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Designing Learning Trajectories to Support Prospective Teachers' Statistical Literacy Skills

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Abstrak

Literasi statistik sangat penting bagi calon guru untuk menafsirkan data secara akurat dan membuat keputusan yang tepat. Namun, banyak yang mengalami kesulitan akibat pendekatan pembelajaran yang terlalu abstrak. Studi ini mengembangkan Learning Trajectory (LT) dengan mengintegrasikan produksi kopi Pagar Alam sebagai konteks dunia nyata untuk mendukung literasi statistik calon guru. Dengan menggunakan metodologi design research tipe validation study, penelitian ini terdiri dari tiga fase yaitu fase *preliminary*, Fase *design experiment* termasuk *pilot experiment* serta *teaching experiment*, dan fase *retrospective analysis*. Studi ini melibatkan 60 calon guru matematika dari Universitas Sriwijaya. Pengumpulan data dilakukan melalui wawancara, observasi, dan lembar kerja. LT yang dikembangkan terdiri dari empat langkah utama yaitu memahami jenis data, menerapkan konsep statistik, menganalisis tren probabilitas, dan menggunakan model statistik untuk prediksi. Studi ini menekankan pentingnya menghubungkan konsep teoretis dengan aplikasi praktis, memberikan wawasan berharga bagi pendidikan calon guru dan pengembangan kurikulum.
Kata Kunci: Design Research; Konteks Produksi Kopi; Lintasan Pembelajaran; Literasi Statistik

Abstract

Statistical literacy is essential for prospective teachers to interpret data accurately and make informed decisions. However, many struggle due to abstract instructional approaches. This study develops a Learning Trajectory (LT) that integrates Pagar Alam coffee production as a real-world context to support statistical literacy of prospective teachers. Employing a design research methodology within a validation study framework, the research consists of three phases: (1) a preliminary phase, (2) a design experiment phase, including a pilot experiment and a teaching experiment, and (3) a retrospective analysis phase. The study involved 60 prospective mathematics teachers from Sriwijaya University. Data collection methods included interviews, observations, and worksheets. The developed LT comprises four key steps: understanding data types, applying statistical concepts, analyzing probability trends, and using statistical models for predictions. This study underscores the importance of linking theoretical concepts with practical applications, providing valuable insights for teacher education and curriculum development.
Keywords: Coffee Production as Context; Design Research; Learning Trajectory; Statistical Literacy

I. INTRODUCTION

In this data-driven era, statistical literacy is a crucial competency for prospective teachers to understand and utilise information effectively (Gunawan et al., 2023). Statistical literacy plays an important role in data-driven decision-making in education (Tiro, 2018), enabling teachers to evaluate programmes (Ben-Zvi, 2020), identify student needs (Sidik et al., 2023), and improve learning quality (Guven et al., 2021). Although essential, learning statistical literacy often faces its own challenges among prospective teachers, ranging from lack of interest to difficulty in understanding complex statistical concepts (Prihastari et al., 2024; Tran, et al., 2023). To face the challenges in learning statistical literacy, structured learning steps known as Learning Trajectory (LT) are needed and can be implemented effectively (Fauziyah & Husniati, 2023).

LT plays a crucial role in supporting statistical literacy learning by providing a framework that illustrates the progression of student understanding (Borremans et al., 2024), from basic to more advanced levels (van Dijke-Droogers et al., 2022). This gradual approach fosters deeper comprehension and enhances their ability to effectively apply statistical literacy in classroom settings (Budgett & Rose, 2017), helping them develop a more meaningful understanding that is ready to be used in classroom learning (Büscher, 2022). Recent studies have highlighted the learning trajectories approach in mathematics and statistics education, which has shown promise in guiding the gradual development of concept understanding (Arnold et al., 2018; Kim et al., 2020). By providing learning trajectories, LT allows students to build a more solid conceptual understanding, as well as assisting educators in designing more effective teaching strategies (Borremans et al., 2024). Therefore, the utilisation of LT in statistics learning is not only beneficial for prospective teachers in mastering statistical concepts, but also in improving their competence in designing meaningful learning experiences for their students (Gravemeijer & Cobb, 2006; Afriansyah & Arwadi, 2021).

One promising approach to strengthening LT-based statistical literacy education is Realistic Mathematics Education (RME) approach, or its Indonesian counterpart *Pendidikan Matematika Realistik Indonesia* (PMRI), emphasizes that mathematics learning, including statistical literacy, should originate from realistic and meaningful situations for students (van den Heuvel-Panhuizen et al., 2014; Zulkardi et al., 2020). Real-world contexts provide concrete learning experiences and enable students to understand how statistical concepts apply to everyday life (Vos, 2020). Although many studies have addressed statistical literacy, most still use abstract or textbook-based approaches (Egorov, 2021). Studies applying context-based learning tend to use global or general contexts, such as macroeconomic data or world population statistics (Guven et al., 2021; Muñiz-Rodríguez et al., 2020), while research incorporating local contexts remains limited (Idris, 2019; Takaria & Talakua, 2018; Utari, Putri, Zulkardi, et al., 2024).

This study seeks to bridge that gap by integrating the Pagar Alam coffee production context into statistical literacy learning. As part of Indonesia's coffee industry, Pagar Alam coffee provides a rich dataset that can be used to illustrate statistical concepts in an applied setting. By utilizing data from the Central Bureau of Statistics (BPS), this study offers a novel approach to statistical education that connects theory with real-world applications. Furthermore, integrating statistical literacy with local economic and cultural aspects not only enhances conceptual understanding but also equips prospective teachers with the ability to design meaningful and contextually relevant learning experiences for their future students.

Although LT has been widely used in mathematics education, its application in statistics learning, especially for prospective teachers, remains underexplored (Arnold et al., 2018; van Dijke-Droogers et al., 2022). Existing research primarily focuses on primary and secondary school students (Schield, 2017; Tishkovskaya & Lancaster, 2010), leaving a gap in the development of LT specifically designed for teacher education. This study aims to address that gap by designing and evaluating an LT based on the local context of Pagar Alam coffee. By doing so, it seeks to support prospective teachers' statistical literacy while demonstrating the significance of integrating local contexts into statistics education.

Moreover, this study contributes to the advancement of statistical literacy in three key aspects: (1) developing an LT that adopts Pagar Alam coffee as a unique and locally relevant context, (2) utilizing real data from BPS to create an engaging and practical learning experience, and (3) bridging the gap between theoretical statistical concepts and their applications in local economic and industrial sectors. By integrating statistical literacy with a meaningful local context, this study not only enhances prospective teachers' understanding of statistical concepts but also equips them to design relevant, engaging, and data-driven instruction for their future classrooms.

II. METHOD

This study employs a design research approach within a validation study framework to develop theories about the learning process and the instructional tools that support it (Bakker, 2018; Gravemeijer & Cobb, 2006). The primary objective of this research is to construct a Hypothetical Learning Trajectory (HLT), which will eventually be refined into a more comprehensive Learning Trajectory (LT). A LT represents a structured sequence of learning steps designed to facilitate students' learning systematically (Bakker, 2018). The aim of designing an LT is to create effective learning experiences that enhance students' conceptual understanding while also identifying and addressing potential difficulties they may encounter during the learning process (Dijke-Droogers et al., 2022).

This study incorporates the production of Pagar Alam coffee as context from South Sumatra to enrich the learning experience. The design research process follows a cyclical structure consisting of three phases: (1) the preparation phase, (2) the design experiment phase, which includes both the pilot experiment (cycle 1) and the teaching experiment (cycle 2), and (3) the retrospective analysis phase (Gravemeijer & Cobb, 2006). The process of designing LT can be seen in Figure 1.

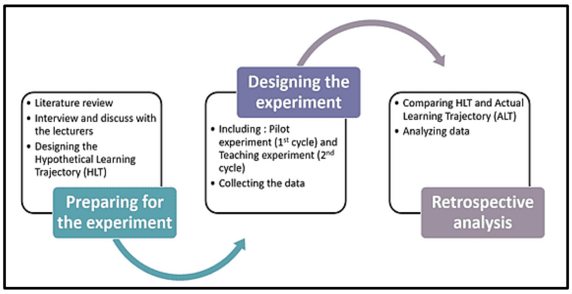

Figure 1. The Research Process in Designing a Learning Trajectory

The figure 1 illustrates the three-phase research process used in the study, starting with preparing for the experiment stage, where a literature review, interviews with lecturers, and the design of the Hypothetical Learning Trajectory (HLT) take place. The next phase, designing the experiment, consists of two cycles: a pilot experiment (first cycle) and a teaching experiment (second cycle), during which data is collected to refine the initial HLT. Finally, the retrospective analysis phase involves comparing the HLT with the Actual Learning Trajectory (ALT) and analysing the collected data to evaluate and improve the learning process. The flow of arrows indicates an iterative approach, emphasizing continuous refinement and validation of the learning trajectory.

This study involved 60 prospective teachers from the mathematics education program at Sriwijaya University, all of whom had completed an introductory statistics course. This research was conducted from January 2024 to September 2024.

The pilot experiment involved 10 prospective teachers and was conducted to assess their prior knowledge, evaluate the initial instructional design, and refine the Hypothetical Learning Trajectory (HLT) based on their responses. The teaching experiment, which took place in the second cycle, engaged 50 additional prospective teachers. In this phase, the revised HLT was implemented in a classroom setting and compared with the Actual Learning Trajectory (ALT) to further develop the Learning Trajectory (LT). Although all 60 participants were part of the same mathematics education program, they were assigned to different class groups.

This study used various data collection methods included interviews, classroom observations, and worksheets, each serving a specific purpose in examining the learning process and its results. Interviews were conducted to explore how well prospective teachers understood statistical concepts and how local context influenced their learning. Meanwhile, observations focused on how actively prospective teachers participated in learning activities and interacted with the materials. In addition, worksheets were used to assess how well prospective teachers grasped and applied statistical concepts. Throughout the data collection process, researchers ensured that they remained aware of their perspectives and potential biases when interacting with participants. The collected data from interviews and observations were then analysed by organizing and identifying patterns, which helped improve and refine the learning design. In the end, these methods provided a comprehensive understanding of prospective teachers' experiences, ensuring that the study's results were reliable, meaningful, and contributed to improving the educational approach.

III. Result and Discussion

The following section presents the findings from each phase of the design research conducted in this study to develop a structured Learning Trajectory (LT). These phases include preparing for the experiment, the design experiment, and retrospective analysis. The findings reflect the process of designing and refining the instructional approach for prospective teachers through the implementation of pilot and teaching experiments.

A. Preparing for the experiment

In the preparing for the experiment stage, three main activities were carried out: (1) conducting a literature review, (2) interviewing and discussing with course lecturers, and (3) designing the hypothetical learning trajectory (HLT). In the literature review stage, the researcher examined studies related to learning trajectories in statistical literacy education, statistical literacy frameworks for prospective teachers, and explored the context of coffee production in Pagar Alam, as published by the Indonesian Central Bureau of Statistics (BPS), which was used as the learning context.

Following this, the researcher conducted interviews and discussions with course lecturers regarding the role of statistics in the curriculum and the integration of contextual learning. The findings from this stage include the selection of research participants, namely prospective teachers who have completed the Basic Statistics course. Additionally, the statistical literacy indicators used in this study focus on the ability to apply statistical concepts such as mean, variability, and probability, in real-world contexts and to make data-driven decisions. The learning approach adopted in this study is the Indonesian Realistic Mathematics Education (PMRI) approach.

The results from the literature review and lecturer interviews served as the foundation for designing the hypothetical learning trajectory (HLT). The designed HLT consists of three main components: determining learning objectives, designing learning activities, and predicting the learning processes of prospective teachers. Furthermore, technology was integrated into the learning design by incorporating the use of Nearpod and Excel to facilitate interactive and data-driven learning experiences. Table 1 presents the outline of the HLT.

Table 1.
The HLT for learning the statistical literacy

Learning Step	Learning Goal	Example of activities	Conjectures of prospective teachers thinking
1. Understanding data types in real-world contexts. (situational or informal mathematics).	Prospective teachers understand data types in real-world contexts.	Prospective teachers review coffee productivity data from BPS, identify whether the data is quantitative or qualitative, and discuss its relevance in statistical analysis using everyday language.	Prospective teachers recognize that coffee productivity data is quantitative and realize its importance in decision-making.

Learning Step	Learning Goal	Example of activities	Conjectures of prospective teachers thinking
2. Applying basic statistical concepts (mean, standard deviation) to analyse real-world data (model of mathematics).	Prospective teachers can apply basic statistical concepts (mean, standard deviation) to analyse real-world data.	Prospective teachers calculate the average and standard deviation of coffee productivity per subdistrict to understand variability.	Prospective teachers understand that a higher standard deviation indicates greater variability in productivity, while a lower value suggests production stability.
3. Using coffee productivity data to understand probability concepts and statistical trends (model for mathematics).	Prospective teachers use coffee productivity data to understand probability concepts and statistical trends.	Prospective teachers analyse coffee productivity trends over five years and predict possible future changes using probability concepts.	Prospective teachers can identify trend patterns (increasing/decreasing) and relate them to external factors that may affect productivity.
4. Applying mathematical calculations and use statistical models for prediction (formal mathematics).	Prospective teachers can systematically apply mathematical calculations and use statistical models for predictions.	Prospective teachers calculate the probability of increasing productivity based on historical data distribution using formal statistical formulas.	Prospective teachers can apply probability concepts and inferential statistics to predict future outcomes and support data-driven decision-making.

Table 1 describes the structured learning trajectory designed to develop prospective teachers' statistical literacy through real-world applications. It outlines four key learning steps, starting from understanding data types in real-world contexts to applying formal statistical models for prediction. Each step includes specific learning goals, example activities, and conjectures about prospective teachers' thinking. The trajectory begins with recognizing data types in a situational context, progresses to applying statistical concepts such as mean and standard deviation, explores probability and statistical trends using real-world coffee productivity data, and culminates in using formal statistical models for prediction. This progression ensures that prospective teachers develop a comprehensive understanding of statistical literacy, bridging informal reasoning with formal mathematical applications essential for data-driven decision-making. The designed HLT consists of various activities for prospective teachers, which have been implemented in the Nearpod application. This allows students to access and interact with the activities directly. Figure 2 below presents the design of prospective teachers' activities in Nearpod.

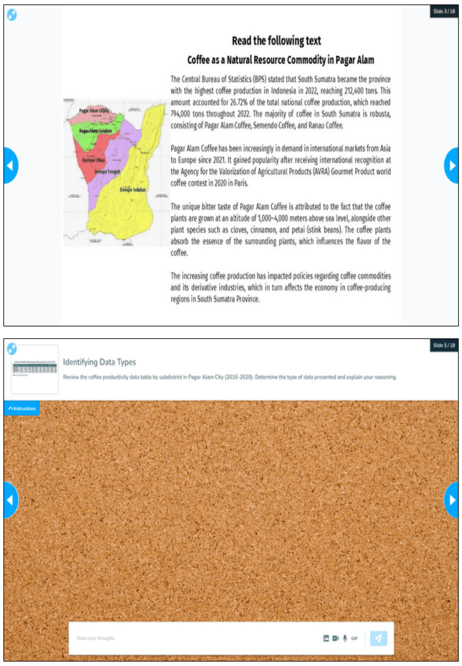

Figure 2. Design of Prospective Teachers Activities in Nearpod

B. Designing the experiment

This stage consists of two cycles: a pilot experiment, involving 10 prospective teachers, and a teaching experiment, involving 50 prospective teachers. Each stage includes four learning activities as follows: (a) understanding data types in

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coffee as real-world contexts, (b) applying basic statistical concepts (mean, standard deviation) to analyse real-world data, (c) using coffee productivity data to understand probability concepts and statistical trends, (d) performing mathematical calculations and applying statistical models for prediction.

The teaching experiment begins with preliminary activities that lead to the development of a hypothetical learning trajectory. This stage includes delivering learning objectives, apperception, and motivation. During the apperception activity, prospective teachers are given questions such as: *"Who among you enjoys drinking coffee? Did you know that South Sumatra is one of the largest coffee producers in Indonesia?"*. Prospective teachers respond to these questions, initiating a discussion that connects statistical concepts to real-world contexts. After they answered the questions, they were presented with information about coffee production in Pagar Alam, the largest coffee-producing region in South Sumatra, based on data from 2016 to 2020. This data was obtained from the Central Bureau of Statistics of South Sumatra.

During the pilot experiment, prospective teachers were divided into two groups, each consisting of five members with heterogeneous mathematical abilities. A similar grouping approach was applied in the teaching experiment, where each group consisted of five prospective teachers. In completing each learning activity, prospective teachers worked collaboratively in groups to discuss and understand the statistical concepts being taught. The following are key findings from each learning activity.

1. **Understanding Data Types in Coffee as Real-World Contexts**

In this activity, prospective teachers reviewed the table of coffee productivity data by subdistrict in Pagar Alam City. They were asked to identify whether the given data was quantitative or qualitative. Afterward, they were required to explain why the data was relevant for statistical analysis. Figure 3a and 3b presents the responses of prospective teachers during the pilot experiment and teaching experiment.

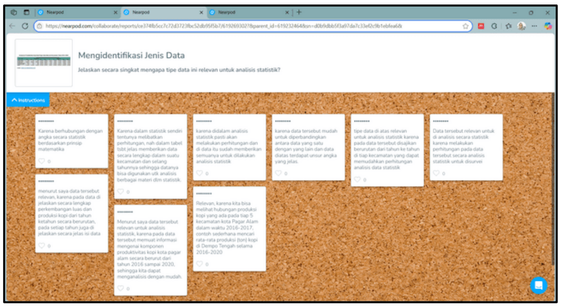


Figure 3a. Prospective Teachers Answered in Pilot Experiment

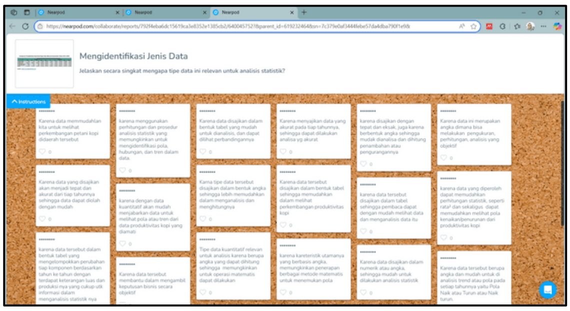


Figure 3b. Prospective Teachers Answered in Teaching Experiment

Figure 3 presents the responses of prospective teachers regarding Activity 1, illustrating a significant improvement in their understanding of the relevance of data in statistical analysis. This improvement can be observed in terms of diversity, conceptual depth, and accuracy of explanations. During the pilot experiment, students' responses were generally brief and focused on basic comprehension, such as distinguishing between data types and broadly relating them to statistical analysis. Most responses highlighted that quantitative data enables statistical calculations but lacked further exploration of how data is applied in more complex analytical contexts. In contrast, responses from the teaching experiment, which involved 50 students, demonstrated greater variation in explaining data relevance. Students incorporated discussions on trends, measurement techniques, table usage, and the role of data in decision-making and real-world phenomena. Additionally, they introduced more advanced concepts, including patterns of data fluctuations, ease of interpretation through tabular representation, and how data supports visualization and predictive analysis.

These findings indicate that the teaching experiment led to a deeper and more comprehensive understanding among students. While not all responses in this stage were entirely precise or highly sophisticated, the increased diversity of perspectives suggests that students became more engaged in connecting statistical concepts with practical applications. This progression highlights the impact of a more intensive learning process, enabling students to develop a richer understanding not only of the nature of data but also of its practical use in various statistical analysis contexts. Table 2 below represents the iterative process in refining learning steps related to understanding data types in the context of coffee production.

Table 2.
Iterative Improvements in Learning Steps: Understanding Data Types In Coffee as Real-World Contexts

Indicators/ learning step	Pilot experiment implementation	Observations & prospective teachers' thinking conjectures	Teaching experiment refinements	Impact on student learning
1.Prospective teachers reviewed the table of coffee productivity data by subdistrict in Pagar Alam City. They were asked to identify whether the given data was quantitative or qualitative.	Responses were generally brief, mostly identifying the data as quantitative without deeper explanation.	Some prospective teachers struggled to differentiate between quantitative and qualitative data, often providing simplistic reasoning.	Provided clearer examples and discussions on the characteristics of quantitative and qualitative data, including real-world contexts.	Improved accuracy and depth in classification, with more prospective teachers articulating why the data is quantitative and how it relates to statistical analysis.
2.Prospective teachers explained why the data was relevant for statistical analysis.	Explanations were mostly limited to stating that numerical data allows statistical calculations.	Many responses lacked depth, with minimal mention of trends, comparisons, or practical applications.	Introduced guiding questions, real-world applications, and discussions on how data supports decision-making and trend analysis.	Increased diversity and depth in reasoning, with more prospective teachers discussing trends, data visualization, and predictive analysis.

2. Applying Basic Statistical Concepts to Analyse Real-World Data

At this activity, prospective teachers engage in learning steps related to calculating measures of central tendency and dispersion. The learning process consists of three steps: a. calculating the average coffee productivity for each subdistrict over five years (2016-2020), b.

calculating the standard deviation to measure the variability of coffee productivity in each subdistrict., and c. comparing the results and explaining which subdistrict has the highest and lowest variability in terms of coffee productivity. To compare subdistricts with the highest and lowest variability, prospective teachers can create graphs of coffee production for each subdistrict and analyse their variability. This process represents a modelling approach, with graphs serving as the model of PMRI approach. Figure 4 presents one of the prospective teachers' responses in calculating the standard deviation to measure the variability of coffee production in each subdistrict. Figure 4a represents the response from the pilot experiment, and Figure 4b from the teaching experiment.

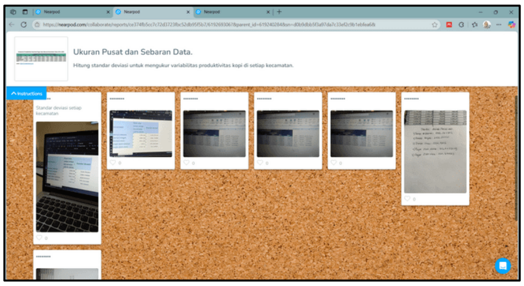


Figure 4b. Prospective Teachers Answered in Teaching Experiment

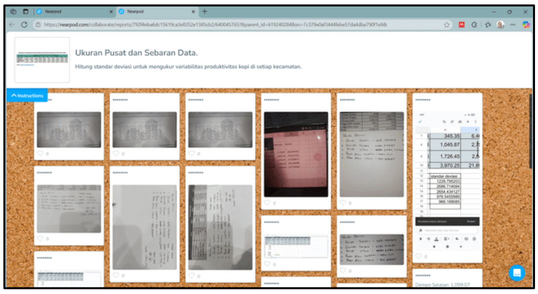


Figure 4b. Prospective Teachers Answered in Teaching Experiment

The figure 4 illustrates that prospective teachers have been able to use Excel to calculate the standard deviation. However, some of them still made errors by using the Excel formula for population instead of the appropriate formula for a sample. To address this issue, the instructor provided guiding questions such as: *"Do you remember what a sample and a population are in statistics? In this calculation, do you think we should use a sample or a population?"*.

During the teaching experiment phase, this question was posed before the prospective teachers worked on the activity together. By reinforcing their understanding of samples and populations, they were able to correctly use the sample formula instead of the population formula. Table 3 presents the iterative process or changes from the pilot experiment to the teaching experiment.

Table 3.
Iterative Improvements in Learning Steps: Applying Basic Statistical Concepts to Analyse the Coffee Production as Real-World Data

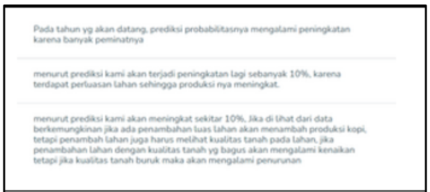
Indicators/ learning step	Pilot experiment implementation	Observations & prospective teachers' thinking conjectures	Teaching experiment refinements	Impact on student learning
1. Calculating the average coffee productivity for each subdistrict over five years (2016-2020)	Prospective teachers computed the average productivity using Excel but did not always interpret the results correctly.	Some prospective teachers focused only on calculations without discussing the meaning of the average in context.	Emphasized interpretation by asking, *"What does the average tell us about coffee production trends in each subdistrict?"*	Improved understanding of the significance of averages, with prospective teachers better explaining trends and comparing subdistricts.
2. Calculating the standard deviation to measure the	Some prospective teachers correctly applied the standard deviation	Several struggled to understand the role of standard deviation in variability	Introduced guiding questions like, *"Should we use*	Increased accuracy in using the correct formula and

Indicators/ learning step	Pilot experiment implementation	Observations & prospective teachers' thinking conjectures	Teaching experiment refinements	Impact on student learning
variability of coffee productivity in each subdistrict	formula, but others mistakenly used the population formula instead of the sample formula.	analysis. Some did not differentiate between sample and population formulas.	*the sample or population formula? Why?"* and reinforced discussions on variability interpretation.	deeper understanding of variability in coffee productivity across subdistricts.
3. Comparing the results and explaining which subdistrict has the highest and lowest variability in terms of coffee productivity	Prospective teachers compared numerical values but did not always justify their conclusions based on variability.	Some merely stated which subdistrict had the highest or lowest standard deviation without explaining the implications.	Incorporated data visualization (graphs) and asked, *"How does variability influence decision-making in coffee production?"*	Enhanced ability to analyze and justify variability differences, with prospective teachers providing clearer explanations supported by graphical representations.

3. Using Coffee Productivity Data to Understand Probability Concepts and Statistical Trends

The next learning activity for prospective teachers is analysing probability based on coffee productivity trends from 2016 to 2020. In this step, prospective teachers are asked to analyse the probability of whether there is an increasing or decreasing trend in productivity in some subdistricts and predict the probability of productivity increasing in future years based on the available data, providing reasoning to support their predictions. The question can be answered using mathematical modelling (model for).

Figure 5 presents predictions made by prospective teachers based on their observations of the graphs they created during the pilot experiment. However, these predictions were not yet supported by valid statistical modelling.


Pada tahun yg akan datang, prediksi probabilitasnya mengalami peningkatan karena banyak peminatnya

menurut prediksi kami akan terjadi peningkatan lagi sebanyak 10%, karena terdapat perluasan lahan sehingga produksi nya meningkat.

menurut prediksi kami akan meningkat sekitar 10%. Jika di lihat dari data berkemungkinan jika ada penambahan luas lahan akan menambah produksi kopi, tetapi penambah lahan juga harus melihat kualitas tanah pada lahan, jika penambahan lahan dengan kualitas tanah yg bagus akan mengalami kenaikan tetapi jika kualitas tanah buruk maka akan mengalami penurunan

English version:

- In the coming years, the predicted probability shows an increase due to high demand.
- According to our prediction, there will be another 10% increase due to land expansion, which will lead to higher production.
- According to our prediction, there will be an increase of around 10%. Based on the data, it is likely that an increase in land area will boost coffee production. However, land expansion should also consider soil quality—if the additional land has good soil quality, production will rise, but if the soil quality is poor, production may decline.

Figure 5. Prospective Teachers Answered in Pilot Experiment

The response on Figure 5 above presents predictions about future coffee production trends, but these predictions are not supported by statistical calculations. While the reasoning considers factors like demand, land expansion, and soil quality, it lacks quantitative analysis or statistical modeling, such as regression analysis or probability calculations, to validate the projected 10% increase. Therefore, we revised the designed activity by incorporating information on the use of linear regression to analyse trends in data during the teaching experiment stage. The following are the answers from prospective teachers on activities in analysing trends using linear regression which can be seen in Figure 6. These results were obtained from the teaching experiment stage.

English version:
We conducted several analyses for each subdistrict. Based on the regression trends, the trend shows an increase in all subdistricts.

Figure 6. Prospective Teachers Answer in Teaching Experiments

Based on Figure 6 the graph shows the trend of coffee productivity in Dempo Selatan, Dempo Tengah, and Dempo Utara. For the example of Dempo Selatan with significant fluctuations between 2016 and 2020. Despite a sharp increase in 2018 and a steep decline in 2019, the linear regression equation $Y = 480.79\ X - 968846$ indicates an average increase of 480.79 tons per year. This suggests long-term growth, although annual variations are considerable. These fluctuations indicate that external factors such as weather conditions or cultivation techniques may influence production, requiring further analysis to understand the actual pattern. Table 4 presents the iterative process or changes from the pilot experiment to the teaching experiment in this activity.

Table 4.
Iterative Improvements in Learning Steps: Applying Basic Statistical Concepts to Analyse the Coffee Production as Real-World Data

Indicators/ learning step	Pilot experiment implementation	Observations & prospective teachers' thinking conjectures	Teaching experiment refinements	Impact on student learning
1. Analysing probability based on coffee productivity trends (2016-2020).	Prospective teachers made predictions about future coffee production based on graphical trends but did not use statistical modelling.	Predictions considered demand, land expansion, and soil quality but lacked quantitative validation.	Incorporated instruction on using linear regression to analyse trends and introduced probability calculations to support predictions.	Improved ability to use regression analysis for trend predictions and better reasoning supported by statistical evidence.
2. Applying regression analysis to model coffee productivity trends.	Initial predictions were based on intuition rather than statistical methods.	Some prospective teachers identified trends but did not quantify them.	Introduced regression modelling, helping students derive equations to explain trends and make data-driven predictions.	Enhanced understanding of trend analysis and probability, with students using regression equations to justify predictions.

4. Performing Mathematical Calculations and Applying Statistical Models for Prediction

After conducting mathematical modelling using linear regression, prospective teachers performed calculations to make predictions, draw conclusions, and provide recommendations to enhance coffee production in the coming years. In the next step, they engaged in discussions based on data and statistical calculations to analyse coffee productivity trends in Pagar Alam City over the 2016-2020 period. This discussion focused on how productivity trends differed between subdistricts with the highest and lowest production, as well as how variability related to the stability of production in each subdistrict. Additionally, prospective teachers explored measures to improve coffee productivity in the future, particularly in subdistricts showing a declining trend, and strategies to maintain or enhance production in subdistricts that had already demonstrated strong results. Table 5 below presents the iterative process or changes from the pilot experiment to the teaching experiment in this activity.

Table 5.
Iterative Improvements in Learning Steps: Performing Mathematical Calculations and Applying Statistical Models for Prediction

Indicators/ learning step	Pilot experiment implementation	Observations & prospective teachers' thinking conjectures	Teaching experiment refinements	Impact on student learning
1. Drawing conclusions about coffee productivity trends.	Prospective teachers analysed coffee productivity trends using graphical representations but did not integrate statistical validation.	Conclusions were based on visual trends without quantifying variability or considering statistical significance.	Introduced linear regression to quantify trends and emphasized discussions on how variability relates to production stability.	Improved ability to draw data-driven conclusions by integrating statistical analysis, leading to a deeper understanding of production trends.
2. Making recommendations for future coffee productivity improvement.	Initial recommendations were based on general assumptions rather than statistical analysis.	Some prospective teachers proposed strategies but lacked data-driven justification. Discussions did not fully incorporate statistical modelling in decision-making.	Integrated regression analysis to support recommendation-making, encouraging students to base their suggestions on quantified trends and variability.	enhanced ability to provide evidence-based recommendations, with prospective teachers considering statistical trends to support productivity improvement strategies.

C. Retrospective analysis

During the teaching experiment phase, various instructional improvements were implemented to enhance prospective teachers' understanding of applying statistical concepts in real-world contexts, particularly in analysing coffee productivity in Pagar Alam City. This retrospective analysis aims to evaluate how the modifications in four key learning activities impacted prospective teachers' comprehension.

The first improvement focused on prospective teachers' understanding of data types in real-world contexts. In the pilot experiment, many participants identified coffee productivity data as quantitative but provided only superficial explanations. This limited understanding also affected their ability to use data for further statistical analysis. To address this, the teaching experiment incorporated clearer examples and discussions on the characteristics of quantitative and qualitative data, emphasizing their relevance in statistical analysis. As a result, prospective teachers demonstrated greater accuracy in classifying data and provided more comprehensive explanations of why the data was relevant for trend analysis and decision-making.

The second improvement involved applying basic statistical concepts to analyse coffee production. In the pilot experiment, prospective teachers were able to compute the mean and standard deviation using Excel; however, their interpretation of these statistical measures remained limited. Many focused solely on numerical results without contextualizing their significance in coffee productivity. To bridge this gap, the teaching experiment introduced guiding questions such as, "What can we conclude from this mean?" and "How does the standard deviation reflect the stability of coffee production in each subdistrict?" This approach helped prospective teachers develop stronger interpretative skills, enabling them to analyse production variability and understand its implications for long-term trend analysis.

The third improvement addressed the use of coffee productivity data to understand probability concepts and statistical trends. Initially, prospective teachers made predictions based on graphical trends without employing appropriate statistical models. While they considered factors such as demand, land expansion, and soil quality in their predictions, these were not supported by valid quantitative analyses. To enhance their reasoning, the teaching experiment introduced linear regression as a tool for systematically analysing trends in data. This intervention enabled prospective teachers to use regression models to support their predictions, improving the accuracy and reliability of their analyses.

The final improvement cantered on prospective teachers' ability to draw conclusions and provide data-driven recommendations. In the pilot experiment, their recommendations were often based on general assumptions rather than statistical evidence. To refine this skill, the teaching experiment encouraged the use of regression analysis and variability assessment in formulating recommendations. As a result, prospective teachers not only made more precise conclusions regarding coffee productivity trends but also developed evidence-based strategies to enhance future productivity.

From this analysis, the iterative improvements implemented in the teaching experiment have demonstrated a positive impact on prospective teachers' ability to apply statistical concepts in real-world contexts. With a more data-driven approach, they became more proficient in trend analysis, understanding variability, making predictions, and formulating recommendations supported by statistical evidence. These findings underscore the importance of integrating model-based statistical approaches in teacher education to enhance statistical literacy among prospective teachers.

D. Discussion

The findings from this retrospective analysis highlight the significance of iterative instructional refinements in supporting prospective teachers' statistical literacy. The progressive improvements in data classification, statistical analysis, probability modelling, and data-driven decision-making illustrate how well-structured interventions can address conceptual gaps (Bakker, 2018). Previous studies emphasize that integrating real-world contexts into statistics education fosters deeper understanding and engagement (Gal, 2019; Phadke, 2022). By incorporating guiding questions and data visualization techniques, prospective teachers moved beyond rote calculations and began interpreting statistical measures meaningfully. This aligns with research by Forbes et al., (2014), and Utari et al. (2024), which suggests that students develop a more profound grasp of statistical reasoning when they actively engage with authentic data and contextual problem-solving. The observed improvements in interpreting averages, standard deviation, and regression analysis demonstrate the effectiveness of these pedagogical strategies in strengthening statistical literacy.

Moreover, the ability of prospective teachers to make data-driven recommendations further reinforces the importance of integrating statistical modelling in teacher education. Initially, recommendations were largely based on intuition, but after structured exposure to regression analysis, they became more evidence-based. This supports findings by Sharma (2017) and Weiland (2017) who argue that statistical literacy is not merely about performing calculations but about making informed judgments using data. The study also aligns with Callingham & Watson (2017) and Tran et al. (2023) who stress that fostering statistical thinking involves recognizing variability and making probabilistic predictions grounded in data trends. The iterative improvements observed in this study suggest that embedding statistical modeling in teacher education can significantly enhance prospective teachers' ability to teach data analysis effectively.

IV. Conclusion

This study demonstrates that the developed learning trajectory (LT) effectively enhances prospective teachers' statistical literacy by integrating real-world data from Pagar Alam coffee production. The LT consists of four key learning steps: (1) understanding data types in real-world contexts, (2) applying basic statistical concepts to analyze coffee production, (3) using coffee productivity data to understand probability concepts and statistical trends, and (4) performing mathematical calculations and applying statistical models for prediction. Through iterative improvements, prospective teachers developed a deeper understanding of statistical concepts, improved their ability to interpret data, and made evidence-based predictions and recommendations.

The findings indicate that using locally relevant contexts not only strengthens conceptual understanding but also bridges the gap between theoretical knowledge and practical applications. However, this study has certain limitations. The LT was implemented in a specific context with a limited number of data series, which may affect the generalizability of the results. Additionally, the focus on a single local context—coffee production in Pagar Alam—may limit its applicability in broader educational settings.

Future research could explore the adaptation of this LT in other contexts and with more diverse participant groups to assess its scalability and impact. It is also recommended to investigate the long-term effects of such context-based learning trajectories on prospective teachers' instructional practices once they enter the teaching profession.

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