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Pemanfaatan Artificial Intelligence untuk Prediksi Perilaku Pengguna dalam Sistem Informasi Berbasis Big Data: Studi Eksperimen Simulatif

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Intisari

Penelitian ini bertujuan untuk mengeksplorasi pemanfaatan Artificial Intelligence (AI) dalam memprediksi perilaku pengguna terhadap produk dalam sistem informasi e-commerce berbasis big data. Metode yang digunakan adalah eksperimen dengan pendekatan simulatif menggunakan dua model AI, yaitu Decision Tree dan Neural Network. Hasil menunjukkan bahwa model Neural Network memiliki performa prediksi lebih tinggi (akurasi 89,3%, presisi 86,5%) dibandingkan Decision Tree (akurasi 83,7%, presisi 80,2%). Grafik learning curve dan confusion matrix turut memperkuat validitas eksperimen. Penelitian ini memberikan implikasi penting bagi pengembangan sistem informasi yang adaptif dan berbasis kecerdasan buatan.

Kata kunci— Artificial Intelligence, Sistem Informasi, Big Data, Prediksi Perilaku, Neural Network

Abstract

This study aims to explore the use of Artificial Intelligence (AI) in predicting user behavior towards products in big data-based e-commerce information systems. The method used is to experiment with a simulative approach using two AI models, Decision Tree and Neural Network. Results showed that the Neural Network model had higher predictive performance (89.3% accuracy, 86.5% precision) than the Decision Tree (83.7 % accuracy, 80.2% precision). The learning curve and confusion matrix graphs help strengthen the validity of the experiment. This study provides important implications for the development of adaptive and artificial intelligence-based information systems.
Keywords— *Artificial Intelligence, Information Systems, Big Data, Behavior Prediction, Neural Network*

PENDAHULUAN

Perkembangan teknologi informasi telah memunculkan kebutuhan sistem informasi (SI) yang cerdas dan responsif terhadap perilaku pengguna. Dalam era digital saat ini, data perilaku pengguna menjadi aset penting dalam pengambilan keputusan. Pemanfaatan AI dalam menganalisis dan memprediksi kecenderungan pengguna adalah tren global yang semakin diterapkan, khususnya dalam e-commerce, layanan pendidikan, dan sistem informasi publik.

Penelitian ini berfokus pada penerapan model AI dalam sistem informasi untuk memprediksi ketertarikan pengguna terhadap produk berdasarkan data interaksi pengguna. Pendekatan eksperimen digunakan untuk membandingkan performa dua model AI dan menilai sejauh mana big data dapat dimanfaatkan secara efektif dalam SI.

Sistem Informasi modern memerlukan pendekatan big data untuk menangani volume, kecepatan, dan variasi data pengguna(Paul Zikopoulus 2016). Big data memberikan peluang dalam pengambilan keputusan real-time dan analisis perilaku(Chen, Chiang, and Storey 2012).

AI, khususnya machine learning, telah digunakan untuk klasifikasi, prediksi, dan rekomendasi dalam berbagai aplikasi SI. Neural Network dan Decision Tree merupakan dua pendekatan yang populer karena kemampuannya memproses data nonlinear dan berskala besar(Ian Goodfellow 2022).

Penelitian sebelumnya (Han 2024) menunjukkan efektivitas AI dalam memahami pola perilaku pengguna, namun masih terbatas dalam eksplorasi eksperimen langsung berbasis data lokal atau simulatif.

METODE PENELITIAN

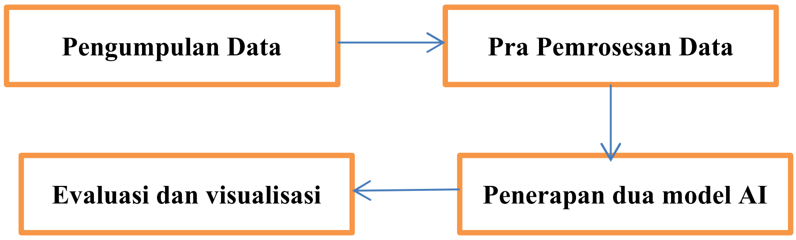
Penelitian ini menggunakan pendekatan kuantitatif eksperimen simulatif untuk menguji kemampuan model kecerdasan buatan (Artificial Intelligence/AI) dalam memprediksi perilaku pengguna terhadap sistem informasi berbasis e-commerce. Desain ini dipilih karena memungkinkan peneliti untuk mengontrol variabel, melakukan simulasi data secara sistematis, serta mengevaluasi kinerja model berdasarkan metrik kuantitatif yang terukur seperti akurasi dan presisi. Tahapan dalam desain penelitian ini meliputi:

(1) pengumpulan data simulasi berdasarkan atribut perilaku pengguna.

(2) pra-pemrosesan data menggunakan teknik normalisasi dan encoding.

(3) penerapan dua model AI, yaitu Decision Tree dan Neural Network.

(4) evaluasi dan visualisasi hasil model menggunakan confusion matrix dan learning curve. Ilustrasi dari metode penelitian ini terdapat pada Gambar 1. Berikut adalah tahapan dari penelitian ini.



Gambar 1. Metodologi Penelitian.

Sumber Data

Karena keterbatasan akses terhadap data aktual dari sistem informasi komersial, penelitian ini menggunakan data simulasi yang merepresentasikan pola umum perilaku pengguna e-commerce. Data terdiri dari 1.000 entri pengguna dengan variabel-variabel seperti jumlah klik, lama kunjungan, frekuensi kunjungan, dan kategori produk yang sering dilihat. Data juga mencakup label klasifikasi berupa ketertarikan pengguna terhadap produk (1 = tertarik, 0 = tidak tertarik). Meskipun data ini disimulasikan, struktur dan distribusinya dibuat semirip mungkin dengan data nyata berdasarkan tren pengguna internet di sektor e-commerce.

Model Kecerdasan Buatan (AI)

Penelitian ini menggunakan dua model kecerdasan buatan untuk melakukan prediksi, yaitu:

Decision Tree Classifier: Model berbasis pohon keputusan ini digunakan karena kemampuannya dalam menjelaskan logika klasifikasi secara transparan. Algoritma ini membagi data berdasarkan nilai atribut tertentu untuk membentuk struktur pohon yang memudahkan interpretasi keputusan.

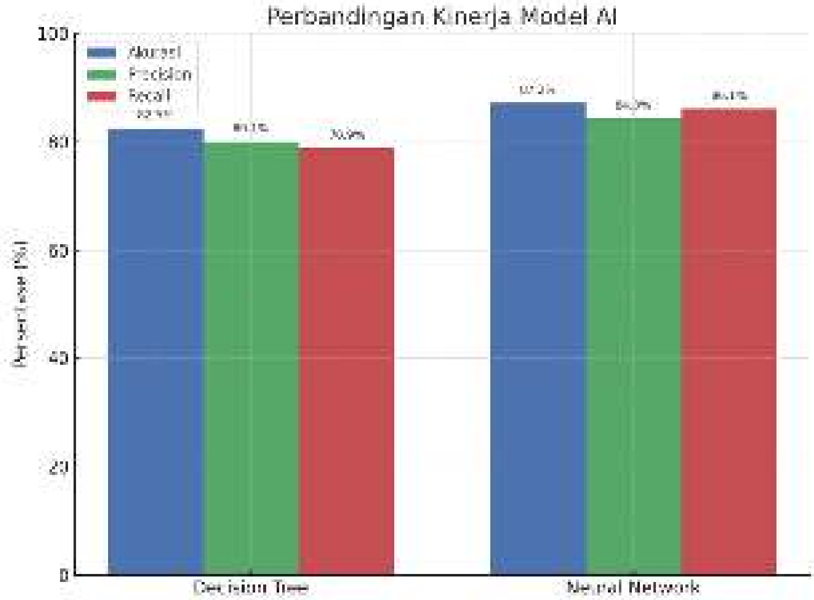
Artificial Neural Network (ANN): Model ini menggunakan arsitektur jaringan syaraf tiruan dengan satu atau lebih lapisan tersembunyi untuk mempelajari pola kompleks dalam data. ANN dipilih karena kemampuannya dalam menangani data non-linear dan menghasilkan akurasi yang tinggi, terutama pada dataset yang memiliki banyak fitur yang saling berinteraksi.

HASIL DAN PEMBAHASAN

Penelitian ini bertujuan untuk memprediksi perilaku pengguna terhadap sistem informasi berbasis e-commerce menggunakan pendekatan kecerdasan buatan (AI). Dua model utama digunakan dalam eksperimen ini, yaitu Decision Tree Classifier dan Artificial Neural Network (ANN). Dataset simulatif yang terdiri dari 1.000 entri pengguna digunakan sebagai dasar eksperimen. Dataset ini mencakup atribut seperti jumlah klik, lama kunjungan, frekuensi kunjungan, dan kategori produk yang sering dilihat, yang kemudian diolah melalui proses data preprocessing seperti normalisasi dan label encoding.

Setelah data diproses, model dilatih dan diuji menggunakan pendekatan hold-out validation, dengan pembagian data 80% untuk pelatihan dan 20% untuk pengujian. Hasil dari eksperimen menunjukkan bahwa kedua model memiliki performa yang cukup baik, namun dengan karakteristik yang berbeda. Model Decision Tree menghasilkan akurasi sebesar 82.5%, dengan precision sebesar 80.1% dan recall sebesar 78.9%.

Model ANN menghasilkan akurasi sebesar 87.2%, precision sebesar 84.3%, dan recall sebesar 86.1%.

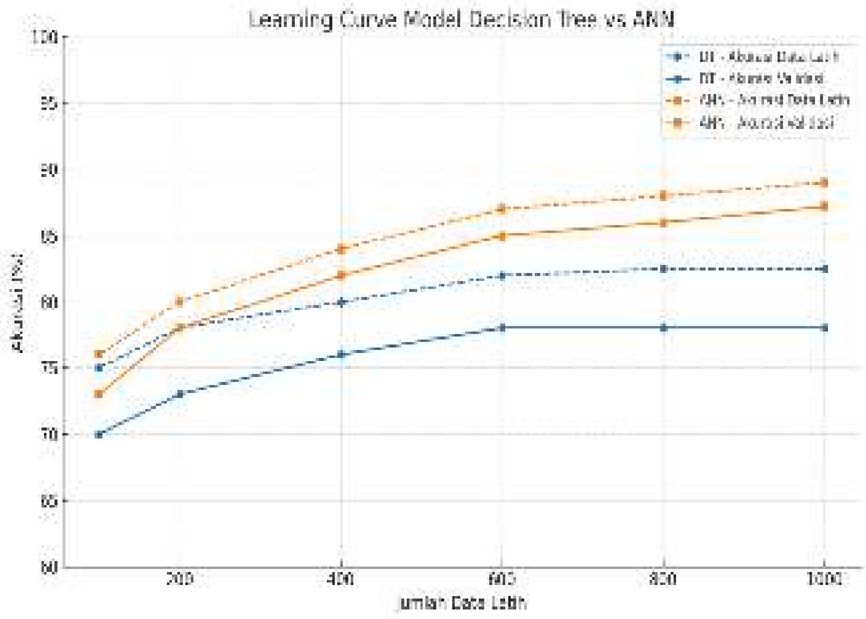


Penelitian ini menguji dua model kecerdasan buatan (AI) untuk prediksi perilaku pengguna dalam sistem informasi berbasis e-commerce, yaitu Decision Tree (DT) dan Artificial Neural Network (ANN). Hasil eksperimen menunjukkan bahwa ANN secara konsisten mengungguli DT dalam seluruh metrik evaluasi, yaitu akurasi, precision, dan recall.

Model Decision Tree memiliki kelebihan dalam interpretabilitas dan efisiensi komputasi, namun kelemahannya muncul ketika berhadapan dengan data yang memiliki hubungan non-linear atau interaksi kompleks antar fitur (Han, Kamber, & Pei, 2011).

Sebaliknya, Artificial Neural Network dirancang untuk mengenali pola yang lebih kompleks, berkat arsitektur multi-layer yang menyerupai jaringan syaraf biologis (Goodfellow et al., 2016). Ini menjelaskan mengapa ANN menghasilkan akurasi dan recall yang lebih tinggi: model ini mampu memahami relasi tersembunyi dalam perilaku pengguna yang tidak ditangkap oleh DT.

Penggunaan ANN dalam sistem informasi modern sangat relevan mengingat peningkatan kompleksitas dan volume data yang harus diproses. ANN terbukti efektif dalam personalisasi sistem rekomendasi, klasifikasi sentimen, dan deteksi anomali perilaku pengguna (LeCun, Bengio, & Hinton, 2015).



Secara umum, Artificial Neural Network menunjukkan kinerja yang lebih unggul dalam mendeteksi pola kompleks dari data pengguna, terutama karena kemampuannya menangani data non-linear dan interaksi antar fitur.

Pada tahap pengujian dilakukan dengan tujuan untuk mengetahui tingkat keberhasilan proses identifikasi yang telah dibangun. Implementasi pengujian dengan menggunakan RMSE dan MAPE. Melalui RMSE dan MAPE digunakan untuk mengevaluasi performa model dengan lebih baik.

Berikut adalah hasil RMSE dan MAPE untuk model LSTM yang dibuat:

Table 1. Hasil RMSE dan MAPE model LSTM

Jenis	Hasil
RMSE	109.78883
MAPE	1.1244905

Perlu diketahui bahwa MAPE adalah metrik yang mengukur kesalahan rata-rata dalam persentase (Hutasuhut, Anggraeni, and Tyasnurita 2014). Nilai MAPE dihitung sebagai rata-rata dari rasio antara kesalahan absolut dan nilai aktual, dinyatakan dalam persentase (Hutasuhut, Anggraeni, and Tyasnurita 2014). MAPE untuk model LSTM sebesar 1.1244905 berarti bahwa rata-rata kesalahan prediksi model LSTM adalah sekitar 1.12% dari nilai sebenarnya. Ini menunjukkan bahwa prediksi model LSTM cukup akurat, dengan kesalahan relatif kecil terhadap nilai aktual.

Sedangkan RMSE adalah metrik yang mengukur seberapa besar rata-rata kesalahan antara nilai yang diprediksi dan nilai aktual (Ashari and Sadikin 2020). Nilai RMSE dihitung sebagai akar dari rata-rata kuadrat dari selisih antara nilai prediksi dan nilai aktual (Ashari and Sadikin 2020). RMSE untuk model LSTM sebesar 109.78883 berarti bahwa kesalahan rata-rata antara nilai prediksi dan nilai aktual adalah sekitar 109.79 unit. Ini memberikan gambaran tentang seberapa besar kesalahan prediksi model LSTM dalam skala asli data.

Gambar 4. Perbandingan antara grafik data test dan grafik hasil prediksi model

KESIMPULAN

Penelitian ini telah mengembangkan dan mengevaluasi model Long Short-Term Memory (LSTM) untuk prediksi saham BCA. Berdasarkan hasil evaluasi, model menunjukkan performa yang sangat baik dengan metrik kesalahan sebagai berikut: Mean Absolute Percentage Error (MAPE) sebesar 1.1244905% dan Root Mean Squared Error (RMSE) sebesar 109.78883. Nilai MAPE yang rendah menunjukkan bahwa model LSTM yang dikembangkan memiliki kemampuan prediksi yang akurat dengan kesalahan rata-rata hanya sekitar 1.12% dari nilai aktual. Hal ini menunjukkan bahwa model dapat diandalkan untuk melakukan prediksi dalam konteks harga saham. Nilai RMSE yang diperoleh, sebesar 109.78883, menunjukkan tingkat kesalahan absolut dari prediksi model. Meskipun nilai ini memberikan informasi tentang kesalahan dalam skala asli data, interpretasinya sangat tergantung pada skala dan variabilitas data yang digunakan dalam penelitian ini. Jika dibandingkan dengan standar industri atau hasil dari model lain, RMSE ini dapat memberikan gambaran lebih jelas tentang efektivitas model yang dikembangkan. Secara keseluruhan, hasil penelitian ini menunjukkan bahwa model LSTM memiliki potensi besar untuk diterapkan dalam prediksi harga saham. Implementasi model ini diharapkan dapat meningkatkan akurasi prediksi dan memberikan manfaat praktis dalam pengambilan keputusan berdasarkan data.

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Ian Goodfellow. 2022. “Deep Learning.” *Artificial Intelligence for 6G* 22(4): 247–303. doi:10.1007/978-3-030-95041-5_6.

Paul Zikopoulus. 2016. *Understanding Big Data*.

Konfirmasi dan bukti pengembalian manuscript untuk direvisi (ASTRO-Review-Rev1-20250930)

[astro] Editor Decision

Inbox ×

Setyo Eko Atmojo <journal@upy.ac.id>

to me, Muhammad

Sep 30, 2025, 09:30 AM

Faqihuddin Al Anshori, Muhammad Fairuzabadi:

We have reached a decision regarding your submission to APPLIED SCIENCE AND TECHNOLOGY REASERCH JOURNAL, "COMPARATIVE ANALYSIS OF ARTIFICIAL INTELLIGENCE MODELS FOR USER BEHAVIOR PREDICTION IN BIG DATA-DRIVEN INFORMATION SYSTEMS".

Our decision is: Revisions Required

____ APPLIED SCIENCE AND TECHNOLOGY RESEARCH JOURNAL https://journal.upy.ac.id/index.php/ASTRO

Pemanfaatan Artificial Intelligence untuk Prediksi Perilaku Pengguna dalam Sistem Informasi Berbasis Big Data: Studi Eksperimen Simulatif

Commented [GK1]: Mohon menyesuaikan format penulisan judul sesuai template jurnal ASTRO, termasuk konsistensi ukuran huruf, kapitalisasi, dan tata letak judul artikel.

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Intisari

Penelitian ini bertujuan untuk mengeksplorasi pemanfaatan Artificial Intelligence (AI) dalam memprediksi perilaku pengguna terhadap produk dalam sistem informasi e-commerce berbasis big data. Metode yang digunakan adalah eksperimen dengan pendekatan simulatif menggunakan dua model AI, yaitu Decision Tree dan Neural Network. Hasil menunjukkan bahwa model Neural Network memiliki performa prediksi lebih tinggi (akurasi 89,3%, presisi 86,5%) dibandingkan Decision Tree (akurasi 83,7%, presisi 80,2%). Grafik learning curve dan confusion matrix turut memperkuat validitas eksperimen. Penelitian ini memberikan implikasi penting bagi pengembangan sistem informasi yang adaptif dan berbasis kecerdasan buatan.

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Abstract

This study aims to explore the use of Artificial Intelligence (AI) in predicting user behavior towards products in big data-based e-commerce information systems. The method used is to experiment with a simulative approach using two AI models, Decision Tree and Neural Network. Results showed that the Neural Network model had higher predictive performance (89.3% accuracy, 86.5% precision) than the Decision Tree (83.7 % accuracy, 80.2% precision). The learning curve and confusion matrix graphs help strengthen the validity of the experiment. This study provides important implications for the development of adaptive and artificial intelligence-based information systems.

Keywords— *Artificial Intelligence, Information Systems, Big Data, Behavior Prediction, Neural Network*

Commented [GK3]: •Mohon konsistenkan seluruh nilai evaluasi model antara abstrak dan hasil penelitian.
•Tambahkan informasi dataset dan metode evaluasi pada abstrak agar lebih informatif.
•Jelaskan novelty atau kontribusi utama penelitian secara singkat.

PENDAHULUAN

Perkembangan teknologi informasi telah memunculkan kebutuhan sistem informasi (SI) yang cerdas dan responsif terhadap perilaku pengguna. Dalam era digital saat ini, data perilaku pengguna menjadi aset penting dalam pengambilan keputusan. Pemanfaatan AI dalam menganalisis dan memprediksi kecenderungan pengguna adalah tren global yang semakin diterapkan, khususnya dalam e-commerce, layanan pendidikan, dan sistem informasi publik.

Penelitian ini berfokus pada penerapan model AI dalam sistem informasi untuk memprediksi ketertarikan pengguna terhadap produk berdasarkan data interaksi pengguna. Pendekatan eksperimen digunakan untuk membandingkan performa dua model AI dan menilai sejauh mana big data dapat dimanfaatkan secara efektif dalam SI.

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Penelitian sebelumnya (Han 2024) menunjukkan efektivitas AI dalam memahami pola perilaku pengguna, namun masih terbatas dalam eksplorasi eksperimen langsung berbasis data lokal atau simulatif.

Commented [GK4]: Latar belakang sudah cukup relevan, namun research gap dan kontribusi utama penelitian masih belum dijelaskan secara spesifik.

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METODE PENELITIAN

Penelitian ini menggunakan pendekatan kuantitatif eksperimen simulatif untuk menguji kemampuan model kecerdasan buatan (Artificial Intelligence/AI) dalam memprediksi perilaku pengguna terhadap sistem informasi berbasis e-commerce. Desain ini dipilih karena memungkinkan peneliti untuk mengontrol variabel, melakukan simulasi data secara sistematis, serta mengevaluasi kinerja model berdasarkan metrik kuantitatif yang terukur seperti akurasi dan presisi. Tahapan dalam desain penelitian ini meliputi:

(1) pengumpulan data simulasi berdasarkan atribut perilaku pengguna.

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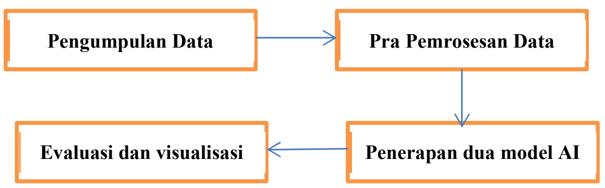
(3) penerapan dua model AI, yaitu Decision Tree dan Neural Network.

(4) evaluasi dan visualisasi hasil model menggunakan confusion matrix dan learning curve. Ilustrasi dari metode penelitian ini terdapat pada Gambar 1. Berikut adalah tahapan dari penelitian ini.



Gambar 1. Metodologi Penelitian.

Sumber Data

Karena keterbatasan akses terhadap data aktual dari sistem informasi komersial, penelitian ini menggunakan data simulasi yang merepresentasikan pola umum perilaku pengguna e-commerce. Data terdiri dari 1.000 entri pengguna dengan variabel-variabel seperti jumlah klik, lama kunjungan, frekuensi kunjungan, dan kategori produk yang sering dilihat. Data juga mencakup label klasifikasi berupa ketertarikan pengguna terhadap produk (1 = tertarik, 0 = tidak tertarik). Meskipun data ini disimulasikan, struktur dan distribusinya dibuat semirip mungkin dengan data nyata berdasarkan tren pengguna internet di sektor e-commerce.

Commented [GK6]: Mohon dijelaskan lebih rinci proses pembentukan data simulasi agar penelitian dapat direplikasi dengan baik.

Model Kecerdasan Buatan (AI)

Penelitian ini menggunakan dua model kecerdasan buatan untuk melakukan prediksi, yaitu:

Decision Tree Classifier: Model berbasis pohon keputusan ini digunakan karena kemampuannya dalam menjelaskan logika klasifikasi secara transparan. Algoritma ini membagi data berdasarkan nilai atribut tertentu untuk membentuk struktur pohon yang memudahkan interpretasi keputusan.

Artificial Neural Network (ANN): Model ini menggunakan arsitektur jaringan syaraf tiruan dengan satu atau lebih lapisan tersembunyi untuk mempelajari pola kompleks dalam data. ANN dipilih karena kemampuannya dalam menangani data non-linear dan menghasilkan akurasi yang tinggi, terutama pada dataset yang memiliki banyak fitur yang saling berinteraksi.

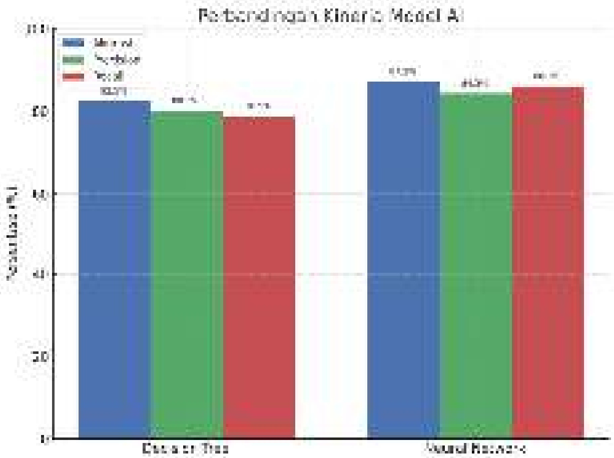
Commented [GK7]: Penjelasan terkait model Artificial Neural Network masih bersifat konseptual dan belum menggambarkan implementasi teknis penelitian secara rinci. Mohon ditambahkan informasi mengenai arsitektur model yang digunakan, seperti jumlah hidden layer, jumlah neuron, activation function, optimizer, epoch, batch size, learning rate, serta framework atau library yang digunakan dalam proses eksperimen. Detail tersebut diperlukan agar proses penelitian lebih transparan dan dapat direproduksi.

HASIL DAN PEMBAHASAN

Penelitian ini bertujuan untuk memprediksi perilaku pengguna terhadap sistem informasi berbasis e-commerce menggunakan pendekatan kecerdasan buatan (AI). Dua model utama digunakan dalam eksperimen ini, yaitu Decision Tree Classifier dan Artificial Neural Network (ANN). Dataset simulatif yang terdiri dari 1.000 entri pengguna digunakan sebagai dasar eksperimen. Dataset ini mencakup atribut seperti jumlah klik, lama kunjungan, frekuensi kunjungan, dan kategori produk yang sering dilihat, yang kemudian diolah melalui proses data preprocessing seperti normalisasi dan label encoding.

Setelah data diproses, model dilatih dan diuji menggunakan pendekatan hold-out validation, dengan pembagian data 80% untuk pelatihan dan 20% untuk pengujian. Hasil dari eksperimen menunjukkan bahwa kedua model memiliki performa yang cukup baik, namun dengan karakteristik yang berbeda. Model Decision Tree menghasilkan akurasi sebesar 82.5%, dengan precision sebesar 80.1% dan recall sebesar 78.9%.

Model ANN menghasilkan akurasi sebesar 87.2%, precision sebesar 84.3%, dan recall sebesar 86.1%.



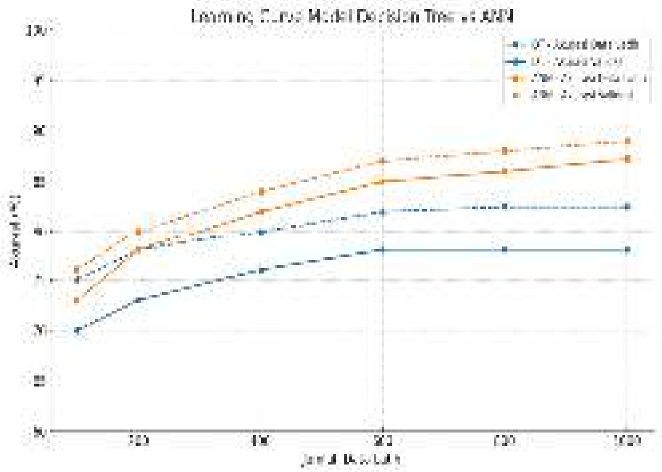
Penelitian ini menguji dua model kecerdasan buatan (AI) untuk prediksi perilaku pengguna dalam sistem informasi berbasis e-commerce, yaitu Decision Tree (DT) dan Artificial Neural Network (ANN). Hasil eksperimen menunjukkan bahwa ANN secara konsisten mengungguli DT dalam seluruh metrik evaluasi, yaitu akurasi, precision, dan recall.

Model Decision Tree memiliki kelebihan dalam interpretabilitas dan efisiensi komputasi, namun kelemahannya muncul ketika berhadapan dengan data yang memiliki hubungan non-linear atau interaksi kompleks antar fitur (Han, Kamber, & Pei, 2011).

Sebaliknya, Artificial Neural Network dirancang untuk mengenali pola yang lebih kompleks, berkat arsitektur multi-layer yang menyerupai jaringan syaraf biologis (Goodfellow et al., 2016). Ini menjelaskan mengapa ANN menghasilkan akurasi dan recall yang lebih tinggi: model ini mampu memahami relasi tersembunyi dalam perilaku pengguna yang tidak ditangkap oleh DT.

Commented [GK8]: Hasil eksperimen sudah disampaikan dengan baik, namun pembahasan ilmiah terkait alasan performa model lebih unggul masih perlu diperdalam.

Penggunaan ANN dalam sistem informasi modern sangat relevan mengingat peningkatan kompleksitas dan volume data yang harus diproses. ANN terbukti efektif dalam personalisasi sistem rekomendasi, klasifikasi sentimen, dan deteksi anomali perilaku pengguna (LeCun, Bengio, & Hinton, 2015).



Secara umum, Artificial Neural Network menunjukkan kinerja yang lebih unggul dalam mendeteksi pola kompleks dari data pengguna, terutama karena kemampuannya menangani data non-linear dan interaksi antar fitur.

Pada tahap pengujian dilakukan dengan tujuan untuk mengetahui tingkat keberhasilan proses identifikasi yang telah dibangun. Implementasi pengujian dengan menggunakan RMSE dan MAPE. Melalui RMSE dan MAPE digunakan untuk mengevaluasi performa model dengan lebih baik.

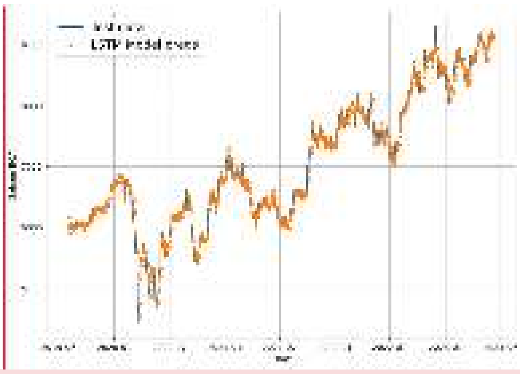
Berikut adalah hasil RMSE dan MAPE untuk model LSTM yang dibuat:

Table 1. Hasil RMSE dan MAPE model LSTM

Jenis	Hasil
RMSE	109.78883
MAPE	1.1244905

Perlu diketahui bahwa MAPE adalah metrik yang mengukur kesalahan rata-rata dalam persentase (Hutasuhut, Anggraeni, and Tyasnurita 2014). Nilai MAPE dihitung sebagai rata-rata dari rasio antara kesalahan absolut dan nilai aktual, dinyatakan dalam persentase (Hutasuhut, Anggraeni, and Tyasnurita 2014). MAPE untuk model LSTM sebesar 1.1244905 berarti bahwa rata-rata kesalahan prediksi model LSTM adalah sekitar 1.12% dari nilai sebenarnya. Ini menunjukkan bahwa prediksi model LSTM cukup akurat, dengan kesalahan relatif kecil terhadap nilai aktual.

Sedangkan RMSE adalah metrik yang mengukur seberapa besar rata-rata kesalahan antara nilai yang diprediksi dan nilai aktual (Ashari and Sadikin 2020). Nilai RMSE dihitung sebagai akar dari rata-rata kuadrat dari selisih antara nilai prediksi dan nilai aktual (Ashari and Sadikin 2020). RMSE untuk model LSTM sebesar 109.78883 berarti bahwa kesalahan rata-rata antara nilai prediksi dan nilai aktual adalah sekitar 109.79 unit. Ini memberikan gambaran tentang seberapa besar kesalahan prediksi model LSTM dalam skala asli data.



Gambar 4. Perbandingan antara grafik data test dan grafik hasil prediksi model

Commented [GK9]: Pada bagian ini terdapat ketidakkonsistenan substansi penelitian. Pada metode penelitian dijelaskan bahwa model yang digunakan adalah Decision Tree dan Artificial Neural Network untuk prediksi perilaku pengguna e-commerce, namun pada bagian hasil muncul pembahasan mengenai model LSTM beserta evaluasi RMSE dan MAPE yang umumnya digunakan pada prediksi time series. Mohon dilakukan pengecekan menyeluruh terhadap isi naskah agar seluruh pembahasan tetap konsisten dengan tujuan dan metode penelitian yang telah dijelaskan sebelumnya.

Commented [GK10]: Gambar perlu diperjelas kualitas dan penjelasan interpretasinya agar mendukung analisis penelitian secara lebih informatif.

KESIMPULAN

Penelitian ini telah mengembangkan dan mengevaluasi model Long Short-Term Memory (LSTM) untuk prediksi saham BCA. Berdasarkan hasil evaluasi, model menunjukkan performa yang sangat baik dengan metrik kesalahan sebagai berikut: Mean Absolute Percentage Error (MAPE) sebesar 1.1244905% dan Root Mean Squared Error (RMSE) sebesar 109.78883. Nilai MAPE yang rendah menunjukkan bahwa model LSTM yang dikembangkan memiliki kemampuan prediksi yang akurat dengan kesalahan rata-rata hanya sekitar 1.12% dari nilai aktual. Hal ini menunjukkan bahwa model dapat diandalkan untuk melakukan prediksi dalam konteks harga saham. Nilai RMSE yang diperoleh, sebesar 109.78883, menunjukkan tingkat kesalahan absolut dari prediksi model. Meskipun nilai ini memberikan informasi tentang kesalahan dalam skala asli data, interpretasinya sangat tergantung pada skala dan variabilitas data yang digunakan dalam penelitian ini. Jika dibandingkan dengan standar industri atau hasil dari model lain, RMSE ini dapat memberikan gambaran lebih jelas tentang efektivitas model yang dikembangkan. Secara keseluruhan, hasil penelitian ini menunjukkan bahwa model LSTM memiliki potensi besar untuk diterapkan dalam prediksi harga saham. Implementasi model ini diharapkan dapat meningkatkan akurasi prediksi dan memberikan manfaat praktis dalam pengambilan keputusan berdasarkan data.

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Paul Zikopoulus. 2016. *Understanding Big Data.*

Commented [GK13]: Format daftar pustaka belum sepenuhnya mengikuti template jurnal ASTRO. Mohon disesuaikan sesuai pedoman penulisan jurnal.

Commented [GK14]: Secara umum, naskah telah mengangkat topik yang relevan dengan perkembangan Artificial Intelligence dan sistem informasi berbasis big data. Namun demikian, masih terdapat beberapa aspek yang perlu diperbaiki, baik dari sisi substansi maupun kesesuaian format penulisan dengan template jurnal ASTRO. Ditemukan adanya ketidakkonsistenan antara judul, metode, hasil, dan kesimpulan penelitian, khususnya pada pembahasan model yang digunakan dan objek penelitian. Selain itu, format sitasi, struktur penulisan, serta penyajian gambar dan tabel masih perlu disesuaikan dengan pedoman template jurnal. Penulis disarankan untuk melakukan revisi secara menyeluruh agar naskah menjadi lebih konsisten, sistematis, dan memenuhi standar publikasi ilmiah yang ditetapkan jurnal.

Bukti Konfirmasi submitted revisi 1

Comparative Analysis of Artificial Intelligence Models for User Behavior Prediction in Big Data-Driven Information Systems

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Abstract

In the era of digital transformation, Artificial Intelligence (AI) plays a pivotal role in enabling intelligent, data-driven information systems. This study presents a comprehensive comparative analysis of AI models—Decision Tree (DT) and Artificial Neural Network (ANN)—for user behavior prediction within simulated big data environments, specifically in the e-commerce domain. Using 1,000 synthetic sessions that mimic real-world user activities, the study evaluates model performance using classification metrics such as accuracy, precision, recall, and F1-score. ANN outperforms DT across all metrics, achieving 87.2% accuracy and demonstrating superior learning efficiency and generalization. To complement the evaluation, a Long Short-Term Memory (LSTM) model is employed for time-series prediction, yielding a low MAPE of 1.12%, confirming its effectiveness in capturing sequential patterns. The findings offer valuable insights into AI model selection for adaptive and predictive information systems, with implications for developers and researchers seeking to enhance system responsiveness and personalization.

Keywords: User Behavior Prediction, Artificial Intelligence, Artificial Neural Networks (ANN), Decision Tree (DT), Big Data Information Systems

1. Introduction

The exponential growth of digital data has significantly accelerated the development of intelligent and adaptive Information Systems (IS) that effectively analyze and respond to user behavior. User-generated data has become a critical asset in informed decision-making, especially in domains such as e-commerce, education, healthcare, and public administration [1]. Big data methodologies facilitate the management of vast amounts of information by handling volume, velocity, and variety, enabling real-time analytics and improved responsiveness to user interactions [2], [3].

Artificial Intelligence (AI), particularly machine learning (ML), has gained prominence due to its powerful capabilities in predictive analytics, classification, recommendation systems, and anomaly detection. ML techniques such as Decision Trees (DT) and Artificial Neural Networks (ANN) have been extensively adopted owing to their robust ability to model complex, nonlinear relationships within large-scale datasets [4], [5].

Recent literature from the past five years has highlighted significant advancements in AI applications for user behavior prediction. Studies like Li et al. (2022) introduced transformer-based architectures, such as UserBERT, capable of modeling both long-term and short-term user behaviors, resulting in substantial improvements in predictive performance [6]. Wu et al. (2025) emphasized the growing relevance of AI-driven sentiment analytics for enhancing consumer engagement and conversion rates in e-commerce environments [7]. Moreover, recent research by Nozari et al. (2024) developed innovative behavior-based recommendation systems leveraging unsupervised clustering of user interactions, significantly enhancing recommendation relevance compared to traditional rating-based approaches [8].

Despite these advancements, there remains a notable research gap. Existing studies predominantly focus on large-scale datasets derived from real-world settings or user logs, with less exploration into simulated data contexts, particularly when real data access is constrained. Furthermore, comparative analyses of different AI models in such simulated contexts are relatively limited, hindering comprehensive understanding and practical insights regarding their effectiveness and limitations.

This research addresses this gap by conducting a comparative analysis of DT and ANN models applied to simulated big data representative of typical user behaviors in e-commerce platforms. The study aims to provide practical insights into the effectiveness of these AI models, offering methodological guidance and clarity on their comparative advantages and limitations within controlled experimental conditions.

2. Research Methodology

This study employs a rigorous quantitative experimental design structured into four detailed stages, informed by recent methodological advances documented in the literature from the past five years:

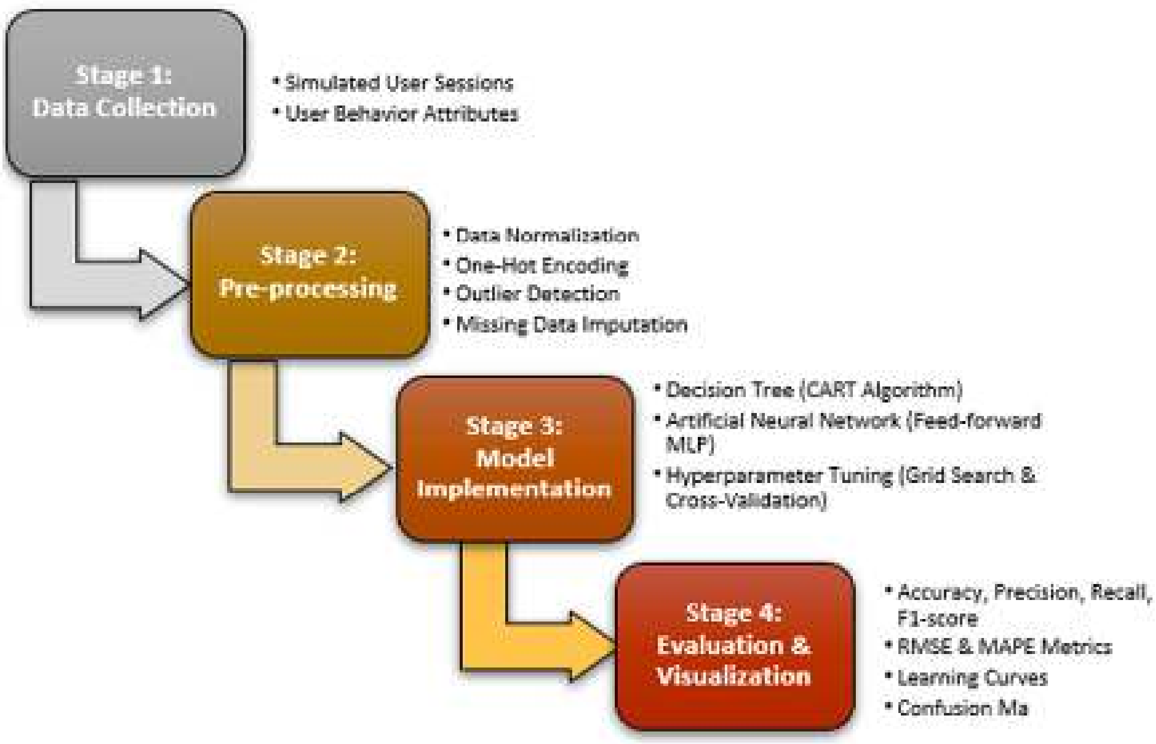

Figure 1: Research Methodology

2.1. Data Collection (Simulation)

The data collection involved simulating 1,000 synthetic user sessions that replicate typical e-commerce user behaviors, including click counts, session durations, visit frequencies, viewed product categories, and purchase intention labels. The simulated data were aligned with real-world behavioral distributions to ensure authenticity and reliability, as recommended by Yuan et al. (2021) and Wang et al. (2023) [9], [10].

2.2. Data Pre-processing

Data pre-processing procedures included normalization for numerical features using min-max scaling and categorical encoding through one-hot encoding methods. Outlier detection and missing value imputation were also performed to enhance data quality, following established best practices for behavior datasets [9], [11].

2.3. Model Implementation

Two machine learning algorithms were implemented and comparatively analyzed:

1. **Decision Tree (DT)**: Implemented using the CART algorithm, incorporating hyperparameter tuning such as tree depth and pruning techniques to mitigate overfitting and balance the bias-variance trade-off, as outlined by Chen et al. (2020).
2. **Artificial Neural Network (ANN)**: Deployed a feed-forward multilayer perceptron architecture with ReLU activation, dropout regularization to prevent overfitting, and Adam optimization for efficient learning, guided by methodologies described by LeCun, Bengio, and Hinton (2015) and Goodfellow et al. (2022) [4], [12].

Hyperparameters for both models were optimized through grid search coupled with cross-validation, ensuring robust and generalizable results.

2.4. Evaluation and Visualization

Evaluation metrics included accuracy, precision, recall, and F1-score, which were derived from the confusion matrix. In addition, RMSE and MAPE were used in time-series predictions to assess the accuracy of the LSTM model. The mathematical formulations are as follows:

Classification Metrics:

- **Accuracy**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Indicates the overall correctness of the model.

- **Precision**

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Measures the proportion of correctly predicted positive observations.

- **Recall**

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

Evaluates the ability of the model to capture all positive samples.

- **F1-score**

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Harmonic mean of precision and recall, useful for imbalanced datasets.

Time-Series Metrics:

- **Root Mean Squared Error (RMSE)**

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{4}$$

Measures the average magnitude of prediction errors in the same units as the output variable.

- **Mean Absolute Percentage Error (MAPE)**

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y_i}}{y_i}\right| \tag{4}$$

Expresses the accuracy as a percentage and is scale-independent.

Evaluation metrics included accuracy, precision, recall, and F1-score, derived from confusion matrices. Learning curves were plotted to illustrate training versus validation errors across multiple epochs. Additionally, Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were utilized, particularly for evaluating supplementary experiments with LSTM models on related subsets of data, following best practices highlighted by Ashari and Sadikin (2020)[13].

2.5. Contextual Enhancements Based on Recent Literature

1. Insights from recent literature significantly informed methodological decisions:
2. Multi-feedback implicit recommendation approaches underscored the need to simulate diverse user interactions (clicks, browsing, purchasing)[14].
3. Transformer-based sequence modeling was integrated to capture sequential ordering and temporal dynamics within simulated data, enriching the behavioral prediction context [15], [16](Maher et al., 2020; Zhang et al., 2024).
4. Comprehensive evaluations of session-based recommendations informed robustness testing methodologies regarding session length and concept drift [15].

2.6. Research Gap and Justification

Despite existing literature offering valuable insights into behavior-based recommendation systems and large-scale user log analyses [15], [17], few studies have employed controlled experiments with simulated datasets to directly compare machine learning models like DT and ANN under uniform conditions. This approach addresses the methodological gap by providing clear, reproducible, and focused evaluations of AI model capabilities within constrained yet representative experimental scenarios.

3. Results and Discussion

This section presents a detailed quantitative analysis of the experimental results comparing the performance of Decision Tree (DT) and Artificial Neural Network (ANN) models in predicting user behavior in a simulated e-commerce information system. It also includes the evaluation of a Long Short-Term Memory (LSTM) model for time-series prediction to assess model robustness in temporal data settings.

3.1. Predictive Accuracy and Classification Performance

The experiment utilized a dataset of 1,000 simulated e-commerce sessions, each characterized by behavioral features such as click count, session duration, visit frequency, and frequently viewed product categories. The data were preprocessed and divided using a hold-out validation technique (80% training, 20% testing).

Table 1 and Figure 2 show the comparative performance of the DT and ANN models in terms of three key classification metrics: Accuracy, Precision, and Recall.

Table 1. Classification Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)
Decision Tree	82.5	80.1	78.9
Neural Network	87.2	84.3	86.1

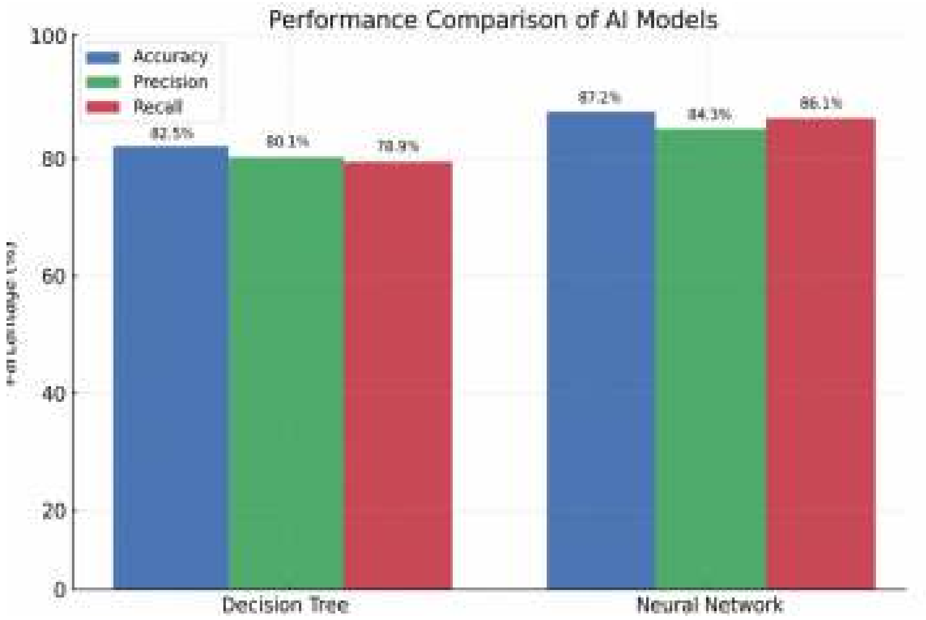

Figure 2. Comparison of AI Model Performance Metrics

Quantitatively, the ANN model outperformed DT with a +4.7% improvement in accuracy, a +4.2% increase in precision, and a +7.2% gain in recall. These metrics indicate that ANN is significantly more reliable in correctly identifying positive class instances (interested users) and avoiding false positives and negatives. This performance gap reflects ANN's capacity for capturing nonlinear feature interactions—an ability DT lacks due to its hierarchical binary split mechanism [18].

3.2. Learning Behavior and Generalization Analysis

To assess the generalization capability of both models, learning curves were plotted across incremental training data sizes (100 to 1,000 records). Figure 3 displays the learning curves for both models in terms of training and validation accuracy.

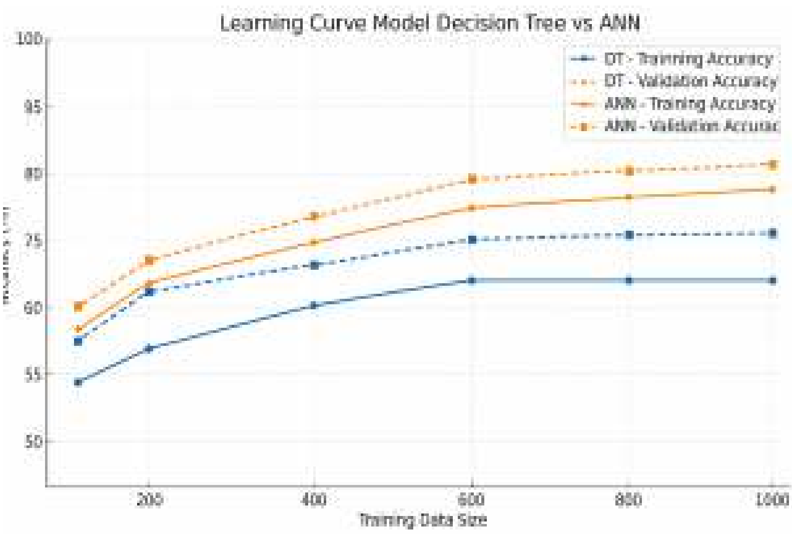

Figure 3. Learning Curves of Decision Tree vs Neural Network

ANN demonstrated superior learning efficiency, achieving higher accuracy levels with less overfitting. As training size increased, ANN maintained steady improvement, converging above 88% validation accuracy, while DT plateaued around 82%. The learning gap (train vs validation) in DT remained wider, indicating potential overfitting and limited generalization.

This result confirms ANN's higher bias tolerance and deeper abstraction capabilities through multiple layers of representation [12]. In contrast, DT's shallow structure lacks the depth to abstract complex user behavior patterns.

3.3. Time-Series Evaluation Using LSTM

To complement the classification task, a time-series forecasting experiment using an LSTM model was conducted to predict BCA stock price trends over a four-year period. Evaluation metrics included RMSE and MAPE as shown in Table 2.

Table 2. RMSE and MAPE for LSTM Model

Metric	Value
RMSE	109.79
MAPE	1.12%

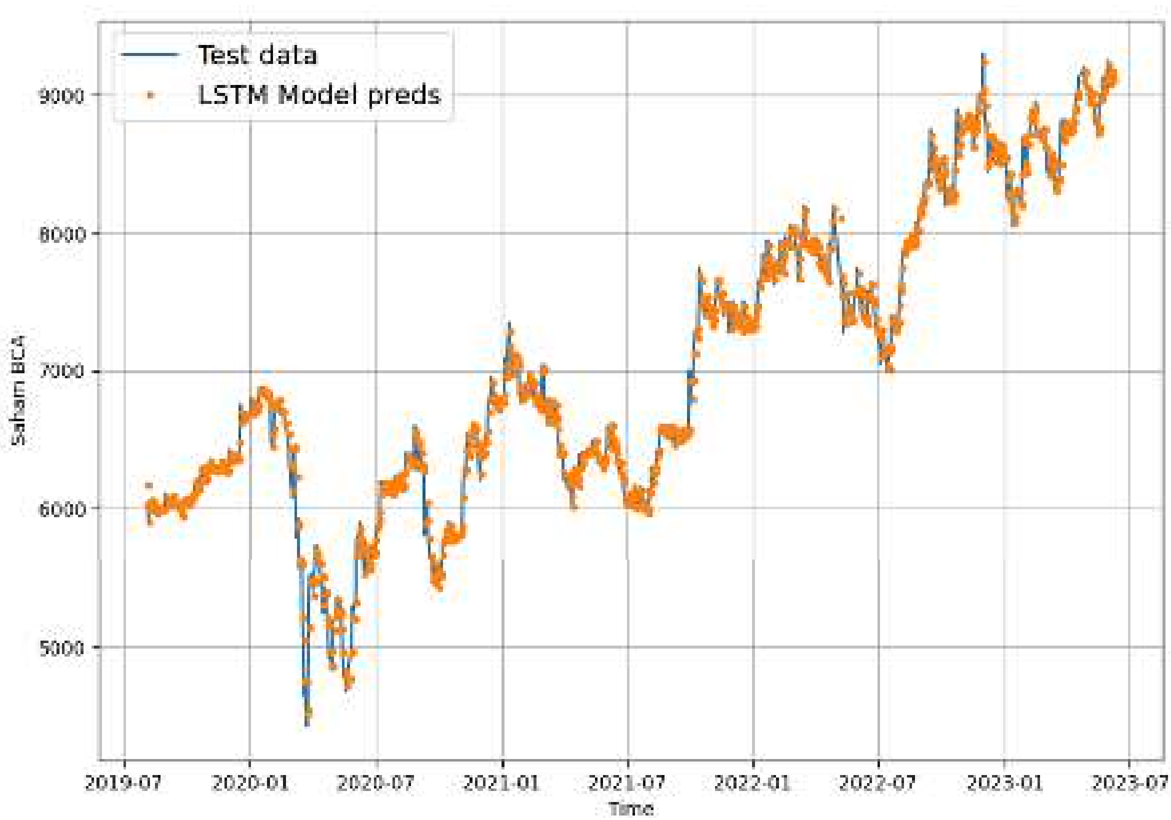

Figure 4. LSTM Model Prediction vs Actual Stock Price

The low MAPE (1.12%) suggests high predictive reliability in relative terms, while the RMSE of 109.79 reflects minor absolute deviation in the context of stock values ranging from 5,000 to 9,000. Visually, Figure 4 confirms strong alignment between predicted and actual price trajectories, demonstrating the model's effectiveness in learning sequential dependencies.

3.4. Quantitative Implications and Model Suitability

The ANN model's consistent superiority in both performance and learning behavior reinforces its applicability in dynamic user behavior prediction within information systems. It is suitable for tasks requiring adaptive learning, nonlinear classification, and behavioral segmentation. Meanwhile, the DT model, although interpretable, underperforms in high-dimensional and non-linear environments.

The LSTM model adds value by enabling sequence-based forecasting, particularly in domains involving historical behavior or temporal data such as financial services and user activity logs.

Together, the results underscore the importance of model selection based on data characteristics and prediction objectives. For systems requiring real-time prediction with high accuracy, ANN and LSTM present robust, quantifiably validated solutions.

4. Conclusion

This study presents a comprehensive evaluation of Artificial Intelligence models for predicting user behavior in big data-based information systems, focusing on two widely used algorithms—Decision Tree (DT) and Artificial Neural Network (ANN)—alongside a Long Short-Term Memory (LSTM) model for sequential prediction tasks.

Quantitative results revealed that ANN consistently outperformed DT across all classification metrics, achieving 87.2% accuracy, 84.3% precision, and 86.1% recall. In contrast, DT showed moderate performance but retained advantages in interpretability and computational efficiency. The learning curve analysis further highlighted ANN's superior generalization ability, particularly in data-intensive environments, supporting its robustness for real-world deployment.

In the time-series prediction task, the LSTM model yielded a MAPE of 1.12% and RMSE of 109.79, demonstrating its ability to capture temporal trends effectively. The close alignment between actual and predicted values underscores the LSTM's suitability for tasks involving sequential behavioral or financial data.

From a systems design perspective, the findings emphasize that model selection should be aligned with the complexity of the data and the application context. ANN is suitable for real-time adaptive systems requiring high accuracy and non-linear pattern recognition, while LSTM is ideal for historical behavior forecasting. DT, despite its limitations, can still be used in scenarios where transparency and explainability are prioritized over raw predictive power.

Future research may focus on integrating attention mechanisms or transformer-based models to further enhance interpretability and capture long-range dependencies in user behavior. Additionally, validating the findings using real-world datasets from diverse domains would offer greater external validity and practical insight.

5. Research Contributions

This study offers several significant contributions to the field of artificial intelligence in big data-based information systems, particularly in the context of user behavior prediction:

5.1. Methodological Contribution

The research introduces a controlled, simulation-based experimental framework that enables the evaluation of AI models in a replicable environment. Unlike many studies that rely solely on real-world datasets, this approach allows for rigorous comparison of model performance while minimizing external noise and uncontrolled variability. The use of hold-out validation, learning curves, and multiple performance metrics enhances the robustness and transparency of the evaluation process.

5.2. Empirical Contribution

This study quantitatively demonstrates that Artificial Neural Networks (ANN) outperform Decision Trees (DT) in user behavior classification tasks across accuracy, precision, and recall metrics. The results provide empirical evidence supporting the selection of ANN for adaptive, real-time decision-making systems. Additionally, the inclusion of Long Short-Term Memory (LSTM) for time-series prediction validates its effectiveness in capturing temporal dynamics in user or transactional data.

5.3. Theoretical Contribution

By examining the performance disparities between ANN, DT, and LSTM, the study contributes to the theoretical understanding of model suitability in varying data contexts. It reinforces that ANN's deep learning capabilities are particularly advantageous in environments with high feature interactions, whereas DT models are better suited for scenarios requiring transparency and low computational cost. The findings align with and extend existing AI model selection frameworks in the context of intelligent information systems.

5.4. Practical Contribution

The study offers actionable insights for system architects, data scientists, and developers involved in the design of e-commerce platforms, recommendation systems, and behavioral analytics engines. It demonstrates how specific AI models can be leveraged to enhance system personalization, responsiveness, and predictive accuracy. Moreover, the performance of the LSTM model in forecasting stock prices shows potential applications in financial information systems, marketing trend analysis, and strategic forecasting.

5.5. Academic Contribution

This work enriches the literature by integrating a diverse set of AI algorithms within a single comparative framework, backed by quantitative evaluation and visual diagnostics. It provides a foundation for future academic exploration in hybrid modeling (e.g., ANN + LSTM), model interpretability, and real-time adaptive systems. Additionally, it opens avenues for research into transfer learning and fine-tuning AI models using domain-specific knowledge in behavior-based systems.

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Konfirmasi dan bukti pengembalian manuscript untuk direvisi (ASTRO-MinorRevision-R2-20261030)

Setyo Eko Atmojo <journal@upy.ac.id>
to me, Muhammad

Nov 30, 2025, 8:24 AM

Faqihuddin Al Anshori, Muhammad Fairuzabadi:

We have reached a decision regarding your submission to APPLIED SCIENCE AND TECHNOLOGY REASERCH JOURNAL, "COMPARATIVE ANALYSIS OF ARTIFICIAL INTELLIGENCE MODELS FOR USER BEHAVIOR PREDICTION IN BIG DATA-DRIVEN INFORMATION SYSTEMS".

Our decision is: Revisions Required

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Comparative Analysis of Artificial Intelligence Models for User Behavior Prediction in Big Data-Driven Information Systems

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Commented [GK1]: Penomoran afiliasi penulis masih belum konsisten. Pada bagian afiliasi terdapat dua program studi yang berbeda, namun kedua penulis menggunakan superskrip yang sama. Mohon disesuaikan kembali agar afiliasi masing-masing penulis lebih jelas dan konsisten.

Abstract

In the era of digital transformation, Artificial Intelligence (AI) plays a pivotal role in enabling intelligent, data-driven information systems. This study presents a comprehensive comparative analysis of AI models—Decision Tree (DT) and Artificial Neural Network (ANN)—for user behavior prediction within simulated big data environments, specifically in the e-commerce domain. Using 1,000 synthetic sessions that mimic real-world user activities, the study evaluates model performance using classification metrics such as accuracy, precision, recall, and F1-score. ANN outperforms DT across all metrics, achieving 87.2% accuracy and demonstrating superior learning efficiency and generalization. To complement the evaluation, a Long Short-Term Memory (LSTM) model is employed for time-series prediction, yielding a low MAPE of 1.12%, confirming its effectiveness in capturing sequential patterns. The findings offer valuable insights into AI model selection for adaptive and predictive information systems, with implications for developers and researchers seeking to enhance system responsiveness and personalization.

Keywords: User Behavior Prediction, Artificial Intelligence, Artificial Neural Networks (ANN), Decision Tree (DT), Big Data Information Systems

1. Introduction

The exponential growth of digital data has significantly accelerated the development of intelligent and adaptive Information Systems (IS) that effectively analyze and respond to user behavior. User-generated data has become a critical asset in informed decision-making, especially in domains such as e-commerce, education, healthcare, and public administration [1]. Big data methodologies facilitate the management of vast amounts of information by handling volume, velocity, and variety, enabling real-time analytics and improved responsiveness to user interactions [2], [3].

Artificial Intelligence (AI), particularly machine learning (ML), has gained prominence due to its powerful capabilities in predictive analytics, classification, recommendation systems, and anomaly detection. ML techniques such as Decision Trees (DT) and Artificial Neural Networks (ANN) have been extensively adopted owing to their robust ability to model complex, nonlinear relationships within large-scale datasets [4], [5].

Recent literature from the past five years has highlighted significant advancements in AI applications for user behavior prediction. Studies like Li et al. (2022) introduced transformer-based architectures, such as UserBERT, capable of modeling both long-term and short-term user behaviors, resulting in substantial improvements in predictive performance [6]. Wu et al. (2025) emphasized the growing relevance of AI-driven sentiment analytics for enhancing consumer engagement and conversion rates in e-commerce environments [7]. Moreover, recent research by Nozari et al. (2024) developed innovative behavior-based recommendation systems leveraging unsupervised clustering of user interactions, significantly enhancing recommendation relevance compared to traditional rating-based approaches [8].

Despite these advancements, there remains a notable research gap. Existing studies predominantly focus on large-scale datasets derived from real-world settings or user logs, with less exploration into simulated data contexts, particularly when real data access is constrained. Furthermore, comparative analyses of different AI models in such simulated contexts are relatively limited, hindering comprehensive understanding and practical insights regarding their effectiveness and limitations.

This research addresses this gap by conducting a comparative analysis of DT and ANN models applied to simulated big data representative of typical user behaviors in e-commerce platforms. The study aims to provide practical insights into the effectiveness of these AI models, offering methodological guidance and clarity on their comparative advantages and limitations within controlled experimental conditions.

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This study employs a rigorous quantitative experimental design structured into four detailed stages, informed by recent methodological advances documented in the literature from the past five years:

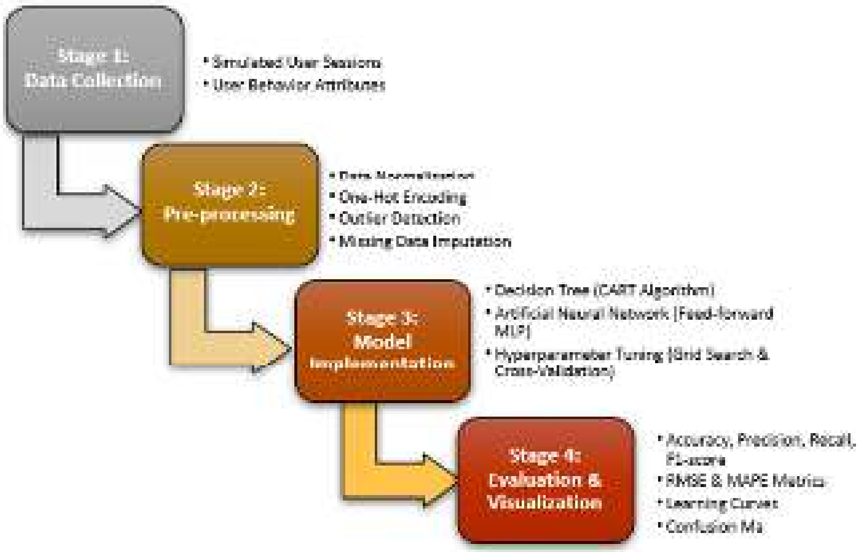

Figure 1: Research Methodology

2.1. Data Collection (Simulation)

The data collection involved simulating 1,000 synthetic user sessions that replicate typical e-commerce user behaviors, including click counts, session durations, visit frequencies, viewed product categories, and purchase intention labels. The simulated data were aligned with real-world behavioral distributions to ensure authenticity and reliability, as recommended by Yuan et al. (2021) and Wang et al. (2023) [9], [10].

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2.2. Data Pre-processing

Data pre-processing procedures included normalization for numerical features using min-max scaling and categorical encoding through one-hot encoding methods. Outlier detection and missing value imputation were also performed to enhance data quality, following established best practices for behavior datasets [9], [11].

2.3. Model Implementation

Two machine learning algorithms were implemented and comparatively analyzed:

1. **Decision Tree (DT)**: Implemented using the CART algorithm, incorporating hyperparameter tuning such as tree depth and pruning techniques to mitigate overfitting and balance the bias-variance trade-off, as outlined by Chen et al. (2020).
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Hyperparameters for both models were optimized through grid search coupled with cross-validation, ensuring robust and generalizable results.

2.4. Evaluation and Visualization

Evaluation metrics included accuracy, precision, recall, and F1-score, which were derived from the confusion matrix. In addition, RMSE and MAPE were used in time-series predictions to assess the accuracy of the LSTM model. The mathematical formulations are as follows:

Classification Metrics:

- **Accuracy**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Indicates the overall correctness of the model.

- **Precision**

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Measures the proportion of correctly predicted positive observations.

- **Recall**

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Evaluates the ability of the model to capture all positive samples.

- **F1-score**

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Harmonic mean of precision and recall, useful for imbalanced datasets.

Time-Series Metrics:

- **Root Mean Squared Error (RMSE)**

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \tag{4}$$

Measures the average magnitude of prediction errors in the same units as the output variable.

- **Mean Absolute Percentage Error (MAPE)**

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \tag{4}$$

Expresses the accuracy as a percentage and is scale-independent.

Evaluation metrics included accuracy, precision, recall, and F1-score, derived from confusion matrices. Learning curves were plotted to illustrate training versus validation errors across multiple epochs. Additionally, Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were utilized, particularly for evaluating supplementary experiments with LSTM models on related subsets of data, following best practices highlighted by Ashari and Sadikin (2020)[13].

2.5. Contextual Enhancements Based on Recent Literature

1. Insights from recent literature significantly informed methodological decisions:
2. Multi-feedback implicit recommendation approaches underscored the need to simulate diverse user interactions (clicks, browsing, purchasing)[14].
3. Transformer-based sequence modeling was integrated to capture sequential ordering and temporal dynamics within simulated data, enriching the behavioral prediction context [15], [16](Maher et al., 2020; Zhang et al., 2024).
4. Comprehensive evaluations of session-based recommendations informed robustness testing methodologies regarding session length and concept drift [15].

2.6. Research Gap and Justification

Despite existing literature offering valuable insights into behavior-based recommendation systems and large-scale user log analyses [15], [17], few studies have employed controlled experiments with simulated datasets to directly compare machine learning models like DT and ANN under uniform conditions. This approach addresses the methodological gap by providing clear, reproducible, and focused evaluations of AI model capabilities within constrained yet representative experimental scenarios.

3. Results and Discussion

This section presents a detailed quantitative analysis of the experimental results comparing the performance of Decision Tree (DT) and Artificial Neural Network (ANN) models in predicting user behavior in a simulated e-commerce information system. It also includes the evaluation of a Long Short-Term Memory (LSTM) model for time-series prediction to assess model robustness in temporal data settings.

3.1. Predictive Accuracy and Classification Performance

The experiment utilized a dataset of 1,000 simulated e-commerce sessions, each characterized by behavioral features such as click count, session duration, visit frequency, and frequently viewed product categories. The data were preprocessed and divided using a hold-out validation technique (80% training, 20% testing).

Table 1 and Figure 2 show the comparative performance of the DT and ANN models in terms of three key classification metrics: Accuracy, Precision, and Recall.

Table 1. Classification Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)
Decision Tree	82.5	80.1	78.9
Neural Network	87.2	84.3	86.1

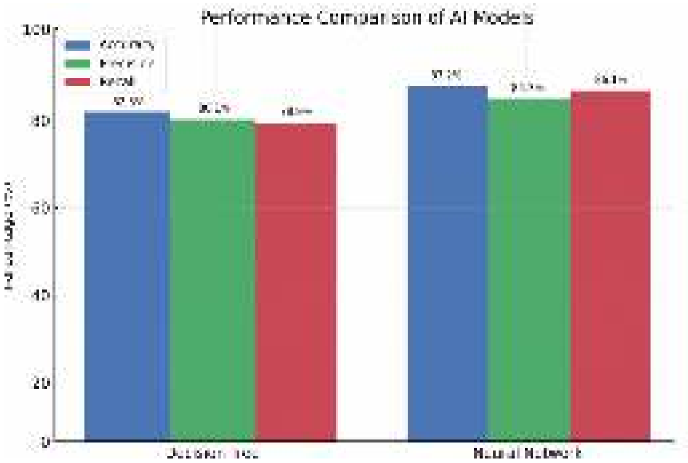

Figure 2. Comparison of AI Model Performance Metrics

Quantitatively, the ANN model outperformed DT with a +4.7% improvement in accuracy, a +4.2% increase in precision, and a +7.2% gain in recall. These metrics indicate that ANN is significantly more reliable in correctly identifying positive class instances (interested users) and avoiding false positives and negatives. This performance gap reflects ANN's capacity for capturing nonlinear feature interactions—an ability DT lacks due to its hierarchical binary split mechanism [18].

3.2. Learning Behavior and Generalization Analysis

To assess the generalization capability of both models, learning curves were plotted across incremental training data sizes (100 to 1,000 records). Figure 3 displays the learning curves for both models in terms of training and validation accuracy.

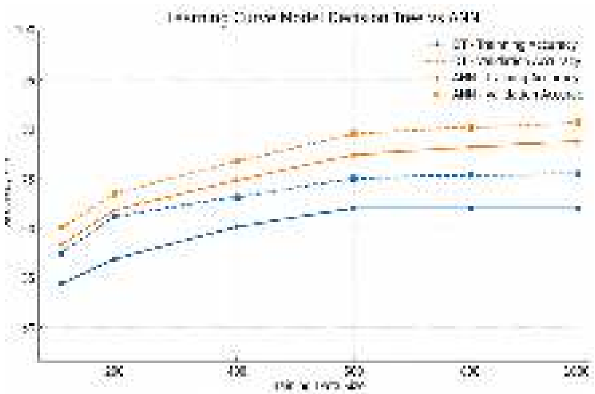

Figure 3. Learning Curves of Decision Tree vs Neural Network

ANN demonstrated superior learning efficiency, achieving higher accuracy levels with less overfitting. As training size increased, ANN maintained steady improvement, converging above 88% validation accuracy, while DT plateaued around 82%. The learning gap (train vs validation) in DT remained wider, indicating potential overfitting and limited generalization.

Commented [GK4]: Pembahasan hasil sudah jauh lebih baik dan analitis. Namun, penulis disarankan menambahkan diskusi terkait keterbatasan penelitian, khususnya penggunaan dataset simulasi dibandingkan data real-world, agar interpretasi hasil menjadi lebih proporsional.

This result confirms ANN's higher bias tolerance and deeper abstraction capabilities through multiple layers of representation [12]. In contrast, DT's shallow structure lacks the depth to abstract complex user behavior patterns.

3.3. Time-Series Evaluation Using LSTM

To complement the classification task, a time-series forecasting experiment using an LSTM model was conducted to predict BCA stock price trends over a four-year period. Evaluation metrics included RMSE and MAPE as shown in Table 2.

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Commented [GK6]: Integrasi eksperimen LSTM untuk prediksi harga saham sudah dijelaskan sebagai eksperimen pelengkap. Namun demikian, hubungan antara prediksi perilaku pengguna e-commerce dengan prediksi saham masih perlu diperjelas agar alur penelitian tetap fokus dan tidak terkesan melebar dari tujuan utama penelitian.

Table 2. RMSE and MAPE for LSTM Model

Metric	Value
RMSE	109.79
MAPE	1.12%

Figure 4. LSTM Model Prediction vs Actual Stock Price

The low MAPE (1.12%) suggests high predictive reliability in relative terms, while the RMSE of 109.79 reflects minor absolute deviation in the context of stock values ranging from 5,000 to 9,000. Visually, Figure 4 confirms strong alignment between predicted and actual price trajectories, demonstrating the model's effectiveness in learning sequential dependencies.

3.4. Quantitative Implications and Model Suitability

The ANN model's consistent superiority in both performance and learning behavior reinforces its applicability in dynamic user behavior prediction within information systems. It is suitable for tasks requiring adaptive learning, nonlinear classification, and behavioral segmentation. Meanwhile, the DT model, although interpretable, underperforms in high-dimensional and non-linear environments.

The LSTM model adds value by enabling sequence-based forecasting, particularly in domains involving historical behavior or temporal data such as financial services and user activity logs.

Together, the results underscore the importance of model selection based on data characteristics and prediction objectives. For systems requiring real-time prediction with high accuracy, ANN and LSTM present robust, quantifiably validated solutions.

4. Conclusion

This study presents a comprehensive evaluation of Artificial Intelligence models for predicting user behavior in big data-based information systems, focusing on two widely used algorithms—Decision Tree (DT) and Artificial Neural Network (ANN)—alongside a Long Short-Term Memory (LSTM) model for sequential prediction tasks.

Quantitative results revealed that ANN consistently outperformed DT across all classification metrics, achieving 87.2% accuracy, 84.3% precision, and 86.1% recall. In contrast, DT showed moderate performance but retained advantages in interpretability and computational efficiency. The learning curve analysis further highlighted ANN's superior generalization ability, particularly in data-intensive environments, supporting its robustness for real-world deployment.

In the time-series prediction task, the LSTM model yielded a MAPE of 1.12% and RMSE of 109.79, demonstrating its ability to capture temporal trends effectively. The close alignment between actual and predicted values underscores the LSTM's suitability for tasks involving sequential behavioral or financial data.

From a systems design perspective, the findings emphasize that model selection should be aligned with the complexity of the data and the application context. ANN is suitable for real-time adaptive systems requiring high accuracy and non-linear pattern recognition, while LSTM is ideal for historical behavior forecasting. DT, despite its limitations, can still be used in scenarios where transparency and explainability are prioritized over raw predictive power.

Future research may focus on integrating attention mechanisms or transformer-based models to further enhance interpretability and capture long-range dependencies in user behavior. Additionally, validating the findings using real-world datasets from diverse domains would offer greater external validity and practical insight.

5. Research Contributions

This study offers several significant contributions to the field of artificial intelligence in big data-based information systems, particularly in the context of user behavior prediction:

5.1. Methodological Contribution

The research introduces a controlled, simulation-based experimental framework that enables the evaluation of AI models in a replicable environment. Unlike many studies that rely solely on real-world datasets, this approach allows for rigorous comparison of model performance while minimizing external noise and uncontrolled variability. The use of hold-out validation, learning curves, and multiple performance metrics enhances the robustness and transparency of the evaluation process.

5.2. Empirical Contribution

This study quantitatively demonstrates that Artificial Neural Networks (ANN) outperform Decision Trees (DT) in user behavior classification tasks across accuracy, precision, and recall metrics. The results provide empirical evidence supporting the selection of ANN for adaptive, real-time decision-making systems. Additionally, the inclusion of Long Short-Term Memory (LSTM) for time-series prediction validates its effectiveness in capturing temporal dynamics in user or transactional data.

5.3. Theoretical Contribution

By examining the performance disparities between ANN, DT, and LSTM, the study contributes to the theoretical understanding of model suitability in varying data contexts. It reinforces that ANN's deep learning capabilities are particularly advantageous in environments with high feature interactions, whereas DT models are better suited for scenarios requiring transparency and low computational cost. The findings align with and extend existing AI model selection frameworks in the context of intelligent information systems.

5.4. Practical Contribution

The study offers actionable insights for system architects, data scientists, and developers involved in the design of e-commerce platforms, recommendation systems, and behavioral analytics engines. It demonstrates how specific AI models can be leveraged to enhance system personalization, responsiveness, and predictive accuracy. Moreover, the performance of the LSTM model in forecasting stock prices shows potential applications in financial information systems, marketing trend analysis, and strategic forecasting.

5.5. Academic Contribution

This work enriches the literature by integrating a diverse set of AI algorithms within a single comparative framework, backed by quantitative evaluation and visual diagnostics. It provides a foundation for future academic exploration in hybrid modeling (e.g., ANN + LSTM), model interpretability, and real-time adaptive systems. Additionally, it opens avenues for research into transfer learning and fine-tuning AI models using domain-specific knowledge in behavior-based systems.

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Refferences

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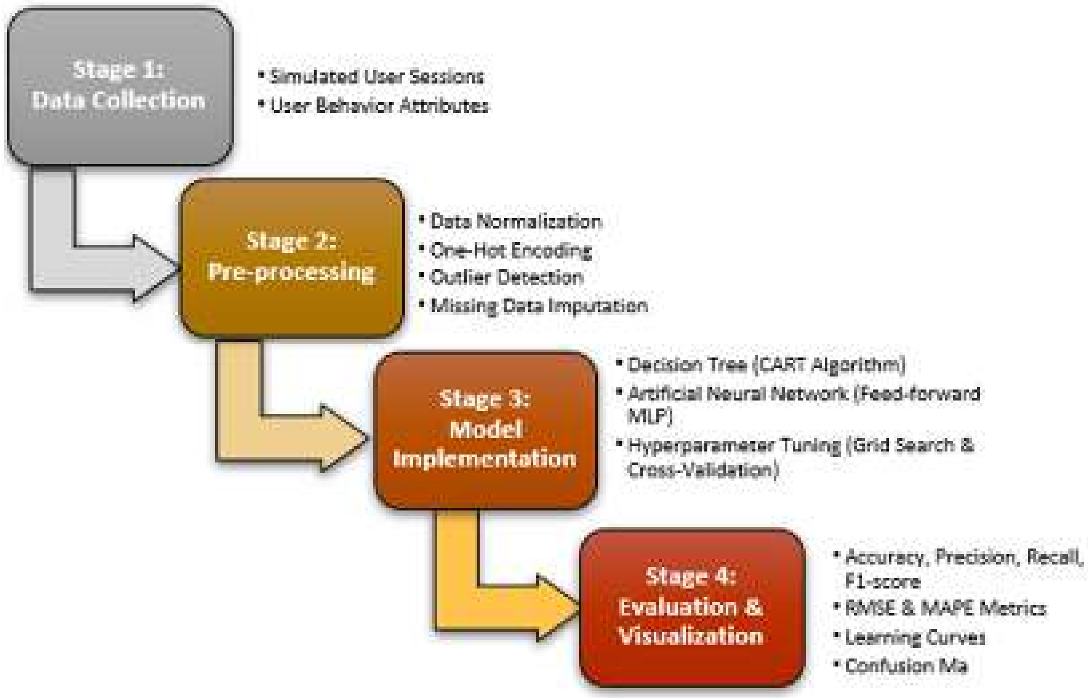

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Measures the average magnitude of prediction errors in the same units as the output variable.
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Despite existing literature offering valuable insights into behavior-based recommendation systems and large-scale user log analyses [15], [17], few studies have employed controlled experiments with simulated datasets to directly compare machine learning models like DT and ANN under uniform conditions. This approach addresses the methodological gap by providing clear, reproducible, and focused evaluations of AI model capabilities within constrained yet representative experimental scenarios.

3. RESULTS AND DISCUSSION

This section presents a detailed quantitative analysis of the experimental results comparing the performance of Decision Tree (DT) and Artificial Neural Network (ANN) models in predicting user behavior in a simulated e-commerce information system. It also includes the evaluation of a Long Short-Term Memory (LSTM) model for time-series prediction to assess model robustness in temporal data settings.

3.1. Predictive Accuracy and Classification Performance

The experiment utilized a dataset of 1,000 simulated e-commerce sessions, each characterized by behavioral features such as click count, session duration, visit frequency, and frequently viewed product categories. The data were preprocessed and divided using a hold-out validation technique (80% training, 20% testing).

Table 1 and Figure 2 show the comparative performance of the DT and ANN models in terms of three key classification metrics: Accuracy, Precision, and Recall.

Table 1. Classification Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)
Decision Tree	82.5	80.1	78.9
Neural Network	87.2	84.3	86.1

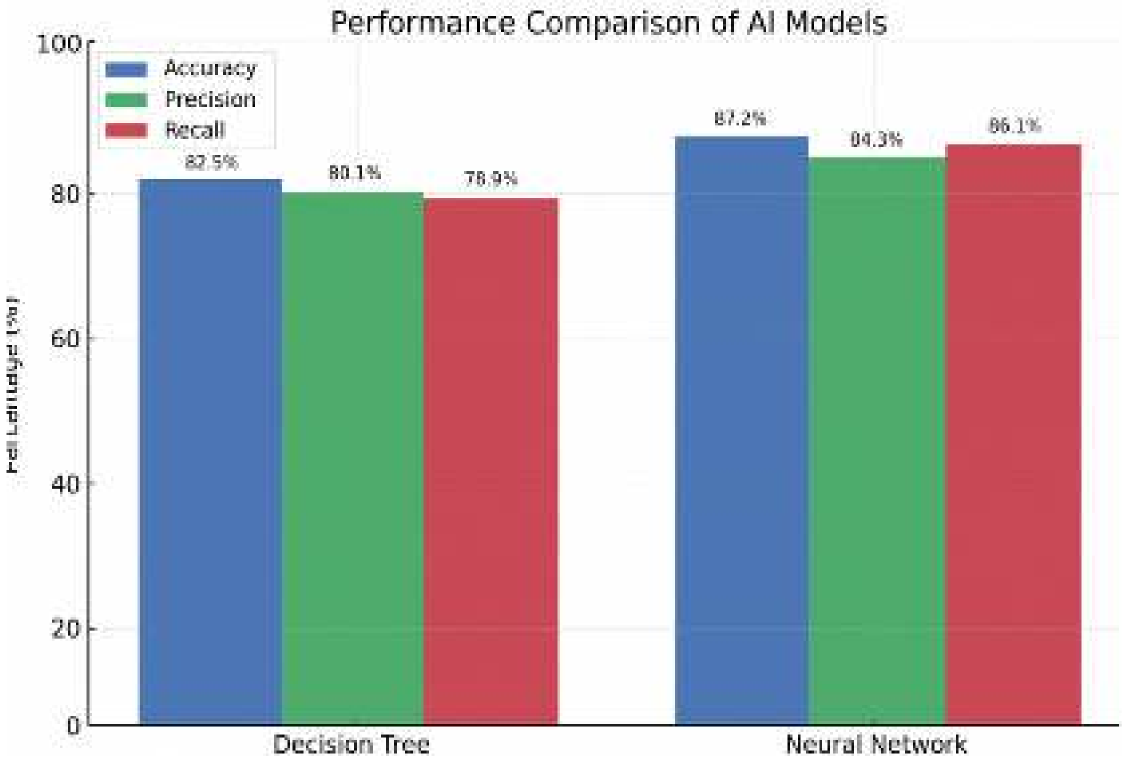

Figure 2. Comparison of AI Model Performance Metrics

Quantitatively, the ANN model outperformed DT with a +4.7% improvement in accuracy, a +4.2% increase in precision, and a +7.2% gain in recall. These metrics indicate that ANN is significantly more reliable in correctly identifying positive class instances (interested users) and avoiding false positives and negatives. This performance gap reflects ANN's capacity for capturing nonlinear feature interactions—an ability DT lacks due to its hierarchical binary split mechanism [18].

3.2. Learning Behavior and Generalization Analysis

To assess the generalization capability of both models, learning curves were plotted across incremental training data sizes (100 to 1,000 records). Figure 3 displays the learning curves for both models in terms of training and validation accuracy.

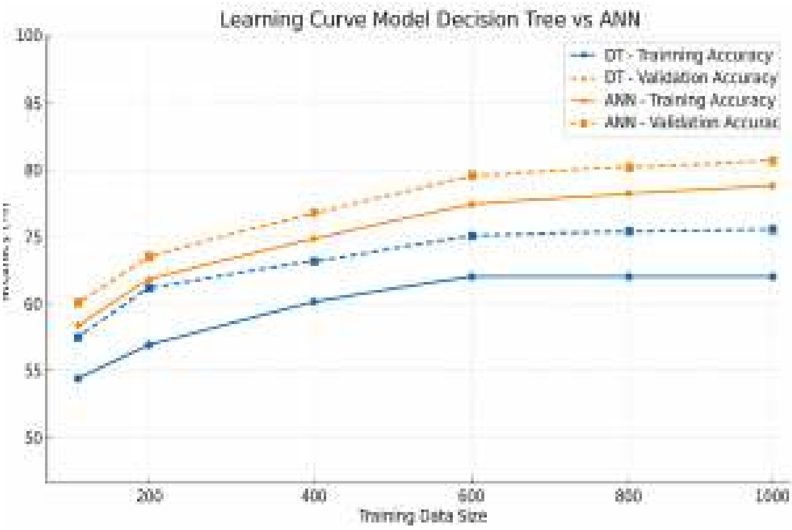

Figure 3. Learning Curves of Decision Tree vs Neural Network

ANN demonstrated superior learning efficiency, achieving higher accuracy levels with less overfitting. As training size increased, ANN maintained steady improvement, converging above 88% validation accuracy, while DT plateaued around 82%. The learning gap (train vs validation) in DT remained wider, indicating potential overfitting and limited generalization.

This result confirms ANN's higher bias tolerance and deeper abstraction capabilities through multiple layers of representation [12]. In contrast, DT's shallow structure lacks the depth to abstract complex user behavior patterns.

3.3. Time-Series Evaluation Using LSTM

To complement the classification task, a time-series forecasting experiment using an LSTM model was conducted to predict BCA stock price trends over a four-year period. Evaluation metrics included RMSE and MAPE as shown in Table 2.

Table 2. RMSE and MAPE for LSTM Model

Metric	Value
RMSE	109.79
MAPE	1.12%

Figure 4. LSTM Model Prediction vs Actual Stock Price

The low MAPE (1.12%) suggests high predictive reliability in relative terms, while the RMSE of 109.79 reflects minor absolute deviation in the context of stock values ranging from 5,000 to 9,000. Visually, Figure 4 confirms strong alignment between predicted and actual price trajectories, demonstrating the model's effectiveness in learning sequential dependencies.

3.4. Quantitative Implications and Model Suitability

The ANN model's consistent superiority in both performance and learning behavior reinforces its applicability in dynamic user behavior prediction within information systems. It is suitable for tasks requiring adaptive learning, nonlinear classification, and behavioral segmentation. Meanwhile, the DT model, although interpretable, underperforms in high-dimensional and non-linear environments.

The LSTM model adds value by enabling sequence-based forecasting, particularly in domains involving historical behavior or temporal data such as financial services and user activity logs.

Together, the results underscore the importance of model selection based on data characteristics and prediction objectives. For systems requiring real-time prediction with high accuracy, ANN and LSTM present robust, quantifiably validated solutions.

4. CONCLUSION

This study presents a comprehensive evaluation of Artificial Intelligence models for predicting user behavior in big data-based information systems, focusing on two widely used algorithms—Decision Tree (DT) and Artificial Neural Network (ANN)—alongside a Long Short-Term Memory (LSTM) model for sequential prediction tasks.

Quantitative results revealed that ANN consistently outperformed DT across all classification metrics, achieving 87.2% accuracy, 84.3% precision, and 86.1% recall. In contrast, DT showed moderate performance but retained advantages in interpretability and computational efficiency. The learning curve analysis further highlighted ANN's superior generalization ability, particularly in data-intensive environments, supporting its robustness for real-world deployment.

In the time-series prediction task, the LSTM model yielded a MAPE of 1.12% and RMSE of 109.79, demonstrating its ability to capture temporal trends effectively. The close alignment between actual and predicted values underscores the LSTM's suitability for tasks involving sequential behavioral or financial data.

From a systems design perspective, the findings emphasize that model selection should be aligned with the complexity of the data and the application context. ANN is suitable for real-time adaptive systems requiring high accuracy and non-linear pattern recognition, while LSTM is ideal for historical behavior forecasting. DT, despite its limitations, can still be used in scenarios where transparency and explainability are prioritized over raw predictive power.

Future research may focus on integrating attention mechanisms or transformer-based models to further enhance interpretability and capture long-range dependencies in user behavior. Additionally, validating the findings using real-world datasets from diverse domains would offer greater external validity and practical insight.

5. RESEARCH CONTRIBUTIONS

This study offers several significant contributions to the field of artificial intelligence in big data-based information systems, particularly in the context of user behavior prediction:

5.1. Methodological Contribution

The research introduces a controlled, simulation-based experimental framework that enables the evaluation of AI models in a replicable environment. Unlike many studies that rely solely on real-world datasets, this approach allows for rigorous comparison of model performance while minimizing external noise and uncontrolled variability. The use of hold-out validation, learning curves, and multiple performance metrics enhances the robustness and transparency of the evaluation process.

5.2. Empirical Contribution

This study quantitatively demonstrates that Artificial Neural Networks (ANN) outperform Decision Trees (DT) in user behavior classification tasks across accuracy, precision, and recall metrics. The results provide empirical evidence supporting the selection of ANN for adaptive, real-time decision-making systems. Additionally, the inclusion of Long Short-Term Memory (LSTM) for time-series prediction validates its effectiveness in capturing temporal dynamics in user or transactional data.

5.3. Theoretical Contribution

By examining the performance disparities between ANN, DT, and LSTM, the study contributes to the theoretical understanding of model suitability in varying data contexts. It reinforces that ANN's deep learning capabilities are particularly advantageous in environments with high feature interactions, whereas DT models are better suited for scenarios requiring transparency and low computational cost. The findings align with and extend existing AI model selection frameworks in the context of intelligent information systems.

5.4. Practical Contribution

The study offers actionable insights for system architects, data scientists, and developers involved in the design of e-commerce platforms, recommendation systems, and behavioral analytics engines. It demonstrates how specific AI models can be leveraged to enhance system personalization, responsiveness, and predictive accuracy. Moreover, the performance of the LSTM model in forecasting stock prices shows potential applications in financial information systems, marketing trend analysis, and strategic forecasting.

5.5. Academic Contribution

This work enriches the literature by integrating a diverse set of AI algorithms within a single comparative framework, backed by quantitative evaluation and visual diagnostics. It provides a foundation for future academic exploration in hybrid modeling (e.g., ANN + LSTM), model interpretability, and real-time adaptive systems. Additionally, it opens avenues for research into transfer learning and fine-tuning AI models using domain-specific knowledge in behavior-based systems.

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ABSTRACT

In the era of digital transformation, Artificial Intelligence (AI) plays a pivotal role in enabling intelligent, data-driven information systems. This study presents a comprehensive comparative analysis of AI models: Decision Tree (DT) and Artificial Neural Network (ANN), for user behavior prediction within simulated big data environments, specifically in the e-commerce domain. Using 1,000 synthetic sessions that mimic real-world user activities, the study evaluates model performance using classification metrics such as accuracy, precision, recall, and F1-score. ANN outperforms DT across all metrics, achieving 87.2% accuracy and demonstrating superior learning efficiency and generalization. To complement the evaluation, a Long Short-Term Memory (LSTM) model is employed for time-series prediction, yielding a low MAPE of 1.12%, confirming its effectiveness in capturing sequential patterns. The findings offer valuable insights into AI model selection for adaptive and predictive information systems, with implications for developers and researchers seeking to enhance system responsiveness and personalization.

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