for GenAI to support business decisions.

ChatGPT-4 prompt: “Task: Create and interpret a histogram that summarizes the distribution of the numerical variable File Size (MB) in the attached dataset with the title File Size Distribution of Songs (MB). Please provide the report. Your report should present:

- **Count:** Number of observations
- **Descriptive statistics:** The 5-number summary
- **Variability analysis:** Range, IQR, mean, and standard deviation
- **Conclusion:** Addressing whether 500 different songs can fit on an iPod Shuffle

Summary of ChatGPT-4 output: Response included histogram, mean, median, minimum, maximum, standard deviation, capacity estimation (with equation), and conclusion. Response included one- to two-sentence explanations of each element produced.

Appendix B presents a regression analysis problem with ChatGPT-4 demonstrating a similar increase in prompt complexity.

By comparing the methodologies used, and outputs created by both Excel and ChatGPT-4, students observed GenAI’s efficiencies and capabilities in data analysis and interpretation for descriptive statistics and regression analysis. By moving from Excel to advanced AI tools, students strengthened their traditional statistical skills and gained the GenAI capabilities required for solving complex business problems. This dual approach reinforced their learning and prepared them for a business environment increasingly dominated by GenAI technologies. This integration serves as a modern enhancement to the traditional curriculum, providing students with insights into how artificial intelligence can streamline and augment analytical processes.

3.2 | Industry-based experiential learning

In addition to the adjustments to course content and assignments, three guest speakers representing different companies joined the class to discuss how GenAI is used in industry applications. Primed with information about current course topics, the speakers provided real-world examples of industry applications of both statistical analysis and GenAI. Two of the speakers were mid-level corporate representatives—

neither brand-new to the industry nor far removed from the student experience—who described how recent course topics were applied in their companies. The third guest speaker was an instructor with substantial work experience as a project manager who directly connected the statistical skills taught in the course to real-world business decisions.

Complementing the guest speaker series was an in-person visit to a nearby corporate headquarters for a leading national logistics company, an experience that demonstrated how quantitative analysis and AI technology are utilized in a dynamic business environment. While quantitative analysis career competencies could be illustrated in a variety of industries, a logistics company was specifically selected to expose students to the role that data analysis plays in planning, scheduling, technological integration, maintenance, and safety, as well as the emerging value of artificial intelligence in those same business functions. To prepare for the visit, students developed questions that connected course content to the organization's mission.

Through the guest speaker series and site visit, students learned how GenAI can analyze large volumes of data to predict trends, optimize processes, and help professionals make informed decisions in business contexts.

4 | RESULTS

Student surveys (administered as part of an IRB-approved protocol) captured students' prior experience with GenAI as well as their impressions of GenAI use in business school and careers. Of the 102 survey responses, nearly 98% of students were already using ChatGPT for personal or academic reasons daily (24%) or weekly (56.9%) to get help with school work (77.5%) or to improve their learning (74.5%), as reported in Table 1. Interestingly, while all students reported concerns about GenAI, with the greatest number reporting concerns about the accuracy of the tool (67%), a large majority of students (81%) also agreed that GenAI should be integrated into operations management because of its ability to enhance data analytics and forecasting.

Student quotes were generated from both the end-of-semester student survey and submitted student artifacts. The quotes showed that students recognized how GenAI skills apply both to the course goals and to workplace demands. Sample quotes are presented in Table 2.

In addition to the survey on students' perceptions of GenAI, students responded to a pre- and post-survey about the value of industry-based experiential learning and their interest in operations management. The first survey was administered approximately 4 weeks into the semester, before the students were exposed to course enhancements. The post-survey was administered during the last week of the semester. As shown in Table 3, results indicate an increased student interest in operations management courses as well as in future career opportunities in data analytics. Indeed, enrollment in this institution's operations management courses increased by 19% in the registration period immediately following this

course, which is attributable, in part, to the changes integrated into this course.

5 | DISCUSSION

The innovative teaching project described in this brief aimed to enhance student competency with GenAI and inspire student interest in the field of operations management. By introducing ChatGPT-4 as one type of technological tool available to augment business decisions, students benefited from exposure to emerging technologies that will be used in their future careers. Through practical business applications, students learned to create added value for their future employers and clients utilizing the same procedures they will use in career settings, thus reducing the gap between academia and industry.

As measured by student reactions, incorporating applied and experiential instructional techniques increased student interest in data analytics and operations management courses and careers, an important outcome for instructors and academic administrators interested in increasing student enrollment. Students' generally positive outlook about GenAI aligns with the desires expressed by industry to hire employees with AI skills. As such, this article provides examples of how teaching management statistics with AI, as well as exposure to employer use of AI tools, can be leveraged to increase students' career readiness.

This project provides insight into several future implications for teaching quantitative courses in business education. First, incorporating real-world experiences can increase student interest and engagement. Second, using advanced technologies like generative AI demonstrates the potential for technology to enhance learning, provide immediate feedback, assist with complex data analysis, and offer personalized learning experiences that make education more interactive and effective. Third, continuing to enhance the curriculum with active and experiential learning methods can help students develop quantitative and career-readiness skills.

At the systems level, achieving this course redesign through an institutional initiative underscores the value of continuous professional development grounded in a theoretically sound framework for high-impact course enhancements. Workshops and cohort-based training equip faculty with the skills and support needed to implement and assess these methods effectively.

Future research will be improved by capturing the impact of AI-based instruction on student learning outcomes. As GenAI products are released, comparisons between the effectiveness of different GenAI tools in teaching statistics can be explored. Another potential line of research might investigate the training of customized ChatBots or AI-powered teaching agents, comparing student learning outcomes using these tools versus traditional instructor-led or peer-based tutoring. Finally, to continue to bridge the gap between education and employment, future research should continue to monitor the GenAI-related skills that are needed in industry and explore

TABLE 1 Results of student survey on use of generative AI.

	% responding Agree or Strongly Agree (ratings of 4 and 5 on 5 pt Likert scale)
Previously used ChatGPT for...*	
Personal use	72.6%
Academic research	66.7%
Writing assistance	65.7%
Programming/coding	47.1%
Creative projects	39.2%
Where did you first learn about GenAI?	
In school	41.2%
From friends or family	30.4%
Social media	20.6%
In educational settings, students use GenAI to...*	
Get help	77.5%
Improve their learning	74.5%
Save time	51.0%
Enhance their creativity	50.0%
Prepare for the future	27.3%
Students report drawback to GenAI include...*	
Accuracy	66.7%
Dependency on technology	65.7%
Academic integrity (cheating)	64.7%
Privacy/security	32.4%

*Multiple responses allowed, total greater than 100%.

TABLE 2 Student comments about value of integration of GenAI into the course.

“AI brings objectivity and efficiency to decision-making processes. Algorithms adeptly sift through copious amounts of data, allowing for data-driven comparisons. This is evident in e-commerce, where AI assesses product features, prices, and user reviews, providing consumers with comprehensive insights to facilitate informed choices.”

“AI is being used to benefit the consulting industry. [The major consulting company] is utilizing GenAI to help clients transform their businesses, teach them how to use AI, teach responsible GenAI skills, and help clients change internal processes to cut down on time.”

“In order to succeed in this environment—both academically and in their future careers—students need a toolkit of abilities and resources. ChatGPT, a cutting-edge AI language model, is one essential tool.”

“I learned how innovative tools like ChatGPT can reshape traditional business problem-solving processes. Applying ChatGPT together with Excel showed how AI might complement quantitative analysis by automating such tasks as cleaning data, building visualizations, and interpreting complex data into natural language. The project showed the distinctive strengths of ChatGPT: it is able to provide speedy high-level summaries and indicate strategies based on perceived trends, making it a very strong tool for initial exploration and decision-making.”

“Excel was a familiar tool, but using ChatGPT helped me understand how Excel produced the information that it did by providing a step-by-step walkthrough of its data analysis and the insights the Generative AI gathered from it.”

“While Excel excelled in organizing and visualizing data, ChatGPT provided robust interpretations and model refinements. For example, both tools produced identical coefficient values and R-squared measures in regression modeling, showcasing ChatGPT’s reliability. However, ChatGPT outperformed in delivering plain-language explanations of results, making complex statistical outcomes more accessible and actionable. This synergy emphasized that combining traditional software with AI solutions can significantly enhance both the speed and depth of data-driven decision-making.”

TABLE 3 Pre/post student survey results ($N = 89$).

Percent of students who “agreed” or “strongly agreed”...	Pre	Post	Change
Interest in working in analytics or operations management	52.8%	76.4%	+21%
Interest in studying operations management	29.2%	58.4%	+29.2%

the impact of ongoing partnerships through site visits and guest speakers in equipping students with career-ready skills.

6 | CONCLUSION

In summary, this teaching brief discussed how a transformative teaching project can enhance students' learning experiences as well as motivation to study operations management. Through a series of scaffolded assignments, a comparison of the usefulness of Excel versus GenAI in statistical analysis, and exposure to industry practices through guest speakers and a site visit, this brief provided a transformative learning model that can be applied to future business education.

ORCID

Kate Z. Williams  <https://orcid.org/0000-0001-5857-0266>

Tatiana Rudchenko  <https://orcid.org/0009-0004-4261-3857>

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APPENDIX A: SAMPLE DESCRIPTIVE STATISTICS PROBLEM DEMONSTRATING INCREASINGLY COMPLEX GENAI PROMPTS

Problem (adapted from Stine & Foster, 2021)

Imagine you work for Apple as part of a product design team. Your boss gives you the following information and wants to know if 500 different songs fit on the iPod Shuffle.

Song	Artist	Genre	Size (MB)	Length (s)
My Friends	D. Williams	Alternative	3.83	247
Up the Road	E. Clapton	Rock	5.62	378
Jericho	k.d. lang	Folk	3.48	225
Dirty Blvd.	L. Reed	Rock	3.22	209
Nothingman	Real Jam	Rock	4.25	275

AI prompts and responses

Prompt 1 provided to ChatGPT-4: Compute descriptive statistics for dataset attached.

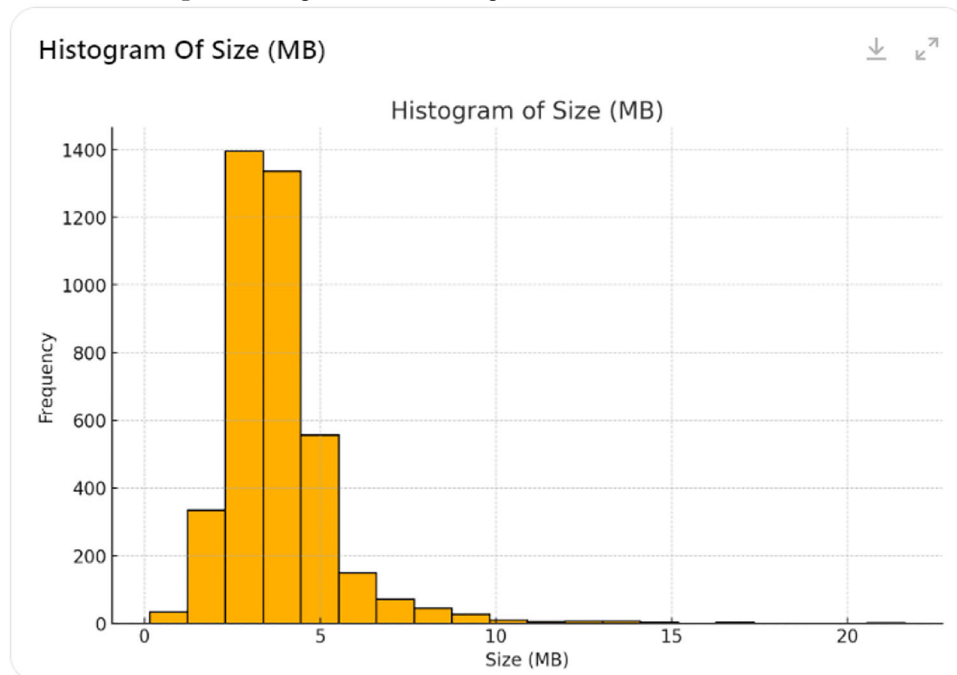
ChatGPT-4 response: It seems you're asking for the descriptive statistics for the file size in MB.

- Count: 3984 entries
- Mean (average): 3.78 MB
- Standard deviation: 1.61 MB
- Minimum: 0.15 MB.
- 25th percentile (Q1): 2.85 MB
- Median (50th percentile, Q2): 3.50 MB
- 75th percentile (Q3): 4.32 MB
- Maximum: 21.62 MB

These statistics give you a comprehensive view of the sizes in your dataset, indicating their average, variability, and distribution. If you need any further analysis or have another request, please let me know!

Prompt 2 provided to ChatGPT-4: Create a histogram showing the distribution of file sizes (in MB) from the attached dataset. Additionally, provide an analysis of the variability of this data, including key statistics such as the mean, standard deviation, and range.

ChatGPT-4 response: I'll generate the histogram to visualize the distribution of the data.



The histogram above shows the distribution of the “Size (MB)” data. Now, let's proceed with the variability analysis by calculating the range, interquartile range (IQR), variance, and standard deviation.

Variability analysis:

To analyze the variability, I will calculate the following statistical measures:

1. Range: The difference between the maximum and minimum values.
2. Interquartile range (IQR): The difference between the third quartile (Q3) and the first quartile (Q1).
3. Variance: The average of the squared differences from the mean.
4. Standard deviation: The square root of the variance.

Let's start with these analyses. [→]

Interpretation:

1. Range: The range is quite large (21.47 MB), indicating a significant difference between the smallest and largest values in the dataset.
2. Interquartile range (IQR): The IQR is 1.47 MB, which shows that the middle 50% of the data values are within this range. This suggests a relatively moderate spread in the central portion of the data.
3. Variance and standard deviation: the variance is 2.58 MB^2 , and the standard deviation is 1.61 MB. These measures indicate the average spread of data points around the mean, with standard deviation providing a more intuitive understanding of spread.

If you need further analysis or visualizations, feel free to let me know!

Prompt 3 provided to ChatGPT-4:

Task: Create and interpret a histogram that summarizes the distribution of the numerical variable "File Size (MB)" in the attached dataset with title File Size Distribution of Songs (MB). Please provide the report. Your report should present:

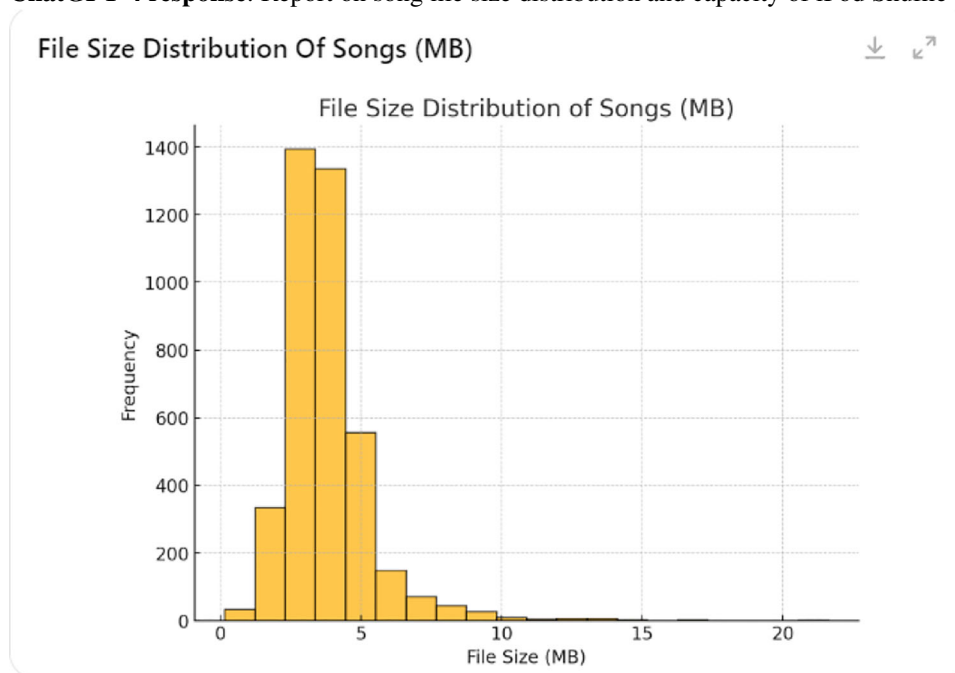
Count: Number of observations

Descriptive statistics: The 5-number summary

Variability analysis: Range, IQR, mean, and standard deviation

Conclusion: Addressing whether 500 different songs can fit on an iPod Shuffle.

ChatGPT-4 response: Report on song file size distribution and capacity of iPod Shuffle



1. Introduction

The purpose of this report is to analyze the distribution of song file sizes in megabytes (MB) and assess whether 500 different songs can fit on an iPod Shuffle, given the storage capacity of such devices. iPod Shuffles typically come with storage capacities ranging from 1 GB to 4 GB (1 GB = 1024 MB). We will analyze the song data provided and conclude whether 500 songs of similar sizes can fit on a 2 GB iPod Shuffle.

2. Descriptive statistics

The key variable under analysis is the “File Size (MB)” of each song. A histogram was constructed to visualize the distribution of file sizes. Below are the detailed statistics:

- Mean file size: 3.78 MB
- Median file sizes: 3.50 MB
- Standard deviation: 1.61 MB
- Minimum file size: 0.15 MB
- Maximum file size: 21.62 MB
- Total number of songs in the dataset: 3984 songs

3. Variability analysis

The histogram reveals that most song files have sizes between 3 and 5 MB, indicating a fairly consistent pattern in file size across the dataset. The standard deviation of 1.61 MB indicates that most of the file sizes are clustered around the mean, with a few larger and smaller outliers. Songs larger than 6 MB are uncommon, and songs over 21 MB are rare.

4. Capacity estimation:

To determine whether 500 songs can fit on a 2 GB iPod Shuffle, we performed the following calculation:
 If the average file size is approximately 3.78 MB:

$$500 \text{ songs} \times 3.78 \text{ MB/song} = 1890 \text{ MB}$$

This equates to 1.89 GB, which would comfortably fit on a 2 GB iPod Shuffle.

In fact, based on the average file size of 3.78 MB, an iPod Shuffle with 2 GB of storage could fit approximately 542 songs.

5. Conclusion

The analysis suggests that it is feasible to store 500 songs on a 2 GB iPod Shuffle, as the average song size of 3.78 MB would allow for around 542 songs. Songs with significantly larger file sizes would need to be minimized to ensure all 500 songs fit within the available space, but for most standard file sizes, the iPod Shuffle will be able to accommodate the full collection.

APPENDIX B: SAMPLE REGRESSION ANALYSIS PROBLEM DEMONSTRATING INCREASINGLY COMPLEX GENAI PROMPTS

Problem (adapted from Stine & Foster, 2021)

The accompanying data report characteristics of 15 types of cars sold in a certain country last year. One column gives the official mileage (combined MPG), and another gives the rated horsepower. Complete parts (a) through (e) below.

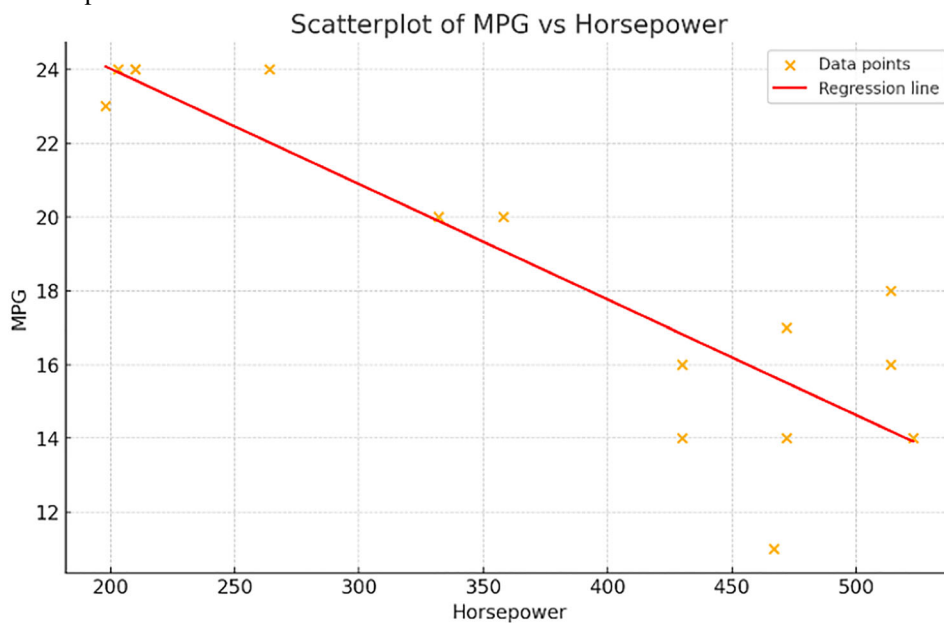
- a. Make a scatterplot of the two variables. Which variable makes the most sense to put on the x-axis, and which belongs on the y-axis?
- b. Describe any pattern in the plot. Be sure to identify any outliers.
- c. Find the correlation between these two variables. Round to three decimal places as needed.
- d. Interpret the correlation in the context of these data. Does the correlation provide a good summary of the strength of the relationship?
- e. Use the correlation line to estimate the mileage of a car with 220 horsepower. Does this seem like a sensible procedure? What if the car has a 1.6-L engine?

Car	Combined MPG	Horsepower	Displacement (L)
1	23	198	2.1
2	24	210	2.1
3	24	210	2.1
4	16	430	4.1
5	14	430	4.1
6	14	523	5.1
7	20	332	3.1
8	20	358	4.1
9	24	203	2.1
10	24	264	2.1
11	14	472	6
12	17	472	6
13	16	514	6
14	18	514	6
15	11	467	6

AI prompts and responses

Prompt 1 provided to ChatGPT-4: Run a regression of MPG on horsepower and create a scatterplot for this analysis.

ChatGPT-4 response: The dataset has been cleaned. Now, I'll run the regression analysis of MPG on Horsepower and create the scatterplot



The regression results show that there is a significant negative relationship between Horsepower and MPG:

- The R^2 value is 0.788, meaning that 78.8% of the variation in MPG is explained by Horsepower.
- The coefficient for Horsepower is -0.0313 , meaning that for each additional unit of Horsepower, the MPG decreases by approximately 0.0313.
- The p -value for Horsepower is less than 0.05, indicating that the relationship is statistically significant.

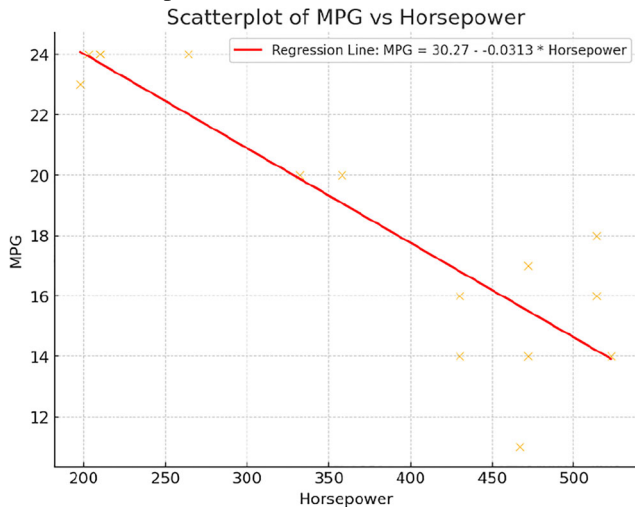
The scatterplot and regression line are displayed, showing the trend that as Horsepower increases, MPG tends to decrease. Let me know if you need further analysis or adjustments!

Prompt 2 provided to ChatGPT-4: Perform a detailed regression analysis of MPG as a function of Horsepower. Include the following components in your analysis:

1. Create a scatterplot to visualize the relationship between MPG and Horsepower.

2. Calculate and interpret the correlation coefficient, explaining the strength and direction of the relationship.
3. Develop a regression equation and explain the significance of the intercept and slope.
4. Assess the goodness of fit using R^2 and explain what it tells you about the model's predictive power.
5. Test the statistical significance of the regression coefficients (using p -values) and interpret the results.
6. Identify and discuss any outliers or influential points and their potential impact on the model.
7. Use the regression model to estimate the MPG for a car with 220 horsepower and evaluate whether this is a reasonable prediction.
8. Provide a critical evaluation of the limitations and assumptions of the model and suggest how the model could be improved or refined for better predictive accuracy.

ChatGPT-4 response:



Detailed regression analysis of MPG on horsepower

1. Scatterplot and pattern
 - a. The scatterplot shows a clear negative linear relationship between MPG and Horsepower.
 - b. The red regression line illustrates the negative slope, indicating that higher horsepower is associated with lower MPG.
2. Correlation coefficient (strength and direction)
 - a. The correlation coefficient (r) = -0.888 (rounded to three decimal places).
 - b. This indicates a strong negative correlation between MPG and Horsepower—as horsepower increases, MPG tends to decrease.
3. Regression equation: the regression equation is

$$MPG = 30.27 - 0.0313 \times \text{Horsepower}$$

- a. Intercept = 30.27 → If horsepower is zero, the estimated MPG would be about 30.27.
- b. Slope = -0.0313 → For each additional unit of horsepower, MPG decreases by approximately 0.0313.
4. Goodness of Fit (R^2):
 - a. $R^2 = 0.788$ → About 78.8% of the variation in MPG is explained by horsepower.
 - b. This is a strong indicator that the model fits the data well.
5. Statistical significance of the coefficients:
 - a. The p -value for the slope coefficient = $9.99 \times 10^{-69.99} \times 10^{-6}$ → This is highly significant (much smaller than 0.05).
 - b. This means there is strong evidence that horsepower is a significant predictor of MPG.
6. Outliers and influential points
 - a. Outliers are defined as residuals greater than two standard deviations from the mean.
 - b. Identified outliers:
 - i. Car #15 has unusually high horsepower and very low MPG.

- c. These points may have a significant impact on the model's accuracy.
7. Prediction
 - a. The estimated MPG for a car with 220 horsepower is 23.39 MPG.
 - b. This seems reasonable given the overall pattern in the data.
 8. Model assumptions and limitations
 - a. Linearity: The scatterplot indicates a roughly linear relationship.
 - b. Independence: The data points are likely independent, but external factors could influence the results.
 - c. Homoscedasticity: The residuals appear to have consistent variance across the range of horsepower values.
 - d. Normality: The Shapiro–Wilk test for normality gave a p -value of 0.747, which means we cannot reject the null hypothesis of normality—the residuals are approximately normally distributed.

Summary and recommendations:

- The model shows a strong negative relationship between MPG and horsepower.
- The R^2 value indicates a good fit, and the p -value confirms that the relationship is statistically significant.
- Removing the outliers could further improve the model's accuracy.
- Adding additional variables (e.g., weight or engine type) might improve the predictive power.
- Despite the strong fit, the negative slope indicates that cars with higher horsepower will generally have lower MPG.

AUTHOR BIOGRAPHIES

Kate Williams is a Principle Academic Professional and Associate Director for Transformative Teaching and Learning in the Center for Teaching and Learning at Georgia Institute of Technology. She earned a bachelor's of business administration from Stetson University, a master of higher education administration from the University of South Carolina, and a PhD in industrial/organizational psychology from Clemson University. She creates and studies the effectiveness of faculty development programs that embed experiential learning into traditional classroom settings.

Tatiana Rudchenko (ORCID 0009-0004-4261-3857) is a Principle Lecturer in the Scheller College of Business at Georgia Institute of Technology. She earned a bachelor of business administration at Voronezh State University and a PhD in mathematics at Voronezh State Technological Academy, Russia. Her innovative teaching methods have earned her the Brady Family Award for Faculty Teaching Excellence and the Center for Teaching and Learning's Curriculum Innovation Award.