International Science and Technology Journal
المجلة الدولية للعلوم والتقنية

Volume 38 العدد
Part 2 المجلد

المجلة الدولية للعلوم والتقنية
International Science and Technology Journal
ISTJ

http://www.doi.org/10.62341/istj-vol38-2-mg15

Received	**2026/04/15**	**تم استلام الورقة العلمية في**
Accepted	**2026/05/09**	**تم قبول الورقة العلمية في**
Published	**2026/05/10**	**تم نشر الورقة العلمية في**

Accuracy Assessment of Python- Implemented Artificial Intelligence Models for Predicting Moment Capacity of FRP Reinforced concrete Beams

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Abstract

Accurate prediction of moment capacity is critical for the safe and efficient design of reinforced concrete (RC) structures. Previous studies have investigated the flexural behaviour of RC beams reinforced with conventional steel and fiber-reinforced polymer (FRP) bars, showing that reinforcement ratio, material properties, beam dimensions, and concrete compressive strength significantly influence ultimate moment capacity. However, the nonlinear behaviour of concrete and the distinct characteristics of FRP continue to challenge precise prediction using conventional methods.

This study evaluates the performance of artificial intelligence (AI) models developed in Python for predicting the moment capacity of simply supported RC beams reinforced with steel and FRP bars. The framework integrates data-driven modelling with systematic parametric analysis to assess the influence of reinforcement ratio, reinforcement type (Steel, CFRP, BFRP, AFRP, GFRP), beam cross-sectional dimensions, and concrete compressive strength (fc′). A control beam was used as a

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reference, and multiple design series examined sensitivity of moment capacity (Mu) to these parameters. The AI model was validated against previously published experimental studies to ensure reliability.

Statistical indicators, including the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE), confirmed strong agreement between predicted and experimental values. Parametric analysis showed that increasing reinforcement ratio from 0.0019 to 0.0074 raised moment capacity from 68.00 kN·m to 259.89 kN·m. Beam dimensions and concrete strength also significantly affected performance, while differences among FRP types and steel highlighted material effects. The results demonstrate that Python-based AI modelling provides an accurate and efficient alternative to extensive experimental testing, offering a reliable data-driven tool for structural design and optimization of concrete beams.

Keywords: Reinforced Concrete (RC) Beams, Moment Capacity, FRP Reinforcement, Steel Reinforcement, Artificial Intelligence (AI), Python-Based Simulation.

Accuracy Assessment of Python- Implemented Artificial Intelligence Models for Predicting Moment Capacity of FRP Reinforced concrete Beams

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تقييم دقة نماذج الذكاء الاصطناعي المُنفذة باستخدام لغة البايثون (Python) للتنبؤ بسعة العزم للكمرات الخرسانية المسلحة بـFRP

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الملخص

يُعد التنبؤ الدقيق بسعة العزم أمرًا بالغ الأهمية للتصميم الآمن والفعال للهياكل الخرسانية المسلحة (RC). وقد تناولت الدراسات السابقة سلوك الانحناء للكمرات الخرسانية المسلحة باستخدام التسليح التقليدي من الصلب وكذلك قضبان البوليمر المقوى بالألياف (FRP)، حيث أظهرت أن نسبة التسليح، وخصائص المواد، وأبعاد الكمرة، ومقاومة الضغط للخرسانة تؤثر بشكل كبير على سعة العزم القصوى. ومع ذلك، فإن السلوك غير الخطي للخرسانة والخصائص المميزة لمواد FRP لا تزال تشكل تحديًا أمام التنبؤ الدقيق باستخدام الطرق التقليدية.

تهدف هذه الدراسة إلى تقييم أداء نماذج الذكاء الاصطناعي (AI) المطورة باستخدام لغة البايثون (Python) للتنبؤ بسعة العزم للكمرات الخرسانية البسيطة الارتكاز والمسلحة بقضبان الحديد وFRP. ويعتمد الإطار المقترح على دمج النمذجة المعتمدة على البيانات مع تحليل بارامتري منهجي لتقييم تأثير نسبة التسليح، ونوع التسليح (الحديد، CFRP، BFRP، AFRP، GFRP)، وأبعاد المقطع العرضي للكمرة، ومقاومة الضغط للخرسانة (f_c'). تم استخدام كمرة مرجعية (Control Beam)كأساس للمقارنة، كما تم دراسة عدة سلاسل تصميمية لتحليل حساسية سعة العزم (Mu) تجاه هذه المتغيرات. تم التحقق من صحة نموذج الذكاء الاصطناعي بمقارنته مع نتائج دراسات تجريبية منشورة سابقًا لضمان موثوقيته.

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وأظهرت المؤشرات الإحصائية، بما في ذلك معامل التحديد (R^2)، ومتوسط الخطأ المطلق (MAE)، والجذر التربيعي لمتوسط مربع الخطأ (RMSE)، توافقًا قويًا بين القيم المتوقعة والتجريبية. كما أظهر التحليل البارامتري أن زيادة نسبة التسليح من 0.0019 إلى 0.0074 أدت إلى زيادة سعة العزم من 68.00 كيلو نيوتن·متر إلى 259.89 كيلو نيوتن·متر . كذلك، كان لأبعاد الكمرة ومقاومة الخرسانة تأثير كبير على الأداء، في حين أبرزت الفروقات بين أنواع FRP والحديد تأثير نوع المادة. تشير النتائج إلى أن النمذجة باستخدام الذكاء الاصطناعي المعتمدة على لغة البايثون (Python) توفر بديلاً دقيقا وفعالًا للاختبارات التجريبية (Experimental Tests)، كما تقدم أداة موثوقة قائمة على البيانات لتصميم وتحسين الكمرات الخرسانية المسلحة.

الكلمات المفتاحية: الكمرات الخرسانية المسلحة، سعة العزم، تسليح FRP، تسليح فولاذي، الذكاء الاصطناعي، المحاكاة باستخدام لغة البايثون (Python).

1. Introduction

Reinforced concrete (RC) beams are among the most fundamental structural elements in buildings, bridges, and infrastructure systems, as they play a primary role in transferring vertical loads and resisting bending moments and shear forces. The flexural capacity of RC beams represents a critical parameter in ensuring structural safety and serviceability, since any underestimation may result in brittle failure or progressive collapse. Conventional design practices rely primarily on codified analytical formulations, particularly those provided by ACI 318, which are based on simplified assumptions such as linear strain distribution, equivalent rectangular stress blocks for concrete and idealized material behaviour. Although these provisions have proven reliable in practical engineering applications, they may not fully capture

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the complex nonlinear response of reinforced concrete, especially after cracking, yielding, or when alternative reinforcement materials are used (ACI 318-19).

To overcome the limitations of simplified analytical approaches, significant efforts have been devoted to advanced numerical modelling techniques. Computational platforms such as MATLAB have enabled researchers to perform finite element analysis (FEA) for accurately simulating the flexural behaviour of RC beams. Recent studies (e.g., Samy et al., 2023; Hossain and Al-Faruk, 2017) demonstrated the capability of numerical models to reproduce load–deflection relationships, cracking evolution, and ultimate moment capacity with improved precision. However, these approaches often require extensive computational effort, expert knowledge in nonlinear modelling, and careful calibration of material constitutive laws.

Parallel to advancements in numerical methods, the introduction of alternative reinforcement materials such as Fiber Reinforced Polymer (FRP) bars has added further complexity to flexural behaviour prediction. Studies such as Kara et al. (2011) and Ashour and Habeeb (2008) highlighted that the lower modulus of elasticity and brittle nature of FRP reinforcement significantly alter the moment–curvature response and increase deflection compared to steel-reinforced beams. Moreover, Beljkaš and Baša (2021) reported that current design provisions may underestimate deflections in continuous GFRP-reinforced beams. Similarly, research on steel fiber reinforced concrete (SFRC) (Rjoub, 2005) demonstrated that fiber addition enhances flexural performance and crack control, yet the overall structural response remains highly nonlinear and difficult to represent through simplified formulations.

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In this context, Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), have emerged as powerful tools for modelling complex nonlinear relationships without the need for explicit mathematical assumptions. Previous research has shown that ANNs can effectively predict concrete compressive strength (Ashrafi et al., 2010), beam deflection (Kaczmarek and Szymańska, 2016; Bai et al., 2020), and flexural and shear strength (Ahmad et al., 2023) with higher accuracy than traditional empirical equations. These studies demonstrate the strong potential of machine learning algorithms to generalize structural behaviour based on data-driven learning.

Despite these advancements, a clear research gap remains. Most existing studies focus either on pure numerical simulations aligned with code-based formulations or on AI models trained directly on experimental datasets for isolated parameters such as deflection or compressive strength. Limited research has integrated code-consistent numerical modelling with AI-based predictive frameworks to directly estimate the flexural capacity of conventionally reinforced concrete beams across a wide range of geometric and material parameters.

Accordingly, this study hypothesizes that integrating numerical datasets generated in accordance with ACI provisions with machine learning algorithms can yield a highly accurate, computationally efficient, and flexible predictive model for estimating flexural capacity. The present work aims to bridge this gap by developing an AI-based model using Python, training it on numerically generated datasets, and systematically validating its performance against numerical simulations and published experimental results. This approach contributes toward establishing intelligent, data-driven design

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tools capable of enhancing reliability and efficiency in structural engineering practice.

2. Methodology (Model Development)

2.1. Design a Python Model with Artificial Intelligence

2.1.1 Numerical Model Concept

In this study, several advanced artificial intelligence (AI) platforms, including ChatGPT, DeepSeek, and Gemini, were utilized to support the development of a Python-based engineering program for predicting the moment capacity of simply supported reinforced concrete beams under a central point load. Multiple simulations were performed to assess the accuracy and effectiveness of these AI models. Based on comparative analysis, DeepSeek was adopted as the primary tool for code development due to its outputs closely matching established reference values.

2.1.2 Computational Framework and Algorithm Development

The proposed computational model is based on Artificial Neural Network (ANN) principles combined with a sectional analysis approach to capture the nonlinear structural behavior of reinforced concrete beams. This hybrid formulation enables accurate representation of the interaction between material properties, geometry, and loading conditions. The algorithm is developed according to the following procedure:

- The beam cross-section is divided into a large number of horizontal slices (discretization).
- The Bisection Method is used to determine the neutral axis depth (c) accurately, a key step in nonlinear analysis of reinforced concrete sections (as illustrated in Figure 1).

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- Stress and strain in each slice are calculated using nonlinear stress–strain curves for concrete and reinforcement.

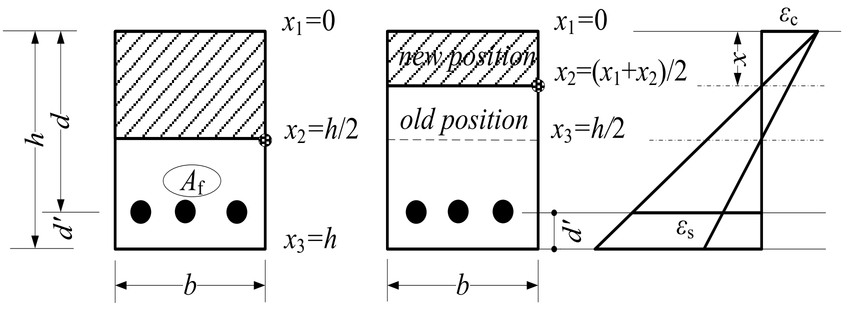

Figure 1. Bisection method for determining the neutral axis depth.

2.1.3 Numerical Data Generation and Processing

Data for the model were prepared by simulating the beam cross-section with approximately 10000 horizontal slices.

- Strain in each slice was computed assuming plane sections remain plane after bending.
- Nonlinear material behaviour of concrete and steel was used to calculate stress for each slice.
- Internal moment was obtained by summing contributions from all slices.

2.1.4 Implementation of the Computational Model in Python

The computational procedure consists of the following main steps (as illustrated in Figure 2):

- The mechanical properties of the materials are defined, including concrete compressive strength (f_c'), steel FRP stress (f_f), and modulus of elasticity of FRP (E_f).

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- The cross-sectional properties are specified, including the width (b), total height (h), effective depth (d), and reinforcement area (A_f).
- The ultimate compressive strain (**ε_{cu}**) of concrete is defined to establish strain compatibility and determine the strain distribution at failure.
- The bisection method is applied to iteratively solve the nonlinear equilibrium equation and determine the neutral axis depth (c), where internal forces are balanced.
- The total moment capacity is computed by integrating the stress distribution in concrete and evaluating the FRP force contribution, then summing their moment effects about a reference axis (as illustrated in Figure 2).

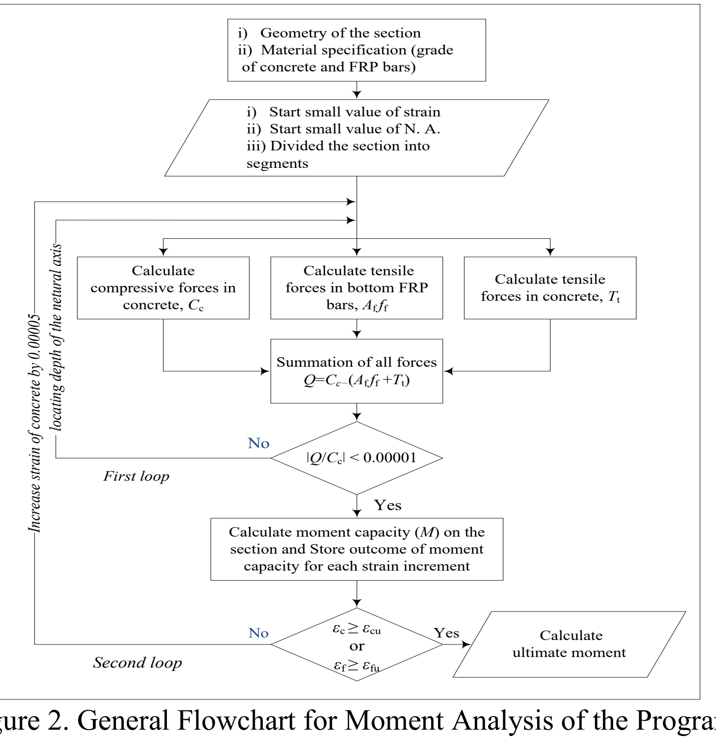

Figure 2. General Flowchart for Moment Analysis of the Program

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2.2 Validation of the Developed Model

To verify the reliability of the developed Python-based nonlinear sectional analysis model, a systematic comparison was conducted between the predicted moment capacity (M_{Pyt}) and experimentally reported values (M_{exp}) from previous studies as shown in Table 1.

Table 1. Comparison between the flexural capacity obtained from numerical analysis (Python) and the experimental results.

Member	Reference	b mm	h mm	d mm	A_f mm²	f_c' MPa	M_{pyt} kN·m	M_{exp} kN·m	M_{Pyt}/M_{exp}
C-S-1	[11]	200	300	265	222.6	26.9	56.6	64.11	0.88
C-S-2		200	300	265	84.8	27.5	41.23	44.28	0.93
C-S-3		200	300	265	84.8	23.6	36.12	44.76	0.80
C-S-4		200	300	265	222.6	27.2	56.6	60.66	0.93
C-S-5		200	300	265	222.6	28	57.15	56.03	1.01
C-S-6		200	300	265	450.5	26.3	66.42	78.12	0.85
COMP75	[10]	200	240	197	524.02	37.5	38.92	44.28	0.87
G2-8		200	300	257	976.6	39.05	85	84.54	1.00
AR-6		200	300	257	462.6	39.05	62.18	70.85	0.87
AR-8		200	300	257	616.8	39.05	68.45	71.75	0.95
G2-6		200	300	257	719.6	39.05	65	71	0.91
KD30-2		200	300	257	544.84	42	68.32	63.8	1.07
KD45-1		200	450	407	553.52	52	104.57	106.53	0.98
ISO30-2		200	300	257	544.84	42	89.72	80.4	1.11
CB2B-1		200	300	257	354.66	52	59.84	57.9	1.03
BEAM8		150	200	157	54.165	50.09	5.43	5.88	0.92
BEAM12		150	300	257	53.97	50.09	5.52	16.75	0.33
ISO2		200	300	257	580.82	43	80.15	80.4	0.99
1FRP1		381	203	160	73.152	27.6	9.87	11.49	0.85
GS1b		200	300	257	406.06	28	48.72	49	0.99

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The M_{Pyt}/M_{exp} ratios range between 0.80 and 1.11, indicating strong agreement with experimental results and confirming the capability of the nonlinear algorithm to represent actual structural behaviour.

2.3 Variables under Study

This study aims to investigate the effect of various geometric parameters and material properties on the moment capacity of simply supported reinforced concrete beams reinforced with both conventional steel and fiber-reinforced polymer (FRP) bars As presented in Table 2 and Figure 3. The studied variables include:

- FRP reinforcement ratio,
- Type of reinforcement (FRP vs. conventional steel),
- Cross-sectional dimensions of the beam,
- Concrete compressive strength.

The analysis was carried out numerically using an artificial intelligence–based simulation model, as previously explained. Key input parameters, including material properties, geometric characteristics, and reinforcement details, were systematically incorporated into the model.

Table 2. Variables for Studying the Effect of Geometric and Material Properties on Moment Capacity

Series No.	Parameters Study	Reinforcement of Section	Dimensions of Beam (mm^2)	f_c' (Mpa)
1	Steel reinforcement ratio	Steel (2ϕ14mm, 4ϕ14mm, 6ϕ14mm, 8ϕ14mm)	300mm×600mm	40
2	Type of Reinforcement	Steel (2ϕ14mm)	300mm×600mm	40
		CFRP (2ϕ14mm)		
		BFRP (2ϕ14mm)		
		AFRP (4ϕ12mm)		
		GFRP (2ϕ14mm)		

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3	Different Dimensions	2ϕ14mm Steel	250mm×500mm	40
			300mm×600mm	
			350mm×350mm	
4	Concrete Compressive Strength	2ϕ14mm Steel	300mm×600mm	25
				30
				35
				40

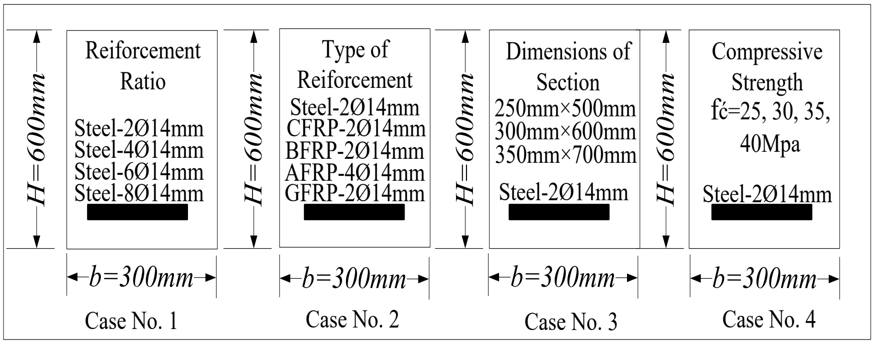

Figure 3. Parametric study cases considered in the analysis of RC beams.

2.3.1 Effect of Reinforcement Ratio

An increase in reinforcement ratio resulted in a significant increase in moment capacity. For example, increasing reinforcement from 2ϕ14mm (ρ=0.0019) to 8ϕ14mm (ρ=0.0074) increased moment capacity from 68.00kN·m to 259.89kN·m. The influence of reinforcement ratio (ρ) on moment capacity (M_u) is illustrated in Table 3.

Table 3. Effect of Steel Reinforcement Ratio on Moment Capacity

Reinforcement	ρ	**f_c' (MPa)**	**M_u (kN·m)**
2ϕ14mm	0.0019	40	68.00
4ϕ14mm	0.0037		130.02
6ϕ14mm	0.0056		194.98
8ϕ14mm	0.0074		259.89

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As shown in Figure 4, the moment capacity increases significantly with the increase in reinforcement ratio. Increasing the reinforcement from 2ϕ14 mm to 8ϕ14 mm results in an approximately fourfold increase in flexural capacity. This clear trend indicates that the tensile reinforcement is the dominant parameter governing the flexural behavior of under-reinforced concrete beams. This behavior can be explained by the fundamental flexural mechanism of reinforced concrete, where the concrete in the tension zone is assumed to crack and lose its tensile resistance, while the internal forces are primarily carried by the steel reinforcement.

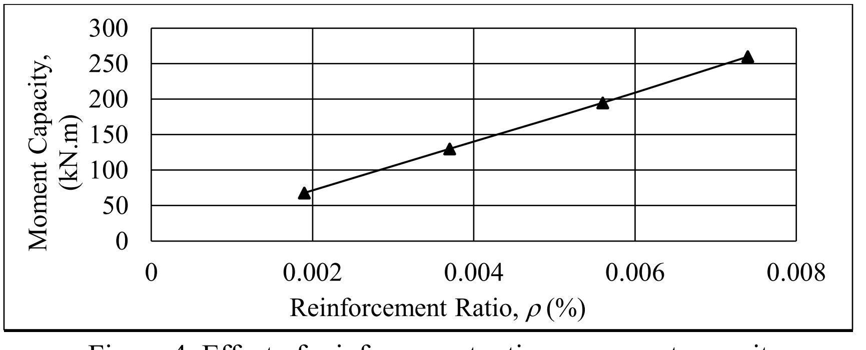

Figure 4. Effect of reinforcement ratio on moment capacity

2.3.2 Effect of Reinforcement Type (Steel vs FRP)

From Table 4, it can be shown that effect of reinforcement type on the flexural capacity of concrete beams with f_c'=40MPa. Conventional steel (2ϕ14mm) provides a baseline capacity of 68.00kN·m. Beams reinforced with FRP achieve much higher capacities due to their superior mechanical properties. CFRP (2ϕ14mm) reaches 194.41kN·m, BFRP (2ϕ14mm) 113.47kN·m, AFRP (4ϕ12mm) 306.15kN·m, and GFRP (2ϕ14mm) 97.21kN·m

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Table 4. Effect of Reinforcement Type (Steel vs FRP) on Moment Capacity

Reinforcement Type	f_c' (MPa)	A_f (mm²)	f_u or f_y (MPa)	E_f (GPa)	M_u (kN·m)
Steel	40	2ϕ14mm	420	200	68.00
CFRP		2ϕ14mm	1200	150	194.41
BFRP		2ϕ14mm	700	45	113.47
AFRP		4ϕ12mm	1300	50	306.15
GFRP		2ϕ14mm	600	40	97.21

As illustrated in Figure 5, variations in flexural capacity are largely influenced by the ultimate stress and modulus of elasticity of the reinforcement. The performance ranking is **AFRP > CFRP > BFRP > GFRP > Steel**, highlighting that FRP reinforcement substantially enhances beam flexural strength compared to traditional steel.

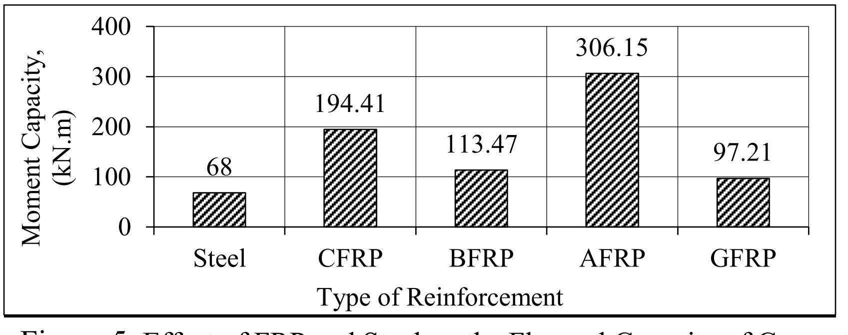

Figure 5. Effect of FRP and Steel on the Flexural Capacity of Concrete Beams.

2.3.3 Effect of Cross-Sectional Dimensions on Moment Capacity

Table 5 and the corresponding Figure 6 illustrate the direct relationship between increasing the cross-sectional dimensions and reinforcement ratio of a reinforced concrete beam and its ultimate moment capacity (Mu).

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Table 5. Effect of Cross-Section Dimensions on Moment Capacity

Dimensions (A_g)	f_c' (MPa)	Reinforcement (A_{st})	$\rho=A_{st}/A_g$	M_u (kN·m)
250mm×500mm	40	2ϕ14mm Steel	0.0027	56.21
300mm×600mm			0.0019	68.00
350mm×700mm			0.0013	82.37

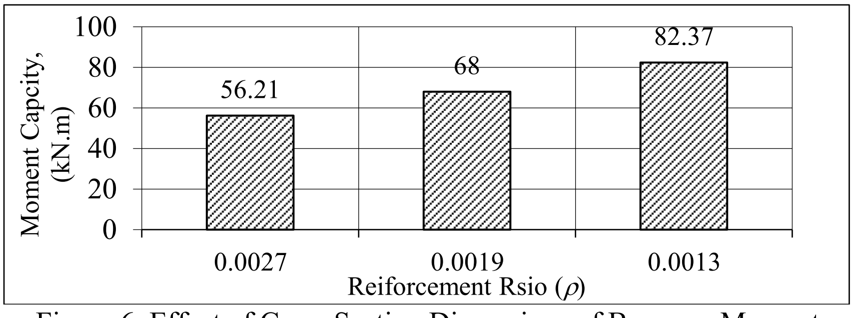

Figure 6. Effect of Cross Section Dimensions of Beam on Moment Capacity

The results can be discussed as follows:

- The results clearly demonstrate that the moment capacity increases significantly with an increase in beam dimensions.
- When the cross-sectional dimensions of beam were increased from 250mm×500mm to 300mm×600mm, the moment capacity increased from 56.21kN·m to 68.00kN·m. Further increasing the dimensions to 350mm×700mm resulted in a higher moment capacity of 82.37kN·m.
- This increase can be attributed to a fundamental principle in flexural behaviour, where the internal lever arm increases as the beam depth increases.
- Larger dimensions also enhance the beam's ability to resist compressive forces in the concrete compression zone, leading to an increase in the total internal resisting forces and, consequently, a higher moment capacity.

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2.3.4 Effect of Concrete Compressive Strength on Moment Capacity

Table 6 presents the relationship between increasing the concrete compressive strength (f_c') and the moment capacity (Mu) of a simply supported reinforced concrete beam, while keeping all other parameters constant (beam dimensions, reinforcement type, and reinforcement area). The results can be discussed as follows:

Increasing the concrete compressive strength from 25MPa to 40MPa has very little impact on the moment capacity of the beam, which stays around 68kN·m. This is because the beam is under-reinforced, so it fails when the steel yields rather than when the concrete is crushed. Since the steel reinforcement (2ϕ14mm) is the same in all cases, it controls the ultimate capacity, and a higher concrete strength only adds a small, almost negligible increase to the moment capacity as shown in Figure 7.

Table 6. Effect of Concrete Compressive Strength on Moment Capacity

f_c' (MPa)	**Reinforcement**	**M_u (kN·m)**
25	2ϕ14mm Steel	68.11
30		68.01
35		68.00
40		68.00

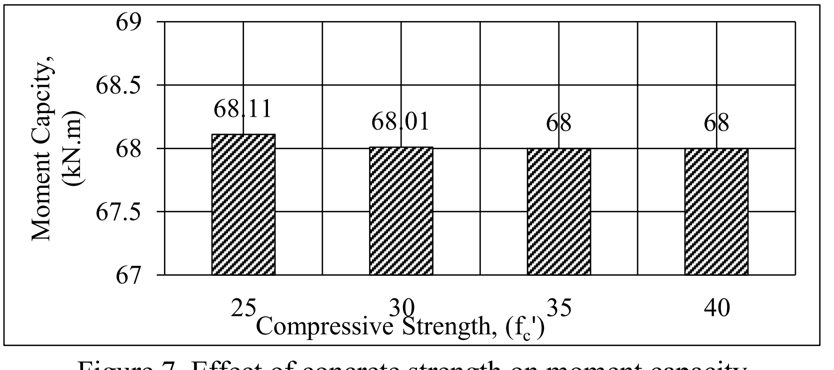

Figure 7. Effect of concrete strength on moment capacity

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3. Results and Discussion

The results clearly confirm that the flexural capacity (Mu) of reinforced concrete beams is predominantly controlled by reinforcement characteristics. Increasing the reinforcement ratio (ρ) resulted in a remarkable enhancement in moment capacity, rising from 68.00kN·m to 259.89kN·m, which highlights the dominant role of tensile reinforcement in under-reinforced sections. Likewise, the use of FRP reinforcement significantly outperformed conventional steel due to its superior tensile strength, with AFRP exhibiting the highest capacity. Furthermore, increasing beam dimensions led to a consistent improvement in moment capacity as a result of the increased effective depth and internal lever arm. In contrast, the influence of concrete compressive strength (f'c) was negligible, confirming that failure is governed by reinforcement yielding rather than concrete crushing. Overall, reinforcement ratio and type are the primary factors governing flexural performance, while concrete strength plays a secondary role under these conditions.

4. Conclusion

1. Development of an advanced numerical model to evaluate the moment capacity of simply supported reinforced concrete beams.

2. The Bisection Method was used to accurately find the neutral axis depth by iteratively narrowing the interval until vertical force equilibrium is satisfied.

3. The study demonstrated the effectiveness of integrating artificial intelligence techniques with numerical modelling to accelerate design processes and structural analysis while maintaining high accuracy.

4. Implementation of the model using Python integrated with artificial intelligence techniques

5. Beam depth and reinforcement area show the greatest influence on moment capacity.

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6**.** Concrete compressive strength has a limited effect in under-reinforced beams.

7. Strong agreement between model results and reference solutions confirms accuracy.

8. Sensitivity analysis showed that beam depth and reinforcement area have the greatest impact on moment capacity, while section width and concrete strength have a relatively smaller effect.

9. Integration of AI with numerical modelling improves efficiency and reduces computational effort.

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