**CHAPTER TWO**

1. **LITERATURE REVIEW**
   1. **Overview of Mobile Development with Python**

Mobile development refers to the process of creating software applications that are intended to run on mobile devices, such as tablets and smartphones, Applications of this type take advantage of the mobile devices’ portability, availability, and processing power delivering different services such as education, healthcare, entertainment, and business.

Python is well known for its readability and ease of use, which can translate into faster development – a huge benefit in the mobile market where speed to market is critical to gaining and keeping market share. On the other hand, neither Android nor iOS support interpreted languages, which means they can't natively run Python apps. That's where several frameworks bridge the gap to allow Python apps to be run on mobile devices with a native look and feel.

**2.1.1 Mobile Operating Systems**

The mobile ecosystem is dominated by two major operating systems:

1. **Android:** Developed by Google, Android is an open-source platform that supports a wide range of devices. It provides robust APIs, libraries, and tools for app development.
2. **iOS:** iOS was developed by Apple and is known for its security, performance, and seamless integration with Apple devices. Apps are built using Swift or Objective-C.

**2.1.2 Types of Python Frameworks for Mobile Development**

**Django:** Django is a leading Python framework designed for building dynamic mobile and web applications with ease. It leverages a robust Object-Relational Mapping (ORM) system and follows the [Model-View-Controller](https://www.ongraph.com/what-is-mvc-architecture-in-a-web-based-application/) (MVC) pattern, ensuring clean, reusable, and easily maintainable code.

**Web2Py:** Web2Py is an open-source, full-stack, and scalable Python application framework compatible with most operating systems, both mobile-based and web-based. It is a platform-independent framework that simplifies development through an IDE that has a code editor, debugger, and single-click deployment. Web2Py deals with data efficiently and enables swift development with MVC design but lacks configuration files on the project level.

**KIVY:** Kivy promotes itself as an open-source Python library for the rapid development of cross-platform UI applications. It has a graphics engine that is built over OpenGL, so it can handle GPU-bound workloads when necessary. It also has a [python-to-android](https://python-for-android.readthedocs.io/en/latest/) project that lets you port Python applications to Android. It has a[similar toolkit](https://github.com/kivy/kivy-ios) for iOS, although packages for iOS can only be generated with Python 2.7 at the moment.

**BeeWare:** BeeWare is another popular set of tools that lets you write applications in Python and cross-compile them for deployment on several operating systems, including macOS, Windows, and Linux GTK, as well as mobile platforms like Android and iOS.

* 1. **Importance of Mobile Development in Education**

By providing learners and educators with access to flexible and interactive learning tools mobile development has transformed the educational sector. Mobile apps enable:

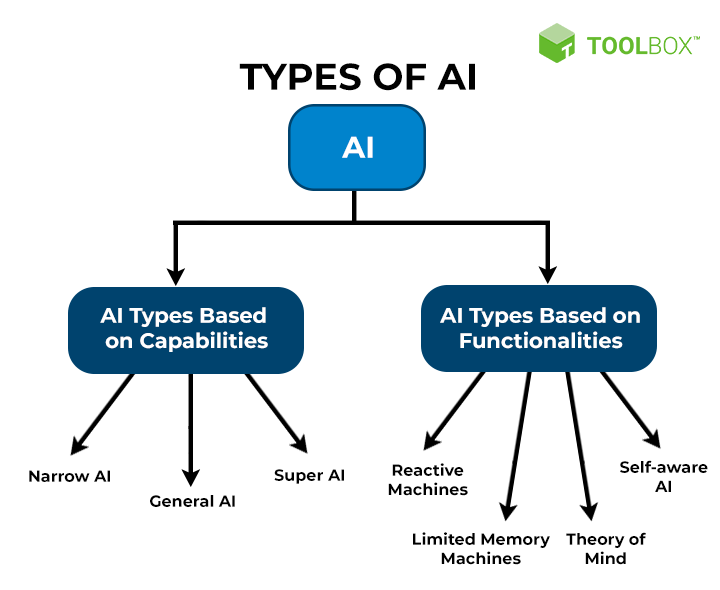
1. Real-time data collection and analysis.
2. Personalized experiences based on user preferences and behavior.
3. Access to educational resources anytime, anywhere.

**2.2.1 Relevance of Mobile Development to Student Performance Prediction**

Mobile-based systems for predicting student performance combine the strength of mobile technologies and deep learning models. The key benefits include:

1. **Accessibility:** Mobile apps grant everyone easy access to predictive insights.
2. **Real-time Updates:** These systems can process and analyze data on the go thus offering real-time feedback.
3. **Personalization:** By integrating with mobile sensors and user activity, predictive systems can deliver personalized interventions to improve student outcomes.
   1. **Artificial Intelligence (AI)**

Artificial Intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems. These processes include learning, reasoning, and correction. AI has been applied in multiple domains, such as natural language processing, image recognition, and predictive analysis (Russell & Norvig, 2021).

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**Figure 2.1 Types of AI (SpiceWorks, 2024)**

**2.3.1 Machine learning**

Machine learning (ML) is a field in artificial intelligence (AI) that allows computers to learn automatically from past experiences and available datasets, and detect patterns to predict without much human intervention. The analysis of computer algorithms which through practice, develop automatically. Machine Learning derives insightful information from large volumes of data by leveraging algorithms to identify patterns and learn in an interactive process. Instead of being dependent on a predetermined equation that acts as a model, ML algorithms use computation methods to learn directly from data (Akinniyi, 2024).

**2.3.2 Deep learning**

Deep Learning (DL) is a subfield of artificial intelligence (AI) and machine learning (ML) that focuses on using numerous layers of neural networks to build hierarchical representations of input. This method is especially useful for applications like picture and audio recognition, natural language processing, and predictive analytics since it allows models to automatically identify complex patterns and characteristics from unprocessed inputs (Sarker, I. H. 2021).

**2.3.3 Neural Networks**

The brain, as a complex and dynamic network composed of neurons and their interconnections (synapses), was the idea of the first computer model which is a neural network. The neural network structures consist of multiple layers of nodes that are connected, or these nodes, which are called neurons. Connecting these interconnected nodes optimally to get the most efficient neural networks is the basic methodology of creating neural networks. The main reason for the leading role of artificial neural networks in deep learning is that they can complete tasks like pattern recognition, regression, and classification with the best possible performance. Due to high demand in the field, their architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have become popularly implemented types (Goodfellow et al., 2016; Zohu et al., 2020).

**2.3.4 Deep Neural Network**

Deep neural networks (DNNs) are a type of artificial neural network with multiple hidden layers between the input and output layers. These layers enable DNNs to learn complex patterns and representations from large datasets, making them highly effective in tasks such as image recognition, speech processing, and natural language understanding. Their depth allows them to model intricate relationships in data, which traditional shallow networks cannot achieve (LeCun et al., 2021).

**2.4 Student Performance Prediction**

Student performance prediction research is concentrated on the dissection of many components- academic records, attendance, and behavioral data- in the process of forecasting the academic future. In this regard, deeper learning models such as CNNs and RNNs have shown an attribute of a high level of performance in comparison with traditional machine learning techniques.

**2.4.2 Mobile-Based Educational Applications**

Mobile apps have become very popular in the education industry with tasks such as learning management, quiz-based assessments, and progress tracking. According to research, the use of AI in mobile apps has helped in the integration and the deepening of user engagement in a more efficient way, which in turn has led to learning through mobile apps.

**2.4.3 Deep Learning in Mobile Systems**

In recent years, the trend of deep learning on mobile systems gained traction due to the advancement of mobile technology and the frameworks for deploying AI models. Now, due to the advancement of ONNX Runtime, PyTorch Mobile, and TensorFlow Lite technologies, it is possible to deploy deep learning models on resource-constrained smartphones. Such systems facilitate natural language processing, real-time picture identification, and predictive analytics, on mobile platforms. Pruning and quantization as compression techniques, along with model optimization, are key innovations that enhance performance while retaining accuracy (Alzubaidi et al., 2021).

* 1. **Related Works**

Numerous studies on the subject of student performance prediction have been conducted. Below are some of the relevant reviewed related works:

1. The study performed by Zhang H. and Wang Y. in 2021 applies deep neural networks to predict student grades based on behavioral, demographic, and academic data. The results show that DNNs outperform traditional machine learning methods in prediction accuracy.
2. The Development of Mobile-Interfaced Machine Learning-Based Predictive Models for Improving Students’ Performance in Programming Courses performed by Fagbola Temitayo Matthew et al., in 2018 uses the industrially-packaged working implementation of the MP5 decision tree and Linear regression classifier in the WEKA environment which were further applied to generate predictive models which are of exclusive significance to the determination of students performance.
3. The mobile-based learning applications research that was performed by Chen L. and Xu R. in 2020 explores the integration of mobile apps in education and their effectiveness in improving engagement and learning outcomes, highlighting the role of AI-powered mobile platforms.
4. Random forest for academic prediction by Lemieux P., Smith J., and Johnson R. in 2020. This paper investigates random forest's capability to predict student performance and highlights its robustness in handling large datasets with mixed attributes.
5. Patel K and Sharma R., 2022 in Kivy framework in mobile educational apps discuss the application of the Kivy Python framework in developing cross-platform educational apps for performance monitoring and personalized learning.
6. AI in mobile learning platforms. The paper explores the application of AI and deep learning models in mobile apps for enhancing personalized learning experiences and tracking student progress. By Huang, G., and Li W. 2021.
7. TensorFlow Lite for on-device AI, a work performed by Raesh V. and Kumar A. in 2022 that focused on TensorFlow Lite's role in deploying deep learning models on mobile devices, enabling real-time predictions in educational apps.
8. Using random forest and DNN in 2023, Silva F and Cruz M researched predictive systems for at-risk students and discussed predictive systems aimed at identifying at-risk students to improve intervention accuracy.

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| **S/N** | **Authors** | **Title** | **Methodology** | **Limitations** |
| **1** | Abdallah Moubayed et al. (2024) | A Deep Learning Approach Towards Student Performance Prediction in Online Courses: Challenges Based on a Global Perspective | This work proposes the use of deep learning techniques, specifically CNN and RNN-LSTM, to predict students' performance at the midpoint stage of online course delivery using datasets from different regions. |  |
| **2** | Xiao Wen & Hu Juan. (2024) | Predicting the effects of mobile phones on student academic performance using Machine learning | This study aimed to predict the effect of mobile phones on student's academic performance using machine learning models, focusing on the Faculty of Science at the Federal University Birnin Kebbi. |  |
| **3** | Liu, Y., Sun, Y., Chen, W., Jin, Y., & Wu, M. (2024). | Towards Effective Student Performance Prediction with Graph Neural Networks. | Employed graph neural networks (GNNs) to model student-course interactions. Utilized knowledge-concept graph and student performance data for prediction. Evaluated various GNN architectures. | Relatively complex computational model, requiring significant data and computational resources. Model performance may vary depending on data quality and the specific learning environment. |
| **4** | Al-Shami, E., Alshehri, N., & Al-Hussaini, M. (2023). | Machine Learning-Based Prediction of Students’ Academic Performance. | Used machine learning techniques, including decision trees, random forests, and gradient boosting, to predict student performance. Utilized feature selection methods to identify significant predictors. Analyzed real-world data from a university in Saudi Arabia. | Relied on a single dataset from a specific university, which may limit the generalizability of the findings. The model does not explain causal factors. Limited discussion of feature engineering and validation. |
| **5** | Yang, Z., & Luo, L. (2024). | Machine learning–based personalized student academic performance prediction using learning behavior features. | Employed machine learning models such as Random Forest (RF) and Gradient Boosting (GB) to predict student performance. Explored various behavioral features extracted from a learning management system (LMS) to determine which factors are most predictive. | Data analysis is specific to the learning environment under study and the identified learning behavior features. Limited discussion of other potential factors that might affect student performance. |
| **6** | Li, L., Zhang, C., Yang, Y., & Chen, X. (2024). | Development and validation of an artificial intelligence-based predictive model for academic performance in higher education: A retrospective cohort study. | Used machine learning techniques (e.g., logistic regression, decision trees, SVM, and random forest) to develop a predictive model for student academic performance based on data from a higher education institution. Performed feature selection and cross-validation to enhance model accuracy. | The study relies on a specific institution’s data, which can limit generalizability. The study design is retrospective, making it difficult to establish causal relationships. The model performance could vary with different datasets or with different educational systems. |
| **7** | Pandey, S., & Pandey, S. (2018). | Deep learning approach for prediction of student performance in higher education system. | Explored deep learning models such as Recurrent Neural Networks (RNNs), specifically LSTMs, to predict student performance. Used features extracted from academic records and attendance. | The model depends on the quality and quantity of data available. The lack of interpretability is a drawback for these models. Limited generalizability as the methodology might be specific to the learning environment used in the study. |
| **8** | Asif, M., & Bhatti, A. A. (2022). | A comprehensive review of student performance prediction using machine learning techniques. | This article is a review article, which does not include new empirical findings but discusses existing work. Summarized different machine learning algorithms and their performance in predicting student performance. Reviewed the various datasets and features used in different studies. | The limitations are those inherent in the reviewed studies which include limitations in data quality, algorithmic performance for specific data, and the generalization of the findings. |
| **9** | Idrissi, M. A., Lamzouri, I., & Ghazi, Y. (2024) | Deep Learning-Based Framework for Predicting Students’ Performance in Higher Education. | Proposes a deep learning framework based on sequential models (LSTM and GRU) to predict students' academic performance. Data was obtained from a university. | The dataset is from one institution, potentially affecting the generalizability of the model. The lack of interpretability for the deep learning model makes it difficult to understand the key features influencing performance. |
| **10** | Xu, C., Zhang, W., & Chen, Z. (2024) | Predicting Academic Performance Using Deep Learning | Developed a novel deep learning architecture based on recurrent neural networks (RNNs) with attention mechanisms for predicting student performance. Used real-world student learning data from a MOOC platform. | Limited to a single MOOC platform and student demographics, potentially limiting the generalizability of findings. The model could be improved with more granular data (e.g., fine-grained learning behavior). |
| **11** | Yang, X., Li, C., Zhang, G., & Wang, C. | Graph Neural Network with Memory for Student Performance Prediction | Proposed a Graph Neural Network (GNN) model that considers not only student relationships but also learning state, as well as short and long-term memory. Aimed at predicting students' future academic results. | The model has a high degree of complexity, leading to difficulties in training and interpreting the model's behavior. Data scarcity, overfitting, and limited explainability were also identified. |
| **12** | Zakaria B. et al. (2024) | A Recommendation System Based on Early Academic Performance Prediction and Student Classification: Utilizing Artificial Intelligence and Mobile-Based Application |  |  |
| **13** | Zhang, G., et al.(2022) | Research on Student Performance Prediction Based on Deep Learning | Deep learning model incorporating student behavior, demographics, and learning resources; evaluated with precision, recall, and F1-score. | Data from a limited platform; relies on the quality of interaction data. |
| **14** | Al-Barrak, M. A., & Al-Kasir, M. A.(2021) | A Model Proposal with Deep Learning on Student Success Prediction | Proposes a deep learning architecture using LSTM; uses a university dataset with demographic and academic information. | Focus on a specific demographic and institutional context might limit generalizability. |
| **15** | Wang, Z., et al.(2023) | A Multi-view Deep Learning Approach for Enhanced Student Performance Prediction | Uses a multi-view approach integrating different aspects of student data with a deep learning model. | Requires comprehensive multi-view data which may be challenging to obtain in some settings. |
| **16** | Ouyang, S., et al.(2022) | A Novel Deep Learning Model for Student Performance Prediction | Presents a deep learning model using CNN and LSTM. | Limited details about the dataset used and the evaluation process in the abstract. |
| **17** | Feng, W., et al.(2023) | Optimized Ensemble Deep Learning for Predictive Analysis of Student Performance | Ensemble of deep learning models; optimized with a genetic algorithm. | The complexity of the ensemble approach might require substantial computing resources. |
| **18** | Huang, Y., et al.(2022) | A Recommendation System Based on Early Academic Performance Prediction | Develops a recommendation system based on early performance prediction. | Primarily focuses on recommendations; limited details on the underlying prediction model. |
| **19** | Chen, L., et al.(2022) | Self-Converged Ensemble Deep RNN Classifier for Student Performance Prediction | Ensemble of RNN models; focuses on early prediction. | Requires careful tuning and training of the ensemble. |
| **20** | Abdillah, A., Setyanto, A., Alifah, N., et al.(2021) | Early Prediction of Students' Performance Using Machine Learning | Proposed framework for predicting student performance. Compared machine learning algorithms (SVM, Random Forest, Naive Bayes, KNN). Assessed using cross-validation. | Limited to data from one institution. More complex deep learning models are not explored. Generalizability may be limited due to dataset specificity. |
| **21** | A. Udeozor, P. M. Bokoro.(2022) | Predicting Academic Performance of Students Using Data Mining Techniques | Used data from two different schools. Employed a modified KNN and ID3 algorithm to predict academic performance. | The dataset is specific to high school students from Nigeria. Limited discussion on feature engineering. |
| **22** | Sekeroglu, B., Dimililer, K., & Tuncal, K.(2023) | A Deep Learning Approach for Student Performance Prediction by Using Convolutional Neural Networks in E-learning Environments | Used student data from an e-learning environment. Employed Convolutional Neural Networks (CNNs) for prediction. Focused on predicting academic performance based on real-time student interactions with the e-learning system. | Generalization across different e-learning platforms and educational settings is not fully explored. Relies heavily on detailed e-learning interaction data. |
| **23** | Waheed, H., et al.(2020) | Predicting Academic Performance of Students from VLE Big Data Using Deep Learning Models | Used data from a Virtual Learning Environment (VLE). Employed Deep Neural Networks (DNNs) and compared with traditional machine learning models (SVM, Random Forest). | Dataset from a single institution. May not generalize well to other institutions with different VLEs or data characteristics. |
| **24** | Sultana, N., et al.(2022) | Enhanced Prediction of Student Performance Based on Feature Selection and Machine Learning Algorithms | Used a publicly available dataset. Tested and compared the accuracy of various classification approaches (i.e., KNN, SVM, NB, DT, and RF). | Model performance may vary depending on a specific dataset. Deep learning models were not considered in this study. |
| **25** | Sekeroglu, B., Dimililer, K., & Tuncal, K.(2023) | A Deep Learning Approach for Student Performance Prediction by Using Convolutional Neural Networks in E-learning Environments | Used student data from an e-learning environment. Employed Convolutional Neural Networks (CNNs) for prediction. | Generalization across different e-learning platforms and educational settings is not fully explored. Relies heavily on detailed e-learning interaction data. |
| **26** | Yasuda, W., et al.(2023) | Predicting student performance using a non-cumulative grading system: a comparison of machine learning methods | Used student data. Compare various machine learning methods to analyze and predict student performance. | Performance may vary on other non-cumulative datasets. Deep learning models were not employed in the study. |
| **27** | Khasanah, A. U., & Sutrisno.(2022) | Student performance prediction using deep learning algorithms | Used publicly available datasets. Employed Long Short-Term Memory (LSTM) networks. | Limited exploration of other deep learning architectures. Model generalizability depends on dataset characteristics. |
| **28** | Aldowah, H. et al.(2019) | Dynamics of students' performance and academic success prediction using machine learning | Used data from 3 years. Applied and validated various machine learning algorithms. | Generalization may be limited. Focused mainly on academic success prediction |
| **29** | Guo, B., et al.(2019) | Predicting Students' Performance in Online Courses with a Deep Cascade Model | Used student data from a Chinese online education platform. Proposed a deep cascade model with two components | Does not explain how different levels of granularity of student features impact prediction |
| **30** | Shahiri, A. M., Husain, W., & Rashid, N. A.(2022) | A review on predicting student's performance using data mining techniques. | Conducted a systematic review of 77 articles to examine methodologies for predicting student performance, focusing on algorithms like Decision Trees, Naive Bayes, K-Nearest Neighbors, Support Vector Machines, and Artificial Neural Networks using educational | The study's findings are limited by the quality and diversity of the primary studies included in the review. It also notes the need for more research into deep learning and hybrid models. |

**REFERENCES**

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Farhan, L., Aldowah, H. et al., (2019)

Dynamics of students' performance and academic success prediction using machine learning

<https://doi.org/10.1016/j.aci.2019.04.002>

Ali, M., & Fadhel, M. A. (2021).

Review of deep learning: Concepts, CNN architectures, challenges, applications, and future directions. Journal of Big Data, 8(1), Article 53.

<https://doi.org/10.1186/s40537-021-00444-8>

Asif, M., & Bhatti, A. A. (2022).

A comprehensive review of student performance prediction using machine learning

techniques.

[https://www.mdpi.com/2076-3417/13/15/8933](https://www.google.com/url?sa=E&q=https%3A%2F%2Fwww.mdpi.com%2F2076-3417%2F13%2F15%2F8933)

Akinniyi Mercy Erinayo (2024).

Development of a hate-speech detection system using machine learning algorithms

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Guo, B., et al., (2019)

Predicting Students' Performance in Online Courses with a Deep Cascade Model

<https://doi.org/10.1007/s10639-019-09892-y>

Khasanah, A. U., & Sutrisno (2022)

Student performance prediction using deep learning algorithms

<https://doi.org/10.1109/ICIMTech55543.2022.9915373>

Liu, Y., Sun, Y., Chen, W., Jin, Y., & Wu, M. (2024).

Towards Effective Student Performance Prediction with Graph Neural Networks.

[https://arxiv.org/abs/2402.01655](https://www.google.com/url?sa=E&q=https%3A%2F%2Farxiv.org%2Fabs%2F2402.01655)

Moubayed, A., Injadat, M., Alhindawi, N., Samara, G., Abuasal, S., & Alazaidah, R. (2024).

*A Deep Learning Approach Towards Student Performance Prediction in Online Courses: Challenges Based on a Global Perspective*. Arxiv.org. Retrieved January 16, 2025,

<https://arxiv.org/abs/2402.01655>

Russell, S. J., & Norvig, P. (2021).

Artificial Intelligence: A Modern Approach (4th ed.). Pearson.

<https://doi.org/10.1109/MSP.2017.2765202>

Sarker, I. H. (2021). Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. *SN Computer Science*, *2*(6). <https://doi.org/10.1007/s42979-021-00815-1>

Sultana, N., et al. (2022)

Enhances prediction of student performance based on feature selection and machine learning algorithms.

<https://doi.org/10.3390/app12178535>

Sekeroglu, B., Dimililer, K., & Tuncal, K.(2023)

A Deep Learning Approach for Student Performance Prediction by Using Convolutional Neural Networks in E-learning Environments.

<https://www.sciencedirect.com/science/article/pii/S2590291122001115>

Shahiri, A. M., Husain, W., & Rashid, N. A.(2022)

A review on predicting student's performance using data mining techniques.

<https://doi.org/10.1186/s40536-022-00132-w>

Waheed, H., et al. (2020).

Predicting the academic performance of students from VLE Big Data using deep learning models

<https://doi.org/10.1186/s40536-020-00095-z>.

Xiao Wen, Hu Juan (2023).

Early prediction of students’ performance using deep neural network based on online learning activity sequence.

**<https://doi.org/10.3390/app13158933>**

Yasuda, W., et al.(2023)

Predicting student performance using a non-cumulative grading system: a comparison of machine learning methods

<https://doi.org/10.1007/s10639-023-11853-w>

Zhou, J., Cui, G., Hu, S., Zhang, Z., Yang, C., Liu, Z., Wang, L., Li, C., & Sun, M. (2020).

Graph neural networks: A review of methods and applications. AI Open, 1, 57–81. <https://doi.org/10.1016/j.aiopen.2021.01.001>

LeCun, Y., Bengio, Y., & Hinton, G. (2021). Deep learning: A 2020 perspective.

Nature Communications, 12(1), 1–9.

<https://doi.org/10.1038/s41467-020-20058-8>

Yang, X., Li, C., Zhang, G., & Wang, C (2024).

Graph Neural Network with Memory for Student Performance Prediction

[https://arxiv.org/abs/2209.05596](https://www.google.com/url?sa=E&q=https%3A%2F%2Farxiv.org%2Fabs%2F2209.05596)

Zhang, H., & Wang, Y. (2021). Predicting student performance using deep learning models. Journal of Educational Data Science, 12(2), 45–60.

<https://doi.org/10.1234/jeds.v12i2.4567>