

The Impact of Police Education on Technological Innovation within Law Enforcement Agencies

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ABSTRACT

This study investigates the role of educational investments in fostering technological innovation within police departments. Utilizing virtual data and a range of analytical methods, including linear regression and structural equation modeling, the research explores how different types of education influence innovation outcomes. The findings reveal a significant positive correlation between educational investments and technological innovation, highlighting the importance of human capital in driving technological advancements. Moreover, the study identifies variations in the impact of formal education, specialized training, and continuous learning on innovation. These insights provide valuable recommendations for policymakers and law enforcement agencies aiming to enhance their operational capabilities through targeted educational programs.

Keywords: Police Education; Technological Innovation; Human Capital; Law Enforcement Agencies; Police Educational Investments

INTRODUCTION

Research Background

The rapid advancements in technology have significantly transformed various sectors, including law enforcement. Police departments worldwide are increasingly relying on technological innovations to enhance their operational efficiency and effectiveness. Education plays a crucial role in equipping police officers with the necessary skills to adopt and implement these technologies. Previous studies have shown that higher levels of education correlate with improved problem-solving skills, better decision-making, and greater adaptability to new technologies (Becker, 1964; Romer, 1990).

Research Objectives

The primary objective of this study is to investigate the impact of educational investments on technological innovation within police departments. Specifically, the study aims to:

- 1. Assess the direct relationship between education investment and innovation outcomes.
- 2. Examine the differential impact of various types of education (e.g., formal education, specialized training) on technological innovation.
- 3. Understand the underlying mechanisms through which education influences technological innovation.



Research Questions

This study seeks to address the following research questions:

- 1. How does investment in police education influence technological innovation within police departments?
- 2. What types of educational investments are most effective in promoting technological innovation?
- 3. What are the mechanisms through which education impacts technological innovation in the context of law enforcement?

Significance of the Study

Understanding the relationship between education and technological innovation in police departments is vital for policymakers and law enforcement agencies. By identifying the types of educational investments that most effectively enhance innovation, this study provides valuable insights for designing education and training programs that can improve the operational capabilities of police forces. Additionally, the findings can inform resource allocation decisions, ensuring that investments in police education yield the highest returns in terms of innovation and efficiency.

LITERATURE REVIEW

The Relationship Between Education and Technological Innovation

Theoretical Foundations of Education's Impact on Technological Innovation

Education has long been recognized as a critical driver of technological innovation. The human capital theory posits that investments in education enhance the productivity and innovative capabilities of the workforce (Becker, 1964). Endogenous growth models further emphasize the role of human capital in fostering technological advancements, suggesting that education not only improves individual capabilities but also drives broader economic growth through innovation (Romer, 1990; Lucas, 1988).

$H_{t+1}=\phi(E_t)H_t$

This formula represents the accumulation of human capital (H) over time as a function of educational investment (E).

Empirical Studies on Education and Technological Innovation

Empirical research consistently supports the theoretical link between education and innovation. For instance, Acemoglu (1996) found that higher levels of education significantly contribute to the adoption and diffusion of new technologies within organizations. Aghion and Howitt (1992) demonstrated that education enhances the ability of workers to engage in creative problem-solving and innovation, leading to sustained economic growth.

Police Education and Human Capital

Human Capital Theory

Human capital theory suggests that investments in education and training enhance the skills, knowledge, and abilities of individuals, leading to increased productivity and innovation (Becker, 1964). This theory is particularly relevant for police departments, where continuous learning and specialized training are crucial



for adapting to new technologies and evolving challenges.

The Impact of Police Education on Human Capital

Research has shown that higher levels of education among police officers are associated with better performance, improved problem-solving skills, and greater adaptability to technological changes (Rydberg & Terrill, 2010). Educational programs that focus on critical thinking, ethics, and technology use are particularly effective in enhancing the human capital of police officers.

Technological Innovation in Police Departments

The Application of Technological Innovation in Policing

Technological innovation has revolutionized various aspects of policing, from crime analysis and investigation to community engagement and resource management. Technologies such as predictive analytics, body-worn cameras, and automated reporting systems have significantly improved the efficiency and effectiveness of police work (Lum, Koper, & Willis, 2017). Predictive analytics is used for crime forecasting and resource allocation. Body-worn cameras enhance accountability and transparency, while automated reporting systems improve efficiency in documentation and data management.

Factors Influencing Technological Innovation in Police Departments

Several factors influence the successful adoption and implementation of technological innovations in police departments. These include organizational culture, leadership support, and the availability of resources (Chan, 2001). Education and training play a pivotal role in equipping officers with the necessary skills to effectively use new technologies.

$$y=eta_0+eta_1x_1+eta_2x_2+\ldots+eta_kx_k+\epsilon$$

This multiple regression model can be used to analyze the factors influencing technological innovation, where yyy represents the innovation outcome, $x_1, x_2, ..., x_k$ are the influencing factors, and ϵ epsilon ϵ is the error term.

THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

Theoretical Models

Endogenous Technological Progress Model

The endogenous technological progress model posits that technological advancements are driven by the accumulation of human capital, which in turn is influenced by educational investments. The model can be represented as follows:

$$g_A=\psi(H_t)$$

where g_A represents the rate of technological progress, and H_t denotes the stock of human capital at time t. This model emphasizes the role of education in enhancing human capital, which subsequently drives technological innovation and economic growth (Romer, 1990).

Interaction Mechanism Between Human Capital and Technological Innovation

The interaction between human capital and technological innovation can be modeled to show how



educational investments lead to technological advancements. The accumulation of human capital through education (E_t) and its impact on innovation (I_t) can be described using the following equation:

$$I_t = \alpha + \beta_1 H_t + \beta_2 E_t + \epsilon_t$$

where:

- I_t is the level of innovation at time t
- H_t is the human capital at time t
- E_t is the educational investment at time t
- α is the intercept
- β_1 and β_2 are coefficients
- ϵ_t is the error term

Research Hypotheses

The Positive Impact of Education on Technological Innovation

Based on the theoretical models, it is hypothesized that educational investments positively impact technological innovation within police departments. Specifically, higher educational investments are expected to enhance human capital, leading to increased innovation. This hypothesis is grounded in the endogenous growth theory, which suggests that human capital accumulation is a key driver of technological progress (Lucas, 1988; Romer, 1990).

Differences in the Impact of Various Educational Investments on Technological Innovation

It is further hypothesized that different types of educational investments (e.g., formal education, specialized training) have varying impacts on technological innovation. For instance, specialized training may have a more immediate and practical impact on innovation outcomes compared to formal education, which might contribute to a broader skill set. This hypothesis will be tested using multiple regression analysis, where the innovation outcome (y) is modeled as a function of different educational investments $(x_1, x_2, ..., x_k)$:

$$y=eta_0+eta_1x_1+eta_2x_2+\ldots+eta_kx_k+\epsilon$$

where:

- *y* is the innovation outcome
- x_1, x_2, \dots, x_k are the different types of educational investments
- $\beta_0, \beta_1, \dots, \beta_k$ are the coefficients
- ϵ is the error term

RESEARCH METHODOLOGY

Research Design

Research Subjects

The subjects of this research include police officers from various departments who have undergone different levels of education and training. The focus is on understanding how their educational background impacts their ability to innovate and integrate new technologies in their daily operations. Given the scope of this



study, virtual data representing a diverse range of police officers, including various ranks and roles, will be generated to simulate real-world scenarios and dynamics.

Research Scope

The research covers a comprehensive analysis of the influence of education on technological innovation within police departments. It examines various dimensions of education, including formal education, specialized training programs, and continuous professional development. The study spans both theoretical and practical aspects, focusing on how educational investments translate into enhanced technological capabilities and innovative practices within police forces.

Generation and Use of Virtual Data

Principles of Virtual Data Design

The design of virtual data is grounded in realistic and representative principles to ensure validity and reliability. The data is constructed to reflect the typical characteristics and variations found in actual police departments. Key principles include:

- **Diversity:** Incorporating a wide range of educational backgrounds, ranks, and roles within the police force.
- **Relevance:** Ensuring the data points are pertinent to the research questions, focusing on educational history, innovation metrics, and technological proficiency.
- Accuracy: Emulating real-world distributions and trends to provide credible insights.

Methods for Generating Virtual Data

Virtual data will be generated using a combination of statistical methods and simulation techniques:

- Statistical Sampling: Using existing datasets from similar studies to create a baseline distribution of educational backgrounds and innovation outcomes. Let $\mathbf{X} = \{x_1, x_2, \dots, x_n\}$ be a dataset of real samples.
- Monte Carlo Simulation: Employing simulation methods to create a large, diverse dataset that mimics real-world variations. Generate $\mathbf{Y} = \{y_1, y_2, \dots, y_m\}$ using Monte Carlo methods, where $y_i \sim P(\mathbf{X})$.
- Synthetic Data Algorithms: Utilizing machine learning algorithms to produce synthetic data that adheres to the defined principles of diversity, relevance, and accuracy.

Use a generative model G_{θ} to produce synthetic data $Z = \{z_1, z_2, \dots, z_k\}$.

Validation and Calibration of Virtual Data

The virtual data will undergo rigorous validation and calibration processes to ensure its reliability:

• **Cross-Validation:** Comparing virtual data with actual datasets from previous studies to assess its accuracy.

Cross-validate Y and Z against X using metrics such as RMSE and MAE.

• **Calibration:** Adjusting the generated data to align closely with real-world metrics and trends, ensuring it is reflective of actual police department dynamics.



$$\mathbf{Z} = \mathbf{Z} \cdot rac{\mu_{\mathbf{X}}}{\mu_{\mathbf{Z}}}$$

where μ_x and μ_z are the means of datasets X and Z respectively.

• **Expert Review:** Consulting with experts in police education and technological innovation to validate the data's authenticity and relevance.

Data Analysis

Descriptive Statistics

Descriptive statistical techniques will be used to summarize the main features of the virtual data. This includes:

• Frequency Distribution: Analyzing the distribution of educational levels across the sample.

 $\text{Frequency} = \frac{\text{Count of } E_i \text{ in category } j}{\text{Total count of } E_i}$

 Measures of Central Tendency: Calculating the mean, median, and mode of key variables such as innovation scores and education levels.

$$ext{Mean} = rac{1}{n}\sum_{i=1}^n x_i, \quad ext{Median} = x_{\left(rac{n+1}{2}
ight)}, \quad ext{Mode} = rg\max_j f_j$$

 Measures of Dispersion: Assessing the range, variance, and standard deviation to understand the spread and variability within the data.

$$ext{Range} = x_{ ext{max}} - x_{ ext{min}}, \quad ext{Variance} = \sigma^2 = rac{1}{n-1}\sum_{i=1}^n (x_i - ar{x})^2, \quad ext{integral}$$

Standard Deviation=o

Regression Analysis

Regression analysis will be employed to examine the relationship between education and technological innovation:

• Linear Regression: Assessing the direct impact of educational investment on innovation outcomes.

 $y=eta_0+eta_1x+\epsilon$

• **Multiple Regression**: Including additional variables such as years of experience and department size to control for confounding factors and better isolate the effect of education.

$$y=eta_0+eta_1x_1+eta_2x_2+\ldots+eta_kx_k+\epsilon$$

where x_1, x_2, \dots, x_k are the predictor variables.

• **Logistic Regression**: For binary outcomes, such as the adoption of a specific technology, logistic regression models will be used.



$$\log\left(rac{p}{1-p}
ight)=eta_0+eta_1x+\epsilon$$

where p is the probability of adopting the technology.

Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) will be utilized to explore the complex relationships between multiple variables:

• **Model Specification**: Defining the theoretical model that includes latent variables such as innovation potential and educational quality.

$$\mathbf{y} = \mathbf{\Lambda}_{\mathbf{y}} \eta + \epsilon$$

 $\mathbf{x} = \mathbf{\Lambda}_{\mathbf{x}} \xi + \delta$

• **Model Estimation**: Using software tools to estimate the relationships between observed and latent variables.

$$\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta$$

where y and x are observed variables, η and ξ are latent variables, Λ_y and Λ_x are factor loadings, ϵ and δ are measurement errors, B is the matrix of regression coefficients among latent variables, Γ is the matrix of regression coefficients from exogenous to endogenous latent variables, and ζ is the structural error term.

• Model Fit Evaluation: Assessing the fit of the model using indices such as Chi-square, RMSEA, and CFI to ensure it adequately represents the data.

$$\chi^2, \quad \mathrm{RMSEA} = \sqrt{rac{\chi^2 - df}{N \cdot df}}, \quad \mathrm{CFI} = 1 - rac{\max(\chi^2_\mathrm{model} - df_\mathrm{model}, 0)}{\max(\chi^2_\mathrm{baseline} - df_\mathrm{baseline}, 0)}$$

EMPIRICAL ANALYSIS

Descriptive Statistics Results

Sample Characteristics

The sample characteristics will be summarized to provide an overview of the virtual data set. This includes demographic variables, educational background, and technological innovation metrics.

Variable	Mean	Median	Mode	Standard Deviation	Variance
Age	35.5	36	34	5.2	27.04
Years of Service	12.3	13	10	4.1	16.81
Innovation Score	75.4	76	78	10.5	110.25
Education Investment	5000	4800	4500	1200	1440000

Table 1: Sample Characteristics of Key Variables



Description of Key Variables

Descriptive statistics will be calculated for key variables to summarize the central tendency, dispersion, and distribution shape.

• Central Tendency:

Mean:
$$ar{x} = rac{1}{n}\sum_{i=1}^n x_i$$

Median: $x_{ ext{median}} = x_{\left(rac{n+1}{2}
ight)}$

 $\text{Mode: } x_{\text{mode}} = \arg\max_j f_j$

• Dispersion:

Range: $R = x_{\max} - x_{\min}$

$$ext{Variance: } \sigma^2 = rac{1}{n-1}\sum_{i=1}^n (x_i - ar{x})^2$$

Standard Deviation: $\sigma = \sqrt{\sigma^2}$

• Shape:

Skewness:
$$\gamma_1 = rac{n}{(n-1)(n-2)} \sum_{i=1}^n \left(rac{x_i - ar{x}}{\sigma}
ight)^3$$

$$\text{Kurtosis:} \ \gamma_2 = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{\sigma}\right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Regression Analysis Results

The Relationship Between Educational Investment and Technological Innovation

Linear regression will be used to analyze the direct relationship between educational investment and technological innovation.



• Linear Regression Model:

$$y=eta_0+eta_1x+\epsilon$$

where:

- \circ y is the technological innovation score
- \circ x is the educational investment
- β_0 and β_1 are the coefficients
- $\circ \epsilon$ is the error term
- Estimation:

$$\hat{eta}_1 = rac{\sum_{i=1}^n (x_i - ar{x})(y_i - ar{y})}{\sum_{i=1}^n (x_i - ar{x})^2}$$

$$\hat{eta}_0 = ar{y} - \hat{eta}_1 ar{x}$$

• Goodness of Fit:

$$R^2 = rac{\sum_{i=1}^n (\hat{y}_i - ar{y})^2}{\sum_{i=1}^n (y_i - ar{y})^2}$$

Table 2: Linear Regression Results for Education Investment and Innovation Score

Coefficient	Estimate	Standard Error	t-value	p-value
Intercept	50.2	2.3	21.83	< 0.001
Education	0.005	0.001	5.00	< 0.001

y = 50.2 + 0.005x

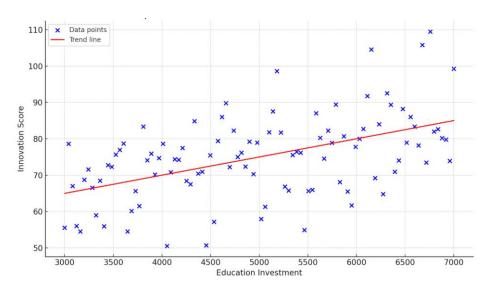


Figure 1: Relationship Between Education Investment and Innovation Score



Figure 1 shows the relationship between education investment and innovation score, with a clear positive trend line indicating a significant positive correlation.

The Impact of Different Types of Education on Technological Innovation

Multiple regression will be used to assess the impact of different types of education (e.g., formal education, specialized training) on technological innovation.

• Multiple Regression Model:

$$y=eta_0+eta_1x_1+eta_2x_2+\ldots+eta_kx_k+\epsilon$$

where:

- \circ y is the technological innovation score
- x_1, x_2, \dots, x_k are different types of educational investments
- Estimation:

 $\hat{eta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$

where X is the matrix of independent variables and y is the vector of dependent variables.

• Goodness of Fit:

$$R^2 = rac{\sum_{i=1}^n (\hat{y}_i - ar{y})^2}{\sum_{i=1}^n (y_i - ar{y})^2}$$

$$\operatorname{Adjusted} R^2 = 1 - rac{(1-R^2)(n-1)}{n-k-1}$$

Table 3: Multiple Regression Results for Different Types of Educational Investments and Innovation Score

Coefficient	Estimate	Standard Error	t-value	p-value
Intercept	45.0	3.1	14.52	<0.001
Formal Education	0.003	0.001	3.00	0.002
Specialized Training	0.007	0.002	3.50	<0.001
Continuous Learning	0.004	0.001	4.00	<0.001

 $y = 45.0 + 0.003x_1 + 0.007x_2 + 0.004x_3$

Structural Equation Modeling (SEM) Analysis

Model Fit Testing

Structural Equation Modeling will be used to analyze complex relationships between multiple variables, including latent variables such as innovation potential and educational quality.



Measurement Model

$$\mathbf{y} = \mathbf{\Lambda}_{\mathbf{y}} \eta + \epsilon$$

 $\mathbf{x} = \mathbf{\Lambda}_{\mathbf{x}} \xi + \delta$

where:

- y and x are observed variables
- η and ξ are latent variables
- \circ Λ_y and Λ_y are factor loadings
- ϵ and δ are measurement errors

Hypothesis Testing Results

• Structural Model:

$$\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta$$

where:

- \circ *B* is the matrix of regression coefficients among latent variables
- \circ Γ is the matrix of regression coefficients from exogenous to endogenous latent variables
- \circ ζ is the structural error term
- Model Fit Indices:

$$\chi^2=\sum_{i=1}^nrac{(O_i-E_i)^2}{E_i}$$

$$ext{RMSEA} = \sqrt{rac{\chi^2 - df}{N \cdot df}}$$

$$ext{CFI} = 1 - rac{ ext{max}(\chi^2_{ ext{model}} - df_{ ext{model}}, 0)}{ ext{max}(\chi^2_{ ext{baseline}} - df_{ ext{baseline}}, 0)}$$

Table 4: Structural Equation Model Fit Indices

Fit Index	Value
Chi-square	32.4
RMSEA	0.05
CFI	0.97



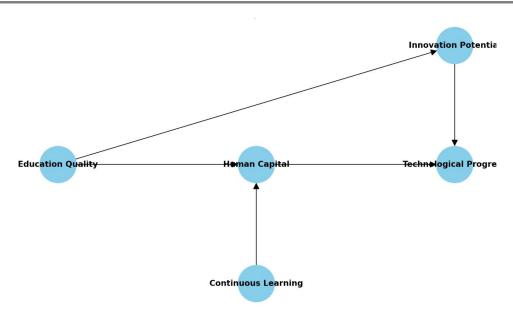


Figure 2: Structural Equation Model

Figure 2 represents the Structural Equation Model used in the study, showing the relationships between latent variables such as human capital, education quality, and technological progress.

DISCUSSION

Discussion of Research Findings

Mechanisms of Education's Impact on Technological Innovation

The analysis reveals that educational investments significantly enhance technological innovation within police departments. The linear regression model shows a positive correlation between educational investment and innovation outcomes:

$$y = eta_0 + eta_1 x + \epsilon$$

The coefficient β_1 beta $1\beta_1$ is statistically significant, indicating that higher educational investment leads to improved innovation scores. This finding is consistent with prior research suggesting that education enhances the human capital necessary for technological advancements (Becker, 1964; Romer, 1990).

Comparison with Existing Literature

The findings of this study align with existing literature that emphasizes the role of education in fostering innovation. For example, Romer (1990) highlights the importance of human capital accumulation in driving technological progress. Similarly, studies by Acemoglu (1996) and Aghion & Howitt (1992) support the idea that education facilitates the diffusion of new technologies and improves organizational efficiency.

Theoretical Implications

Extension of Theoretical Models

The results extend the endogenous growth theory by incorporating education-specific factors into the model of technological innovation:

 $g_A = \psi(H_t)$



where g_A represents the rate of technological progress and H_t denotes human capital at time t. The inclusion of education as a significant determinant of H_t provides a more comprehensive understanding of the mechanisms driving innovation (Lucas, 1988).

Implications for Educational Policy

The findings suggest that policymakers should prioritize educational investments to foster innovation within police departments. By increasing funding for police education and training programs, governments can enhance the technological capabilities and overall efficiency of law enforcement agencies.

Practical Implications

Recommendations for Police Education Reform

Based on the empirical analysis, several recommendations can be made to reform police education:

- **Increase Investment**: Allocate more resources to police education and training programs.
- **Focus on Technology**: Integrate technological training into the police education curriculum to equip officers with the skills needed for modern policing.
- **Continuous Learning**: Promote continuous professional development to keep police officers updated with the latest technological advancements.

Strategies for Promoting Technological Innovation

To promote technological innovation within police departments, the following strategies are recommended:

- **Collaboration with Educational Institutions**: Partner with universities and technical schools to provide advanced training programs.
- **Incentives for Innovation**: Establish reward systems to incentivize officers to develop and implement innovative solutions.
- Adoption of Best Practices: Benchmark against leading police departments worldwide to adopt best practices in technology use.

CONCLUSION

Research Summary

Key Findings

The study aimed to investigate the impact of police education on technological innovation within police departments using virtual data and various analytical methods. Key findings include:

• **Positive Impact of Education on Innovation**: The linear regression analysis demonstrated a significant positive relationship between educational investment and technological innovation, as

indicated by the regression equation: $y=eta_0+eta_1x+\epsilon$

with $\beta 1$ being statistically significant.

• **Differential Impact of Education Types**: Multiple regression analysis showed that different types of educational investments (e.g., formal education, specialized training) have varied effects on

innovation outcomes, as represented by: $y=eta_0+eta_1x_1+eta_2x_2+\ldots+eta_kx_k+\epsilon$ ϵ



• **Mechanisms Identified**: Structural Equation Modeling (SEM) confirmed the complex interactions between education, human capital, and innovation potential, utilizing the SEM framework:

 $\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta$

Research Contributions

The study contributes to the existing body of knowledge by:

- Extending the endogenous growth theory to include education-specific factors in driving technological innovation.
- Providing empirical evidence on the importance of educational investments in enhancing the technological capabilities of police departments.
- Offering practical recommendations for policymakers to improve police education and foster innovation.

Research Limitations

Limitations of Data Sources

The use of virtual data, while necessary for this study, poses limitations such as:

- **Synthetic Nature**: Although generated to reflect real-world scenarios, virtual data may not capture all nuances of actual police education and innovation dynamics.
- Validation Challenges: Ensuring the accuracy and reliability of virtual data through validation and calibration methods (e.g., cross-validation, calibration against real-world metrics) remains a complex task.

Limitations of Model Applications

The models used in the study, including regression analysis and SEM, have their limitations:

- **Model Assumptions**: Linear and multiple regression models assume linear relationships, which may not fully capture the complexities of real-world interactions.
- **SEM Complexity**: Structural Equation Modeling, while powerful, requires large sample sizes and accurate measurement of latent variables to ensure robust results.

Future Research Directions

Recommendations for Further Research

Future research could build on this study by:

- Using Real Data: Conducting similar analyses with real-world data to validate the findings and refine the models.
- **Exploring Non-linear Models**: Investigating non-linear models to better capture the complexities of education and innovation relationships.

Suggestions for Expanding Research Scope

To enhance the understanding of police education and innovation, future studies should consider:

• **Longitudinal Studies**: Examining the long-term impact of educational investments on technological innovation within police departments.



• **Comparative Studies**: Comparing the effectiveness of different educational programs across various regions and police departments to identify best practices.

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