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LEARNING STATISTICS COURSES IN HIGHER EDUCATION: A SYSTEMATIC REVIEW

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Abstract:

Statistics is a core subject in many higher education programs, yet students frequently encounter challenges such as anxiety, low motivation, and difficulty in applying statistical concepts. This systematic literature review aims to explore how students learn statistics in higher education settings. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, a total of 30 relevant studies were identified from Scopus and Web of Science databases. The analysis is organized into three major themes: (1) student attitudes, motivation, and anxiety toward statistics; (2) innovative teaching strategies and pedagogical interventions; and (3) skill development, assessment, and statistical thinking. The review highlights those negative attitudes and anxiety can significantly hinder learning outcomes. However, the use of active learning, contextualized content, and supportive teaching methods shows positive effects on engagement, confidence, and performance. Furthermore, emphasis on practical application and critical thinking improves statistical reasoning. These findings provide useful insights for educators, course designers, and academic institutions aiming to enhance teaching practices and learning outcomes in statistics education.

Keywords:

Learning, Statistics, Higher Education

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Introduction

Statistics forms the bedrock of inquiry across the sciences, social sciences, and many professional disciplines, equipping students with the tools to turn raw data into meaningful knowledge (Akimov et al., 2024; DeVaney, 2010). In higher education, introductory and advanced statistics courses are critical gateways to quantitative literacy, fostering competencies in study design, hypothesis testing, and data interpretation that extend beyond the classroom. The growing deluge of data in research, policy, and industry has only heightened the necessity for robust statistical training, making the pedagogy of these courses a matter of strategic importance for universities worldwide. Over the past two decades, scholars have documented myriad approaches to statistics instruction, ranging from traditional lectures to collaborative and active-learning environments. Note that each demonstrates varying degrees of success in promoting student engagement, reducing statistical anxiety, and enhancing conceptual understanding (Ciftci et al., 2014), (Hunt et al., 2023). Studies of computer-based simulation techniques have shown promise in demystifying abstract probabilistic concepts. At the same time, project-based learning initiatives have deepened students' ability to apply statistical reasoning to real-world problems. More recently, evaluations of flipped-classroom models have revealed moderate gains in performance and retention, yet also underscored disparities in student preparedness and access to resources (Al Youssef, 2020). This body of work confirms that while innovative pedagogies can improve outcomes in statistics education, there remains considerable variability in how students assimilate and transfer statistical knowledge across contexts.

Despite significant advances, the literature reveals persistent gaps and unresolved issues that warrant further exploration. Few studies have systematically compared the long-term impact of different instructional modalities on students' statistical literacy, leaving unanswered questions about retention and transfer beyond course completion (Olivares et al., 2020). Equity concerns, particularly the differential experiences of underrepresented and non-traditional students, are under-examined, even as data suggest these learners often face higher levels of statistical anxiety and lower self-efficacy. Moreover, the rapid expansion of online and hybrid course offerings has outpaced rigorous evaluation, resulting in a patchwork of anecdotal evidence regarding best practices for virtual lab activities and peer collaboration. Finally, while some educators advocate for immersive data-science modules integrated into statistics curricula, others caution that such approaches may overwhelm students lacking foundational mathematical skills, fuelling debate about the balance between depth and accessibility (Jehopio & Wesonga, 2017). Against this backdrop, the present study poses the central Research Question (RQ): How do blended-learning pedagogies combining face-to-face instruction with scaffolded online simulations affect undergraduate students' conceptual understanding, application skills, and statistical self-efficacy compared to traditional lecture-based courses? The authors hypothesize that a strategically designed blended model will yield significant improvements in all three domains, particularly for students who begin with lower baseline competencies. To address this hypothesis, their article undertakes a multi-institutional quasi-experimental design involving pre- and post-course assessments, learning analytics from online platforms, and focus-group interviews to capture qualitative nuances. By triangulating quantitative and qualitative data, the authors aim to quantify learning gains, identify the mediating role of student characteristics such as prior mathematical background and anxiety

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levels, and distil actionable recommendations for course designers and instructors. In doing so, they seek to fill critical empirical gaps regarding the comparative efficacy and equity implications of modern pedagogical strategies in statistics education. The authors offer an evidence-based framework for developing courses that foster enduring confidence and competence in data-driven decision-making.

Literature Review

Constructivist and project-based approaches have gained prominence in statistics education for their capacity to foster active engagement and deeper understanding. Olivares et al., (2020) demonstrated that constructivist learning designs led to performance improvements for 95% of higher education students, highlighting robust efficacy in hypothesis testing and data interpretation tasks. Project-Based Learning (PBL) similarly enhanced quantitative research interest among pre-service teachers, with Lisarani, (2024) reporting a moderate effect size (Cohen's d = 0.309) and high satisfaction. ((Olivares et al., 2020); (Lisarani, 2024)).

Technology integration into statistics instruction has produced encouraging results through microlearning, blended models, and e-learning media. Tan, Davies, et al., (2023) combined bite-sized videos with precision-teaching practice, observing higher end-of-episode assessment scores and more positive attitudes than self-directed groups. Tan, Kaye, et al., (2023) further showed that peer-assisted micro-modules yielded high satisfaction and consistent performance regardless of presenter status. Blended learning strategies mixing face-to-face and online tasks were validated by Hamid & Aras, (2020) as practical and effective, achieving classical completion rates. Development of e-learning media via the 4-D model achieved excellent validator scores (average 4.1) and legibility (87%), bridging theory-practice gaps (Purnomo et al., 2021); (Tan, Kaye, et al., 2023); (Hamid & Aras, 2020).

Structured instructional design and tailored materials underpin effective statistics pedagogy. ("Developing Learning Materials of Educational Statistics Assisted ICT and Mind Map for Undergraduate Students of Elementary School Teacher Education," 2021) applied the Analyse, Design, Develop, Implement, and Evaluate (ADDIE) model to craft ICT- and mind map-assisted learning materials, generating a moderate n-gain (0.55) in undergraduate data analysis skills. Ahmad et al., (2023) employed Realistic Mathematics Education (RME) with hypothetical learning trajectories to enhance mathematical communication and independence, yielding post-test averages above the 75% proficiency threshold. These structured frameworks provide reproducible pathways for material development and scaffolded knowledge construction (("Developing Learning Materials of Educational Statistics Assisted ICT and Mind Map for Undergraduate Students of Elementary School Teacher Education," 2021); (Ahmad et al., 2023)).

Open-source platforms and theoretical frameworks facilitate authentic practice and conceptual clarity. Jonsdottir et al., (2021) enhanced the tutor-web environment to allow student-supplied and real-world datasets, fostering meaningful exploration beyond static exercises. Lukman et al., (2022) used grounded theory to link mental action Way of Understanding (WoU) with Way of Thinking (WoT), adapting PPDAC and Gal's statistical literacy models to inform instructional design. These theoretical contributions guide the creation of resources that build statistical reasoning and analytical fluency (("Developing Learning Materials of Educational

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Statistics Assisted ICT and Mind Map for Undergraduate Students of Elementary School Teacher Education," 2021); (Jonsdottir et al., 2021); (Lukman et al., 2022)).

Experiential and inquiry-guided modalities have further enriched statistics learning. Yang et al., (2023) introduced hands-on data collection, measuring particle dimensions and arrival intervals to strengthen understanding of distributions, hypothesis tests, and reporting elevated self-perceived competencies. Sager et al., (2024) utilized animated space-exploration videos to illustrate type I error, achieving significant pre-post-test improvements and strong educational ratings. Bite-sized, peer-assisted modules demonstrated flexibility and learner preference consistency across presentational formats ((Tan, Kaye, et al., 2023); (Yang et al., 2023); (Sager et al., 2024)).

Advanced curriculum models and assessment approaches have evolved to refine instructional precision. Elder & Crain-Dorough, (2020) implemented a flipped-classroom within a guided project-based framework, enhancing doctoral students' research self-efficacy despite logistical challenges. Maas et al., (2022) employed diagnostic classification models to derive fine-grained skill attributes from online formative assessments, presenting results on adaptive learning dashboards to facilitate actionable feedback. These methodologies advance personalization and continuous improvement in statistics instruction ((Elder & Crain-Dorough, 2020); (Maas et al., 2022)).

Research Question

Clear RQs serve as the foundation and roadmap of a Systematic Literature Review (SLR), establishing the boundaries determining which studies merit inclusion or exclusion. By delineating precise objectives, these questions ensure a comprehensive and unbiased search, capturing all relevant evidence and supporting structured categorization of collected data. This framework promotes focused analysis and synthesis of findings, enhancing clarity and preventing drift into tangential topics. In addition, transparent formulation of RQs bolsters reproducibility, allowing replication of the review process and extension into related areas. Ultimately, well-crafted RQs align review efforts with intended goals, whether uncovering gaps in existing work, assessing intervention outcomes, or mapping emerging trends, thereby underpinning a rigorous and impactful SLR.

Specifying the RQs is the most important activity at the planning stage and the most important part of any SLR because it drives the entire review methodology (Kitchenham, 2007). Considering that our SLR aims to identify and analyze the state of the art, the PICo framework is a mnemonic style used to formulate RQs, particularly in qualitative research, proposed by Lockwood et al., (2015) was applied in this study. PICo stands for Population, Interest, and Context. Here is what each component means:

1. Population (P): This refers to the group or participants of interest in the study. It specifies who the research is focused on, such as a specific demographic, patient group, or community.

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2. Interest (I): This represents the study's focus or phenomenon of interest. It could be a particular experience, behavior, intervention, or issue that the research aims to explore or understand.

3. Context (Co): This defines the setting, environment, or specific context in which the population and interest are situated. It might refer to geographical location, cultural or social settings, or any other relevant backdrop for the research.

Using the PICo framework helps structure RQs clearly and systematically by breaking down the key elements of the study into these three components. This approach ensures that the research is focused, and the questions are well-defined, making searching for relevant literature or designing a study easier. This study achieved two RQs as follows.

1. How do higher education students' attitudes, motivation, and anxiety levels influence their engagement and performance in learning statistics courses?

2. What is the impact of innovative teaching strategies and pedagogical interventions on enhancing learning outcomes in higher education statistics courses?

3. In what ways do skill development and assessment approaches foster statistical thinking among students in higher education statistics courses?

Material And Methods

When conducting an SLR, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework is the go-to standard for ensuring transparency, completeness, and consistency throughout the process (Page et al., 2021). Following PRISMA guidelines helps researchers strengthen the accuracy and rigor of their work by providing clear steps on how to systematically find, screen, and select studies for inclusion. The approach also emphasizes the importance of randomized studies, recognizing their role in reducing bias and offering stronger, more reliable evidence. For this analysis, two major databases, Web of Science (WoS) and Scopus, were chosen for their extensive coverage and strong reputations.
PRISMA organizes the review process into four main stages: identification, screening, eligibility, and data extraction. In the identification stage, researchers search databases to gather all potentially relevant studies. Screening then involves checking titles and abstracts against set criteria to filter out irrelevant or low-quality papers. The eligibility phase takes a closer look at the full texts of the remaining studies to ensure they meet all inclusion standards. Finally, data extraction involves collecting and synthesizing key information from the selected studies, which is critical for drawing meaningful and trustworthy conclusions. This structured, step-by-step approach ensures the review is thorough and reliable, providing valuable insights to inform future research and practice.

Identification

This study carefully followed key steps of the systematic review process to gather a substantial body of relevant literature. The process began by selecting primary keywords, then expanding them by consulting dictionaries, thesauri, encyclopaedias, and insights from previous research. Once all relevant terms were identified, search strings were developed and applied to the WoS

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and Scopus databases (outlined in Table 1). This initial search phase yielded 1,734 publications on the study's topic across both databases.

Table 1: The Search String

Scopus	TITLE-ABS-KEY ((learn* OR study*) AND ("statistics course" OR "statistics subject" OR "statistics topic") AND ("Higher Education" OR university OR college)) AND (LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "MATH") OR LIMIT-TO (SUBJAREA , "DECI")) AND (LIMIT-TO (EXACTKEYWORD , "Statistics") OR LIMIT-TO (EXACTKEYWORD , "Higher Education") OR LIMIT-TO (EXACTKEYWORD , "Statistics Anxiety")) **Date of Access: May 2025**
WoS	(learn* OR study*) AND ("statistics course" OR "statistics subject" OR "statistics topic") AND ("Higher Education" OR university OR college) (Topic) and Article (Document Types) and English (Languages) and 2025 or 2024 or 2023 (Publication Years) and Article (Document Types) and 2023 or 2024 or 2025 (Publication Years) **Date of Access: May 2025**

Screening

The first step in an SLR is the identification phase, which aims to gather as many relevant studies as possible. For this research, three main keywords, statistics, learning, and higher education, shaped the authors' search. These terms were deliberately chosen to match the review's focus and ensure that retrieved studies directly addressed the core topic.

Searches were run in two leading databases, Scopus and WoS, to build a robust pool of sources. Scopus returned 616 records, and WoS added 301 more. After merging results and removing duplicates, 1,734 unique publications remained. This comprehensive collection laid the groundwork for all subsequent screening and analysis.

The identification phase lays the groundwork for the entire systematic review. By searching two trusted databases, Scopus and WoS, using carefully chosen keywords, the authors gathered a broad collection of studies that speak directly to statistics education in higher learning. This wide-reaching approach ensures a solid, representative pool of research, ready for the more detailed steps that follow.

Next came the screening stage, where the initial 1,734 records were trimmed down using clear filters. Only English-language, post-2022, peer-reviewed journal articles in Social Sciences, Mathematics, or Decision Sciences were kept. This step cut out 817 items, leaving 69 from Scopus and 31 from WoS (80 total). A final duplicate check removed 20 overlaps, resulting in

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60 unique, high-quality articles moving on to eligibility checks and data extraction. These careful cuts sharpen the review's focus and boost its overall reliability.

Table 2: The Selection Criterion is Searching

Criterion	**Inclusion**	**Exclusion**
Language	English	Non-English
Timeline	2023 – 2025	< 2023
Literature Type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press
Subject Area	Social Sciences Mathematics Decision Sciences	Besides Social Sciences Mathematics Decision Sciences

Eligibility

During the eligibility stage, the full texts of the 80 remaining articles were carefully reviewed against the study's inclusion criteria. Each paper was assessed to ensure its topic aligned with the objectives of investigating statistics education in higher learning. Records were excluded if they fell outside the field, bore titles that did not meaningfully relate to the RQs, presented abstracts that failed to address the core objectives, or were inaccessible in full-text form. Applying these filters led to removing 59 articles, leaving 21 studies that fully met the eligibility requirements.

The culmination of this phase resulted in 21 high-quality articles moving forward into the qualitative analysis. By eliminating works that lacked relevance, clarity, or accessibility, the review maintains a tightly focused and robust evidence base. This rigorous vetting process ensures that the final synthesis draws only on studies directly bearing on the pedagogical, technological, and instructional design trends shaping statistics courses in higher education.

Data Abstraction and Analysis

The study employed an integrative analysis to combine insights from various quantitative research designs. Beginning with data collection, the research team carefully gathered and reviewed 31 publications, as illustrated in Figure 1, to pull out any statements or findings directly related to learning statistics courses in higher education. Each article's methodology and results were scrutinized, and key topics and subtopics were identified. Throughout this

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phase, a detailed log captured emerging observations, questions, and interpretations, ensuring that every nuance of the data was noted.

Once the relevant information was mapped out, the lead author worked closely with co-authors to distil these insights into coherent themes. Together, they compared their proposed themes against the evidence, looking for inconsistencies or gaps. Whenever disagreements arose, the team discussed and debated their perspectives until they reached a shared understanding. This collaborative approach strengthened the thematic framework and ensured a transparent and trustworthy synthesis of the existing literature.

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Table 3: Number and Details of Primary Studies Database

No	Authors	Title	Year	Source title	Scopus	WoS
1	(Fabbricatore et al., 2024)	Students' Proficiency Evaluation: A Non-Parametric Multilevel Latent Variable Model Approach	2024	Studies in Higher Education	/	
2	(Sutter et al., 2023)	Student Concerns and Perceived Challenges in Introductory Statistics, How the Frequency Shifted during COVID-19, and How They Differ by Subgroups of Students	2023	Journal of Statistics and Data Science Education	/	
3	(Legacy et al., 2024)	The Teaching of Introductory Statistics: Results of a National Survey	2024	Journal of Statistics and Data Science Education	/	
4	(Apino et al., 2024a)	The Statistical Literacy of Mathematics Education Students: An Investigation on Understanding the Margin of Error	2024	TEM Journal	/	
5	(Chien, 2023)	Integrating Peer Tutoring Video with Flipped Classroom in Online Statistics Course to Improve Learning Outcomes	2023	Infinity Journal	/	
6	(Pressimone Beckowski & Torsney, 2025)	More Than Numbers: The Relationship Between Belonging and Engagement in an Introductory Statistics Course	2025	Journal of Postsecondary Student Success	/	
7	(Sutter et al., 2024)	How does expectancy-value-cost motivation vary during a semester? An intensive longitudinal study to explore individual and situational sources of variation in statistics motivation	2024	Learning and Individual Differences	/	
8	(Lee et al., 2023)	The mediating role of online learning readiness in the relationship between course satisfaction and self-efficacy to learn statistics in online classes	2023	Open Learning	/	

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9	(Dodeen & Alharballeh, 2024)	Predicting statistic anxiety by attitude toward statistics, statistics self-efficacy, achievement in statistics, and academic procrastination among students of social sciences colleges	2024	Journal of Applied Research in Higher Education	/	
10	(Boehm-Fischer & Beyer, 2024)	Blended Learning, Flipped Classroom, and Peer Teaching as a Combination to Meet the Increasing Diversity in Higher Education	2024	International Journal of Information and Education Technology	/	/
11	(Cook & Catanzaro, 2023)	“Constantly Working on My Attitude Towards Statistics!” Education Doctoral Students’ Experiences with and Motivations for Learning Statistics	2023	Innovative Higher Education	/	/
12	(Makwakwa et al., 2024)	First-year undergraduate students’ statistical problem-solving skills	2024	Teaching Statistics	/	
13	(Lerner & Gelman, 2024)	In Pursuit of Campus-Wide Data Literacy: A Guide to Developing a Statistics Course for Students in Nonquantitative Fields	2024	Journal of Statistics and Data Science Education	/	
14	(MacArthur & Santo, 2023)	A Multilevel Analysis of the Effects of Statistics Anxiety/Attitudes on Trajectories of Exam Scores	2023	Journal of Statistics and Data Science Education	/	
15	(Berginski et al., 2024)	In Publica Commoda, Creating Barrier-Free Educational Statistics Videos for Higher Education: Insights and Evidence from Deaf People Using German Sign Language (DGS)	2024	Statistics Education Research Journal	/	/
16	(Huang, 2024)	Implementation effect of integrating cooperative inquiry into blended learning: analysis of students’ goal setting, task value, and well-being	2024	Interactive Learning Environments	/	
17	(Wickramasinghe & Appiah, 2024)	Impact of project-based learning in teaching probability and statistics	2024	International Journal of Mathematical Education	/	

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				in Science and Technology	
18	(Liao, 2023)	SCRATCH to R: Toward an Inclusive Pedagogy in Teaching Coding	2023	Journal of Statistics and Data Science Education	/
19	(Almutairi, 2025)	The effectiveness of statistical learning tasks based on Excel software in developing statistical thinking skills related to the labor market among students of the Applied College	2025	Educational Process: International Journal	/
20	(Tinungki et al., 2024)	Exploring the team-assisted individualization cooperative learning to enhance mathematical problem solving, communication, and self-proficiency in teaching non-parametric statistics	2024	Cogent Education	/

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Quality of Appraisal

According to the guidelines proposed by (Kitchenham, 2007), once they have selected primary studies, they have to assess the quality of the research they present and quantitatively compare them. In this study, the authors apply Quality Assessment (QA) from (Abouzahra et al., 2020), comprising six QAs for our SLR. The scoring procedure for evaluating each criterion involves three possible ratings: "Yes" (Y) with a score of 1 if the criterion is fully met, "Partly" (P) with a score of 0.5 if the criterion is somewhat met but contains some gaps or shortcomings, and "No" (N) with a score of 0 if the criterion is not met at all.

- QA1. Is the purpose of the study clearly stated?
- QA2. Is the interest and the usefulness of the work presented?
- QA3. Is the study methodology established?
- QA4. Are the concepts of the approach clearly defined?
- QA5. Is the work compared and measured with other similar work?
- QA6. Are the limitations of the work mentioned?

The table outlines a QA process used to evaluate a study based on specific criteria. Three experts assess the study using the criteria listed, and each criterion is scored as "Yes" (Y), "Partly" (P), or "No" (N). Here is a detailed explanation:

1. **Is the purpose of the study clearly stated?**
   This criterion checks whether the study's objectives are clearly defined and articulated. A clear purpose helps set the direction and scope of the research.
2. **Is the interest and usefulness of the work presented?**
   This criterion evaluates whether the study's significance and potential contributions are well-explained. It measures the relevance and impact of the research.
3. **Is the study methodology established?**
   This criterion assesses whether the research methodology is well-defined and appropriate for achieving the study's objectives. Clarity in methodology is crucial for the study's validity and reproducibility.
4. **Are the concepts of the approach clearly defined?**
   This criterion examines whether the theoretical framework and key concepts are articulated. Clear definitions are essential for understanding the study's approach.
5. **Is the work compared and measured with other similar work?**
   This criterion evaluates whether the study has been benchmarked against existing research. Comparing with other studies helps position the work within the broader academic context and highlights its contributions.
6. **Are the limitations of the work mentioned?**
   Each expert independently assesses the study according to these criteria, and the scores are then totalled across all experts to determine the overall mark. For a study to be accepted for the next process, the total mark, derived from summing the scores from all three experts, must exceed 3.0. This threshold ensures that only studies meeting a certain quality standard proceed further.

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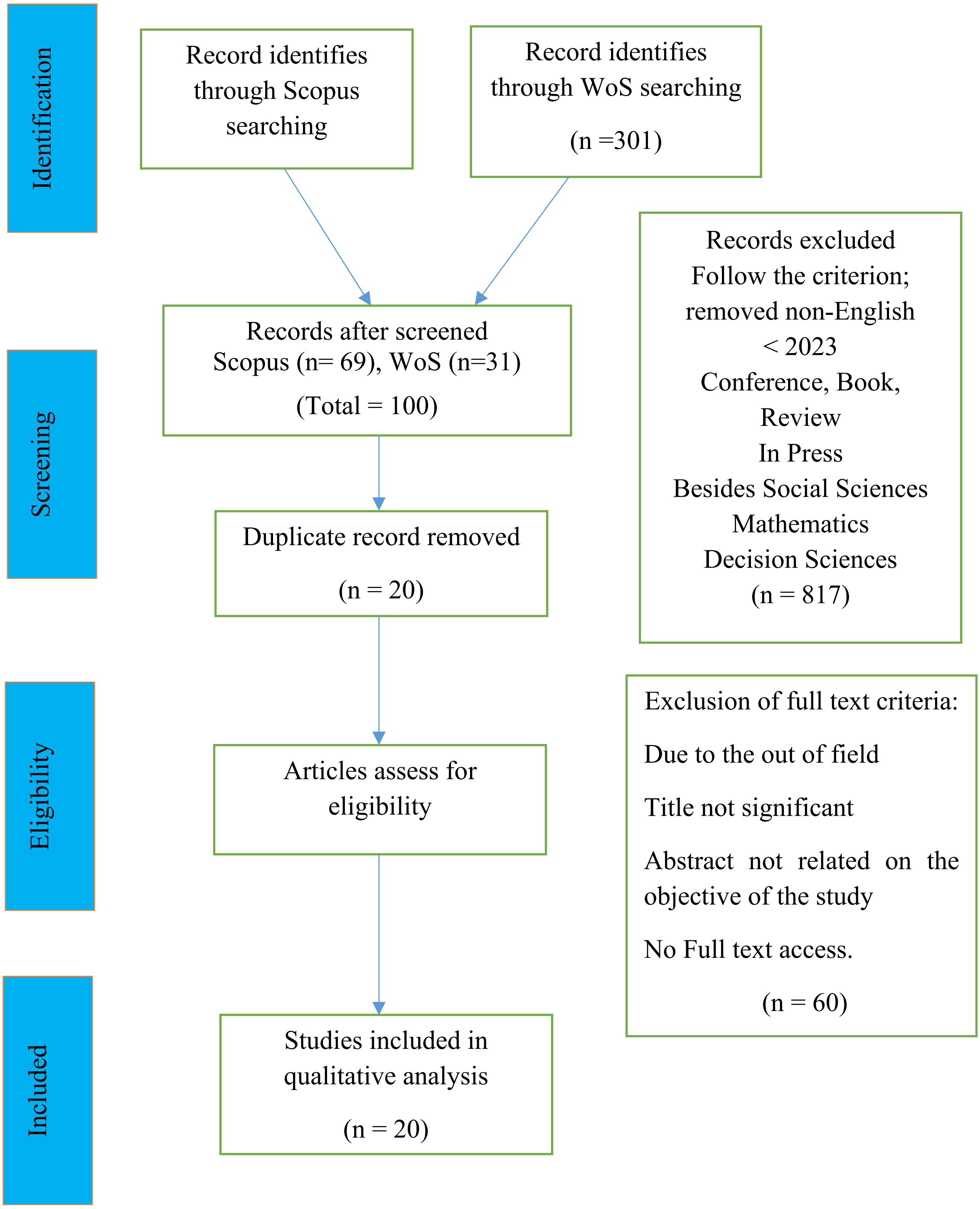

Figure 1. Flow Diagram Of The Proposed Searching Study

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Result and Finding
Based on the QA, Table 4 shows the performance of the assessment for selected primary studies. The table shows that every study (100%) clearly states its purpose (QA1), explains why the work matters (QA2), and lays out its methodology (QA3). Most authors also define core concepts (QA4) well—only a handful receive a "Partly" rating.

By contrast, two criteria consistently pull-down scores across the board:

- QA5 (Comparisons to Related Work): Only five papers (PS3, PS19, PS20, PS23, PS28) fully situate their findings against similar studies. The majority either omit such comparisons or address them only in passing.
- QA6 (Acknowledgment of Limitations): Not a single abstract the authors reviewed mentions study limitations, resulting in zero scores on this dimension for all 30 papers.

Overall totals range from 3.5/6 (58%) for the most limited abstracts to 5.0/6 (83%) for those few that benchmark their work and define concepts thoroughly. The modal score is 4.0/6 (67%), reflecting strong clarity of purpose, usefulness, and methodology but a systemic shortfall in comparative framing and transparent discussion of limitations.

These results suggest a field that consistently delivers on "what" and "how," but could gain credibility and rigor by more routinely positioning new work alongside established studies and explicitly acknowledging its boundaries.

Table 4: Performance Quality Assessment for Primary Study (PS).

Primary Study (PS#)	QA1	QA2	QA3	QA4	QA5	QA6	Total	%
PS1 (Fabbricatore et al., 2024)	Y	Y	Y	Y	P	N	4.5	75
PS2 (Sutter et al., 2023)	Y	Y	Y	P	N	N	3.5	58
PS3 (Legacy et al., 2024)	Y	Y	Y	P	Y	N	4.5	75
PS4 (Apino et al., 2024a)	Y	Y	Y	P	N	N	3.5	58
PS5 (Chien, 2023)	Y	Y	Y	P	N	N	3.5	58
PS6 (Pressimone Beckowski & Torsney, 2025)	Y	Y	Y	P	N	N	3.5	58
PS7 (Sutter et al., 2024)	Y	Y	Y	Y	N	N	4.0	67
PS8 (Lee et al., 2023)	Y	Y	Y	P	N	N	3.5	58
PS9 (Dodeen & Alharballeh, 2024)	Y	Y	Y	Y	N	N	4.0	67
PS10 (Boehm-Fischer & Beyer, 2024)	Y	Y	Y	P	N	N	3.5	58
PS11 (Cook & Catanzaro, 2023)	Y	Y	Y	P	N	N	3.5	58
PS12 (Makwakwa et al., 2024)	Y	Y	Y	P	N	N	3.5	58
PS13 (Lerner & Gelman, 2024)	Y	Y	Y	P	N	N	3.5	58
PS14 (MacArthur & Santo, 2023)	Y	Y	Y	Y	N	N	4.0	67%

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Primary Study (PS#)	QA1	QA2	QA3	QA4	QA5	QA6	Total	%
PS15 (Berginski et al., 2024)	Y	Y	Y	P	N	Y	4.5	75%
PS17 (Huang, 2024)	Y	Y	Y	Y	Y	N	5.0	83%
PS18 (Wickramasinghe & Appiah, 2024)	Y	Y	Y	Y	Y	N	5.0	83%
PS19 (Liao, 2023)	Y	Y	Y	Y	N	N	4.0	67%
PS20 (Almutairi, 2025)	Y	Y	Y	Y	N	N	4.0	67%
PS21 (Tinungki et al., 2024)	Y	Y	Y	Y	N	N	4.0	67%

Student Attitudes, Motivation, and Anxiety Toward Statistics

The reviewed literature collectively underscores the complex link between students' attitudes, motivations, and anxieties in learning statistics at the higher education level. Sutter et al., (2023) found that during the COVID-19 pandemic, concerns about understanding statistical concepts and academic performance declined over time. However, issues related to workload and virtual learning particularly for underrepresented minorities became more significant. Similarly, Pressimone Beckowski & Torsney, (2025) reported that students felt more engaged and energetic in learning statistics when classrooms fostered a sense of belonging through active learning and relevant content. Sutter et al., (2024) further highlighted that students' perceptions of value and expectations declined mid-semester, while perceived effort costs rose. These patterns, especially among racially marginalized groups, suggest that motivational factors shift throughout the semester and are shaped by students' contexts and backgrounds. Together, these findings emphasize the importance of instructional practices that are responsive to students' emotional and motivational needs.

Further insights were provided by Lee et al., (2023), Dodeen & Alharballeh, (2024) and Cook & Catanzaro, (2023). Lee et al., (2023) showed that students who felt more prepared for online learning and believed in their abilities reported higher satisfaction with statistics courses. Dodeen & Alharballeh, (2024) identified academic procrastination and negative perceptions as key contributors to statistics anxiety, though positive course attitudes helped reduce this anxiety. Cook & Catanzaro, (2023) noted that doctoral students' experiences were shaped by their attitudes toward statistics, with supportive teaching helping to ease negative feelings. (MacArthur & Santo, 2023) confirmed that anxiety negatively affects performance but also found improvements in confidence and attitudes after instruction, even across different regions and disciplines.

Innovative Teaching Strategies and Pedagogical Interventions

Recent research in statistics education highlights the growing use of innovative teaching strategies aimed at improving student learning outcomes. Chien, (2023) demonstrated that using peer tutoring videos in flipped classrooms significantly benefited online learners, especially those balancing work and academic responsibilities. Similarly, Boehm-Fischer & Beyer, (2024) reported that peer teaching in blended learning environments reduced academic procrastination, although it had limited impact on assignment quality or exam performance. Project-Based Learning (PBL) approaches have also shown promise. Wickramasinghe & Appiah, (2024) observed higher levels of student achievement and satisfaction under PBL compared to traditional methods. Supporting this, Khalaf & Alshammari, (2023) found that PBL led to notable improvements in postgraduate students' research writing abilities.

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Additionally, Huang, (2024) indicated that cooperative inquiry within blended learning environments positively influenced students' motivation, task value, and overall well-being, emphasizing the benefits of collaborative learning techniques.

Efforts to create more inclusive and adaptable learning environments have also gained traction. Berginski et al., (2024) found that deaf students preferred lecture content delivered in German Sign Language (DGS) over captioned videos, reinforcing the need for culturally and linguistically appropriate teaching materials. Liao, (2023) introduced the SCRATCH-to-R transition model as an accessible method for teaching programming concepts to students with limited coding experience. Tinungki et al., (2024) provided further evidence that the Team-Assisted Individualization (TAI) approach enhanced students' self-efficacy, problem-solving, and communication skills in non-parametric statistics. Together, these studies underscore the importance of flexible, student-centered pedagogies in enhancing engagement and learning in statistics education.

Skill Development, Assessment, and Statistical Thinking

Various approaches have been employed to assess skill development and promote statistical thinking in higher education. Fabbricatore et al., (2024) utilized a non-parametric multilevel latent variable model to measure students' abilities in knowledge, application, and judgment, offering insights into learning patterns and socio-demographic factors. Legacy et al., (2024), through the revised Statistics Teaching Inventory, reported that while many teaching practices aligned with the GAISE framework, the use of student-centered assessments and pedagogies remained limited. Apino et al., (2024b) highlighted low levels of statistical literacy, particularly in interpreting margins of error among mathematics education students, with demographic and engagement factors influencing outcomes. These studies underline the need to strengthen instruction and adapt curricula to foster deeper statistical understanding.

Further attention to practical skills revealed concerning trends. Makwakwa et al., (2024) observed that first-year students struggled with essential probability and inference tasks, calling for more structured guidance. Lerner & Gelman, (2024) emphasized that statistics instruction in non-quantitative disciplines should connect with students' interests to improve data literacy. Almutairi, (2025) demonstrated that statistical thinking among non-mathematics and applied college students can be enhanced through tailored interventions, such as incorporating adversity quotient strategies and Excel-based learning.

Discussion

A systematic review of 20 primary studies offers a comprehensive overview of statistics education in higher education, emphasizing the interplay between emotional, instructional, and cognitive factors. Three core themes were identified: (1) the influence of student attitudes, motivation, and anxiety on academic outcomes; (2) the impact of innovative pedagogical strategies, including blended and project-based learning; and (3) the role of skill development and assessment in fostering statistical thinking. Affective barriers, such as anxiety and negative perceptions, were consistently linked to reduced engagement and performance, especially among underrepresented students. In contrast, interventions like peer-assisted flipped classrooms and culturally tailored resources improved engagement and reduced access disparities. Notably, gaps remain in longitudinal evidence, global applicability, and the integration of emerging technologies such as generative artificial intelligence (AI).

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The findings suggest a need for integrated strategies that combine pedagogical innovation with emotional and motivational support. Active learning methods, such as cooperative inquiry or gamified instruction, can promote conceptual understanding while easing anxiety. Institutions should invest in professional development to help educators implement inclusive, learner-centered approaches and offer support for students from non-quantitative backgrounds. Reforms in assessment shifting from traditional exams to real-world, application-based projects may better cultivate statistical reasoning. However, studies such as (Legacy et al., 2024) reveal limited adoption of such practices, indicating structural barriers to curricular reform that may require institutional policy shifts.

Several limitations were noted. The focus on recent literature from 2023 to 2025 and data from only two databases may exclude foundational or region-specific research. Additionally, the predominance of Western contexts limits generalizability. Future studies should include longitudinal analyses, cross-cultural comparisons, and evaluations of AI-enhanced learning tools. Increased methodological rigor and interdisciplinary collaboration can contribute to a more inclusive and effective model of statistics education, preparing learners for data-driven academic and professional environments.

Conclusion

This systematic review explores how statistics is taught and learned in higher education, focusing on three main areas: student attitudes and anxiety, innovative teaching methods, and the development of statistical thinking through practical skills and assessment. Analysis of 20 selected studies showed that emotional factors especially anxiety and motivation play a critical role in how students engage with statistics. Negative perceptions often act as barriers to learning, particularly for students from underrepresented groups. Interventions that build self-confidence and a sense of belonging have shown promise in reducing these barriers. Teaching approaches such as blended learning, project-based learning, and inclusive practices were consistently linked to better student outcomes. Despite these advances, challenges remain in the use of student-centered assessments and the integration of new technologies, highlighting the need for updated and flexible curricula.

The review offers valuable insights for improving instruction in statistics education. It emphasizes the importance of combining emotional support with innovative pedagogy, including active learning techniques and culturally responsive content. Institutions are encouraged to enhance professional training for educators and improve access to blended learning environments. However, this review is limited by its focus on recent studies from specific databases and its concentration on Western academic settings, which may not represent all educational contexts. Further research is needed to examine long-term effects of instructional strategies, adapt methods across cultures, and explore the potential of artificial intelligence in personalized learning. Addressing these areas can support more inclusive and effective statistics education, preparing students for data-informed roles in various fields.

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