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# Research On Analysis Of Chinese University Students' Learning Behaviors And Learning Outcomes Through Big Data Mining Visual Portrait As An Intermediary And Learning Early Warning As A Moderator

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**ARTICLE INFO** **ABSTRACT**

This study explores the multifaceted factors influencing academic outcomes among Chinese university students through the lens of educational data analytics. Utilizing a mixed-methods approach, demographic characteristics, learning behaviors, early warning indicators, and the mediating and moderating effects of visual portraits and early warning systems are examined across three prominent Chinese universities: Tsinghua, Peking, and Fudan. Descriptive statistics reveal variations in mean age, gender ratios, and mean Grade Point Average (GPA) among students, while correlation and regression analyses highlight the significant positive associations between learning behaviors (such as study hours and online engagement) and academic outcomes (such as GPA). Chi-square tests demonstrate the predictive power of early warning indicators in identifying students at risk of academic underperformance. Additionally, mediation and moderation analyses elucidate the intermediary and moderating roles of visual portraits and early warning systems in shaping the relationship between learning behaviors and academic outcomes. Findings underscore the importance of adopting a holistic approach to student support and educational practice, informed by evidence-based interventions derived from educational data analytics.

**Keywords**: Chinese University, educational data analytics, student success, learning behaviors, early warning indicators

## Introduction

In recent years, the landscape of higher education has undergone significant transformation, driven by technological advancements and an increasing emphasis on data-driven decision-making (Hora et al., 2017; Ashaari et al., 2020; Raja et al., 2023). Educational institutions worldwide are increasingly turning to educational data analytics to gain insights into student behaviors (Taylor, 2020), preferences (Williamson, 2018), and learning outcomes (Liu et al., 2017; Dawodu et al., 2023), with the aim of enhancing teaching effectiveness (Laux et al., 2017), improving student engagement (Miller, 2019), and optimizing academic success (Chaurasia et al., 2018). Within this context, understanding the complex interplay between various factors influencing student success (Nikou & Aavakare, 2021) has become a central focus of research in the field of higher education (Korhonen et al., 2019; Phyo et al., 2023).
In China, as in many other countries, universities face the challenge of supporting a diverse student body with varying academic backgrounds (Heublein, 2014; Wang, 2017; Song, 2018), learning styles (Han & Dong, 2024), and socio-economic circumstances (Hang, 2023). The ability to identify and address the needs of individual students is crucial for promoting equitable access to education (Simek & Stewart, 2024) and fostering inclusive learning environments (Yu & Moskal, 2019). Educational data analytics offers a promising avenue for achieving these goals (Yan & Berliner, 2011) by providing educators and administrators with actionable insights into student behaviors and performance indicators (Jiang, W., & Saito, 2024).

## Demographic Characteristics

The demographic profile of students within higher education institutions plays a crucial role in shaping their educational experiences (Pandya et al., 2023) and outcomes (Gu et al., 2023). Factors such as age (Jones, L., & Castellanos, 2023), gender (Balakrishna, 2023), and socio-economic status (Wang et al., 2023) can influence students' access to resources, level of engagement, and academic performance (Kumar et al., 2023). Understanding the demographic characteristics of students is essential for designing targeted interventions (Polyportis, 2024) and support services that meet their diverse needs (Li et al., 2023).

## Learning Behaviors and Academic Outcomes

Central to the study of student success is the examination of learning behaviors and their impact on academic outcomes. Learning behaviors encompass a range of activities, including study habits (Ewell et al., 2022), participation in class discussions (Wang, 2023), and engagement with course materials (Gasiewski et al., 2012). Research has consistently shown that students who exhibit proactive learning behaviors, such as effective time management and active participation in learning activities, are more likely to achieve higher academic success (Richardson et al., 2012).

## Early Warning Indicators

Early identification of students at risk of academic underperformance is critical for providing timely interventions and support services. Early warning indicators, such as attendance (Suldo et al., 2019), course completion rates (Maclean & Law, 2022), and assignment submissions, can serve as valuable predictors of student success (Huang et al., 2021). By monitoring these indicators, educators can identify students who may need additional assistance and implement targeted interventions to prevent academic setbacks (Albreiki et al., 2021).

## Mediation and Moderation Effects

In addition to direct relationships between learning behaviors and academic outcomes, the study of mediation and moderation effects provides insights into the underlying mechanisms (Chen et al., 2022) and conditions that influence these relationships (Tandon et al., 2020). Mediation analysis examines the role of intermediary variables in explaining the relationship between an independent variable (e.g., learning behavior) (Zhou et al., 2023) and a dependent variable (e.g., academic outcome) (Guo et al., 2021). Moderation analysis, on the other hand, explores how the relationship between two variables is influenced by a third variable (e.g., early warning system) (Hölzel et al., 2011).

## Purpose of the Study

Against this backdrop, the present study aims to investigate the relationships between demographic characteristics, learning behaviors, early warning indicators, and academic outcomes among Chinese university students. Specifically, we seek to:

- ❖ Examine the demographic characteristics of students across three prominent Chinese universities, including age, gender, and socio-economic status.
- ❖ Investigate the associations between learning behaviors (e.g., study hours, online engagement) and academic outcomes (e.g., GPA).
- ❖ Explore the predictive power of early warning indicators in identifying students at risk of academic underperformance.
- ❖ Investigate the mediating role of visual portraits and the moderating effect of early warning systems in shaping the relationship between learning behaviors and academic outcomes.

## Significance of the Study

This study holds significant implications for educational practice, policy, and research in the context of Chinese higher education. By gaining a deeper understanding of the factors influencing student success, educators and administrators can develop evidence-based interventions and support services that effectively address the diverse needs of students. Furthermore, the findings of this study contribute to the growing body of literature on educational data analytics and its potential to transform teaching and learning practices in higher education. This study seeks to advance our understanding of the complex interplay between demographic characteristics, learning behaviors, early warning indicators, and academic outcomes among Chinese university students. By examining these relationships through the lens of educational data analytics, we aim to inform evidence-based interventions and support services that promote student success and enhance the overall quality of higher education in China.

## Methodology

The research adopts a quantitative approach to analyze the relationship between Chinese university students' learning behaviors and learning outcomes, utilizing big data mining visual portraits as an intermediary and learning early warning systems as a moderator. The methodology encompasses data collection, sampling procedures, variables, and analysis techniques.

## Data Collection

Data for this study are collected from three prominent Chinese universities: Tsinghua University, Peking University, and Fudan University. The dataset comprises information on students' demographic characteristics, academic performance, learning behaviors (e.g., study hours, online engagement), and early warning indicators (e.g., attendance, assignment submissions).

**Sample Size**: A uniform sampling size of 500 students per university is employed to ensure adequate representation while maintaining feasibility and manageability.

## Variables

The key variables examined in this research include:

- Dependent Variable: Academic outcomes (e.g., GPA, exam scores)
- Independent Variables: Learning behaviors (e.g., study hours, participation in online forums)
- Mediating Variable: Big data mining visual portraits
- Moderating Variable: Learning early warning systems

## Analysis Techniques

The analysis involves several steps:

- **Descriptive statistics**: Describing the demographic characteristics and learning behaviors of the sample.
- **Correlation, regression and chi-square analysis**: Examining the relationships between learning behaviors, academic outcomes, and other relevant variables.
- **Mediation analysis**: Investigating the mediating role of big data mining visual portraits in the relationship between learning behaviors and outcomes.
- **Moderation analysis**: Assessing the moderating effect of learning early warning systems on the relationship between learning behaviors and outcomes.

The statistical software package SPSS (Statistical Package for the Social Sciences) is utilized for data analysis.

# Results

**Table 1:** Descriptive Statistics of Demographic Characteristics

| University | Sample Size | Mean Age | Gender Ratio (M/F) | Mean GPA |
|---|---|---|---|---|
| Tsinghua | 500 | 20.5 | 1:1.2 | 3.6 |
| Peking | 500 | 21.0 | 1:1.1 | 3.8 |
| Fudan | 500 | 20.8 | 1:1.3 | 3.5 |

The descriptive statistics presented in Table 1 provide insights into the demographic characteristics of students across three prominent Chinese universities: Tsinghua, Peking, and Fudan. The mean age of students varies slightly, with Peking University having the highest mean age of 21.0 years, followed closely by Fudan University at 20.8 years and Tsinghua University at 20.5 years. Gender ratios also exhibit slight variations, with Peking University having the most balanced ratio (1:1.1) compared to Tsinghua (1:1.2) and Fudan (1:1.3). Mean GPA scores differ among the universities, with Peking University having the highest mean GPA of 3.8, followed by Tsinghua University at 3.6 and Fudan University at 3.5.

**Table 2:** Correlation Matrix of Learning Behaviors and Academic Outcomes

| | Study Hours | Online Engagement | GPA |
|---|---|---|---|
| Study Hours | 1 | 0.45 | 0.60 |
| Online Engagement | 0.45 | 1 | 0.55 |
| GPA | 0.60 | 0.55 | 1 |

The correlation matrix presented in Table 2 reveals the relationships between learning behaviors (study hours and online engagement) and academic outcomes (GPA). Across all universities, significant positive correlations are observed between study hours and GPA ($r = 0.60$, $p < 0.001$), as well as between online engagement and GPA ($r = 0.55 - 0.45$, $p < 0.001$). These findings suggest that students who dedicate more time to studying and engage actively in online learning activities tend to achieve higher GPAs.

**Table 3:** Regression Analysis Results - Predicting GPA from Learning Behaviors

| University | Predictor | Coefficient | SE | p-value |
|---|---|---|---|---|
| Tsinghua | Study Hours | 0.25 | 0.03 | <0.001 |
| | Online Engagement | 0.15 | 0.02 | <0.01 |
| Peking | Study Hours | 0.28 | 0.02 | <0.001 |
| | Online Engagement | 0.18 | 0.03 | <0.01 |
| Fudan | Study Hours | 0.24 | 0.03 | <0.001 |
| | Online Engagement | 0.12 | 0.02 | <0.05 |

Regression analysis results presented in Table 3 further reinforce the importance of learning behaviors in predicting GPA. Across all universities, both study hours and online engagement demonstrate significant positive coefficients ($p < 0.001$ or $p < 0.01$), indicating that these factors positively influence academic outcomes. Specifically, for every additional hour spent studying, GPA is predicted to increase by approximately 0.24 to 0.28 points, while each unit increase in online engagement is associated with a predicted GPA increase ranging from 0.12 to 0.18 points.

**Table 4:** Chi-Square Test Results - Association between Early Warning Indicators and Academic Outcome

| University | Chi-Square Value | df | p-value |
|---|---|---|---|
| Tsinghua | 45.67 | 4 | <0.001 |
| Peking | 53.21 | 4 | <0.001 |
| Fudan | 38.92 | 4 | <0.001 |

Chi-square test results in Table 4 indicate a significant association between early warning indicators (e.g., attendance, assignment submissions) and academic outcomes (e.g., GPA) across all universities ($p < 0.001$). This suggests that early warning indicators play a crucial role in predicting academic success and can be valuable for identifying students at risk of underperformance.

**Table 5:** Cluster Analysis Results - Student Segmentation based on Learning Behaviors

| University | Cluster | Number of Students | Average GPA |
|---|---|---|---|
| Tsinghua | Cluster 1 | 250 | 3.5 |
| | Cluster 2 | 250 | 3.8 |
| Peking | Cluster 1 | 300 | 3.6 |
| | Cluster 2 | 200 | 4.0 |
| Fudan | Cluster 1 | 200 | 3.3 |
| | Cluster 2 | 300 | 3.7 |

Cluster analysis results in Table 5 reveal distinct student segments based on learning behaviors and their corresponding average GPAs. Across the universities, Cluster 2 consistently demonstrates higher average GPAs compared to Cluster 1, indicating that students exhibiting certain learning behaviors tend to achieve better academic outcomes.

**Table 6:** Mediation Analysis Results - Three Universities

| University | Mediator (Visual Portrait) | Coefficient | SE | p-value |
|---|---|---|---|---|
| Tsinghua | Learning Behavior (X) | 0.25 | 0.03 | <0.001 |
| | Outcome (Y) | 0.40 | 0.04 | <0.001 |
| | Mediation Effect | 0.10 | 0.02 | <0.001 |
| Peking | Learning Behavior (X) | 0.28 | 0.02 | <0.001 |
| | Outcome (Y) | 0.38 | 0.03 | <0.001 |
| | Mediation Effect | 0.12 | 0.02 | <0.001 |
| Fudan | Learning Behavior (X) | 0.24 | 0.03 | <0.001 |
| | Outcome (Y) | 0.37 | 0.05 | <0.001 |
| | Mediation Effect | 0.09 | 0.02 | <0.001 |

**Table 7**: Moderation Analysis Results - Three Universities

| University | Moderator (Early Warning) | Coefficient | SE | p-value |
|---|---|---|---|---|
| Tsinghua | Learning Behavior (X) | 0.15 | 0.03 | <0.001 |
| | Outcome (Y) | 0.35 | 0.04 | <0.001 |
| | Interaction Effect | 0.08 | 0.02 | <0.001 |
| Peking | Learning Behavior (X) | 0.18 | 0.02 | <0.001 |
| | Outcome (Y) | 0.36 | 0.03 | <0.001 |
| | Interaction Effect | 0.10 | 0.02 | <0.001 |
| Fudan | Learning Behavior (X) | 0.14 | 0.03 | <0.001 |
| | Outcome (Y) | 0.33 | 0.05 | <0.001 |
| | Interaction Effect | 0.07 | 0.02 | <0.001 |

Mediation and moderation analysis results in Tables 6 and 7 elucidate the mediating role of visual portraits and the moderating effect of early warning systems on the relationship between learning behaviors and academic outcomes. The significant coefficients and mediation/moderation effects highlight the importance of these intermediary and moderating factors in shaping students' educational trajectories and success.

## Discussion

The findings presented in this study provide valuable insights into the complex interplay between various factors influencing Chinese university students' academic outcomes. Through a comprehensive analysis of demographic characteristics, learning behaviors, early warning indicators, and the role of mediation and moderation effects, we can better understand the dynamics of student success in higher education institutions. This discussion synthesizes the key findings, their implications, and potential avenues for future research.

The descriptive statistics presented in Table 1 offer an overview of the demographic profiles of students across three prominent Chinese universities. Variations in mean age, gender ratios, and mean GPA highlight the diversity within each institution. These differences underscore the importance of considering institutional context when analyzing learning behaviors and outcomes (Johnson et al., 2020). Furthermore, the correlations revealed in Table 2 between learning behaviors (study hours and online engagement) and academic outcomes (GPA) emphasize the significant positive associations between these variables. These findings align with previous research (Macfadyen & Dawson, 2010) indicating that students who dedicate more time to studying and engage actively in online learning activities tend to achieve higher academic performance (Richardson et al., 2012).

Regression analysis results (Table 3) further support the importance of learning behaviors in predicting GPA, with both study hours and online engagement demonstrating significant positive coefficients across all universities. These results are consistent with the literature on the predictive power of learning behaviors for academic success (Crede et al., 2017). Additionally, the significant associations revealed by the chi-square test (Table 4) highlight the role of early warning indicators in identifying students at risk of underperformance. Early intervention based on these indicators can be crucial for providing timely support and improving student outcomes (Huang et al., 2021; Nimy et al., 2023).

Cluster analysis results (Table 5) provide insights into the segmentation of students based on their learning behaviors and average GPAs. The existence of distinct clusters suggests the presence of different student profiles with varying levels of academic achievement (Xie et al., 2020). Understanding these profiles can inform targeted interventions tailored to meet the specific needs of different student groups (Baker et al., 2010).

The mediation and moderation analyses (Tables 6 and 7) shed light on the underlying mechanisms influencing the relationship between learning behaviors and academic outcomes. The significant mediation effects of visual portraits and the moderating effects of early warning systems highlight the importance of considering these intermediary and moderating factors in educational interventions (Yang et al., 2020). Visual portraits provide educators with valuable insights into students' learning trajectories and patterns (Manire et al., 2023), facilitating personalized interventions (Bernacki et al., 2021) and support strategies (Gaeta et al., 2014). Similarly, early warning systems enable timely interventions for students at risk of academic underperformance (Peña-Ayala, 2018), thereby enhancing student retention and success rates (Fischer et al., 2020).

Overall, the findings of this study underscore the importance of adopting a holistic approach to understanding and supporting student success in Chinese universities. By considering demographic characteristics, learning behaviors, early warning indicators, and the role of mediation and moderation effects, educators can develop targeted interventions to foster academic achievement and holistic development among students. However, it is essential to acknowledge the limitations of this study, including the use of limited data and the need for further empirical research to use the findings in learning behaviors of the students.

This study contributes to the growing body of literature on educational data analytics and its implications for improving student outcomes in higher education. By leveraging quantitative analyses and data-driven insights, educators can enhance their understanding of the factors influencing student success and implement evidence-based interventions to support student learning and development. Future research should focus on longitudinal studies to explore the long-term effects of interventions and further elucidate the complex dynamics of student success in diverse educational contexts.

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## Conclusion

This study provides a comprehensive examination of the factors influencing academic outcomes among Chinese university students through the lens of educational data analytics. By analyzing demographic characteristics, learning behaviors, early warning indicators, and the mediating and moderating effects of visual portraits and early warning systems, this research contributes valuable insights into the dynamics of student success in higher education. The findings underscore the importance of adopting a holistic approach to student support, leveraging data-driven insights to inform targeted interventions and enhance educational practices. Moving forward, it is essential for educators and policymakers to continue harnessing the power of data analytics to optimize student learning experiences, improve retention rates, and foster holistic development among students. Furthermore, future research should focus on longitudinal studies to validate the findings and explore additional factors that may influence student outcomes in diverse educational contexts. Ultimately, by leveraging evidence-based practices and continuous innovation, we can work towards creating a more inclusive, supportive, and effective learning environment for all students in Chinese universities and beyond.

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