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Research Article

Knowledgebase Ontology Driven Model for Student Development Through Swot Analysis

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ARTICLE INFO	ABSTRACT
Received: 29 Dec 2024 Revised: 15 Feb 2025 Accepted: 24 Feb 2025	Traditional educational systems often rely on rigid, siloed databases that do not capture the multifaceted nature of student development. This limits the ability of institutions to provide personalized support and informed guidance. To address this challenge, this paper proposes a knowledge-based, ontology-driven framework for the holistic development of students. The model integrates diverse dimensions—including academic performance, personal background, extracurricular involvement, cultural context, behavioral patterns, and SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis—into a unified semantic structure. By leveraging technologies such as RDF, OWL, and SPARQL, the system constructs a dynamic knowledge graph that enables intelligent querying, semantic reasoning, and real-time data analysis. The inclusion of SWOT data enhances the ability to uncover latent potential and identify areas for targeted intervention. Unlike conventional systems, this approach supports context-aware decision-making and adaptive learning strategies. Experimental results demonstrate the effectiveness in identifying critical patterns—such as the relationship between financial status and academic performance, behavioral insights, and self-directed learning tendencies—ultimately promoting more effective educational planning and student development. **Keywords:** Ontology-based framework, Knowledge graph, Holistic student development, Semantic web, SWOT analysis

1. INTRODUCTION

Under the context of accelerated tech development, educational frameworks are more and more shifting from traditional, static platforms to smarter and more automated ones. Although ontology editors like Protégé have long been typical tools for manual and visual knowledge representation editing, recent trends reflect a categorical shift toward programmatic methods, especially those facilitating dynamic ontology building and interoperability with data analytics and machine learning frameworks [19]. Even with different semantic web frameworks available, a gap still exists in utilizing such tools for thorough student development—something this research seeks to close. Education, rooted in the Latin term educare, meaning "to lead out," has long been recognized as a multidimensional force in shaping individuals intellectually, morally, and socially. From the philosophical teachings of Plato, Aristotle, and Confucius to contemporary educational theory, the purpose of education has evolved significantly. In the 21st century, it extends well beyond academic instruction to encompass emotional well-being, behavioral insight, extracurricular engagement, and professional readiness [2],[13].

Current education centers more on inclusivity, individualization, and data-driven planning to nurture the well-rounded growth of students. Consequently, there has been heightened need for intelligent systems to handle and make sense of disparate learner data. Traditional database management systems (DBMS), as powerful as they are in maintaining structured data, tend to underperform in modeling the subtle, multifaceted aspects of student profiles—

such as the correlation of academic achievement, socio-economic status, after-school activities, and psychological dispositions [18].

Conversely, ontology-based systems provide a richer semantically and more connected representation of learning data.

Ontologies organize domain knowledge in a machine-interpretable and reasonable form that enables

the derivation of meaningful relations among heterogeneous student attributes [2], [4]. The tools including the Resource Description Framework (RDF), Web Ontology Language (OWL), and SPARQL Protocol and RDF Query Language (SPARQL) allow semantic reasoning, automated retrieval of data, and intelligent support in decision making—abilities very applicable to regulating complexity in students' development [6], [7]. This paper presents a thorough ontology-based model that combines personal, academic, extracurricular, cultural, and SWOT (Strengths, Weaknesses, Opportunities, and Threats) qualities into one cohesive knowledge graph. Adopting semantic web technologies, the model supports automated generation of ontologies, smart querying, and scalable examination. Compared to common tools such as Protégé, the suggested strategy offers greater flexibility, reasoning, and real-time adaptability, rendering it a powerful solution to data-driven educational planning and individualized student support [1], [14].

2. LITERATURE SUMMARY

The growing sophistication of learning data and the necessity for smart, adaptive learning systems have spurred a worldwide move toward ontology-based education. Ontologies provide systematic, semantically rich representations of knowledge that can support reasoning, flexibility, and data fusion. Tkachenko et al. [1] designed an ontological model for contemporary learning processes, emphasizing the benefits of reusable structures to deliver consistency and scalability. In a similar vein, Reddy et al. [2] developed a student ontology in OWL to represent personal and academic growth in a machine-interpretable form. Ontology learning has also gained attention, with Wątróbski [3] and Konys & Drążek [4] studying how ontologies can be learned automatically from texts and domain sources in order to limit manual intervention and improve scalability. With reference to personalization, Clemente et al. [5] created an ontology-based adaptive recommender system and Ibrahim et al. [6] proposed personalized recommendation architecture, both relying on ontologies to provide custom learning experiences.

Interoperability and semantic integration between systems are highlighted in Rejeb et al. [7], which traces the Semantic Web's growth and promotes data compatibility across platforms. Chang et al. [8] combine data mining with ontology to develop intelligent tutoring systems that are adaptive to student performance. Duran and Ramírez [9] improve the usability of Open Educational Resources (OERs) through semantic platforms, and Alsobhi et al. [10] promote inclusivity through the use of ontologies to personalize learning materials for dyslexic learners. The application of ontologies to transdisciplinary education is investigated by Butt et al. [11], who apply generic educational ontologies to model product design processes.

Natural language processing and querying are also very important. Karim et al. [12] show that natural language questions can be translated into SPARQL for learning search engines. Gröschner [13] addresses ontological foundations within teacher education, further emphasizing the general applicability of semantic technologies. Rahayu et al. [14] provide a systematic overview of ontology-driven e-learning recommender systems, demonstrating their effect on student participation and learning performance in universities. Almendros-Jiménez et al. [15] extend SPARQL with fuzzy logic to aid in uncertain queries, and Kang et al. [16] suggest augmenting knowledge graph embeddings to improve query processing.

Meenachi & Baba [17] and Stancin et al. [18] give background reviews of use of ontology across different fields, including education, whereas Slimani [19] contrasts tools and formalisms for developing ontologies, ensuring proper system design. Liang et al. [20] discuss knowledge aggregation in schismatized learning environments with a focus on intelligent support systems. Palombi et al. [21] present OntoSIDES to track student performance in medical schools through ontology-based measures. Chen, Lu, & Lin [22] construct effective SPARQL query generators for learning question answering systems, and Chen, Zhang, & Zou [23] improve multi-query SPARQL processing in big data environments.

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As scalability emerges as an issue, Banane et al. [24] introduce ScalSPARQL, a system which translates SPARQL queries to NoSQL representations to accommodate versatile storage solutions. Zhang & Xu [25] add spatial-temporal attributes to SPARQL for more dynamic educational queries, and Vcelak et al. [26] create a query builder for medical temporal data with SPARQL. Gupta & Malik [27] compare SPARQL semantics and execution across tools and provide insights into performance optimization. Ferru & Atzori [28] present portable custom SPARQL functions, and Fujino & Fukuta [29] create a query rewriting method based on ontology mapping reliability. Lastly, Kyu & Oo [30] improve SPARQL query execution time using optimized processing methods.

Taken together, these researches illustrate the enormous potential of ontology-based systems in education—from adaptive learning and intelligent tutoring to semantic querying and real-time analysis. Nevertheless, the necessity of real-time integration, automation, and scalability continues to exist. The present work overcomes such limitations by presenting a Python-based student development model based on RDF, OWL, and SPARQL that constructs and queries ontologies dynamically, enabling comprehensive and adaptive student learning environments.

3. PROPOSED WORK

3.1 Description of Dataset

To support the development of an Knowledge-based model for holistic student analysis, a **s**urvey conducted through both face-to-face interactions and Google Forms in online mode. The survey captured a broad spectrum of information reflecting the cognitive, behavioral, academic, financial, and emotional dimensions of students. The questionnaire was divided into logically categorized sections corresponding to different educational phases, with questions designed to uncover key factors influencing student development and SWOT (Strengths, Weaknesses, Opportunities, and Threats) dimensions.

Sample Questions:

a) Personas (Self and identity)

- What is your favourite colour?
- Are you born with any disability?
- How do you often spend your free time?

b) Pre-Primary (Early cognitive development)

- How good were your learning and writing skills?
- Were you able to recognize objects in early learning stages?
- How good were you at singing rhymes?

c) Primary School

- Did you participate in school events?
- Was the school area sufficient for outdoor play?
- Were you able to answer questions in class?

d) Mid-School *(Interests and environment)*

- Which genre of entertainment did you prefer at that age?
- Were you interested in solving mathematical problems?
- Did your environment encourage participation in activities?

e) High School *(Academic interests and motivation)*

- What are your favourite subjects?

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- What was your **Grade 10 CGPA or percentage**?
- Who is your role model?

f) Intermediate *(Academic and decision-making)*

- Which stream/group did you choose?
- Who decided your course of study?
- Did movies or media influence your thinking?

g) Graduation *(Mental health, career perception, and academics)*

- What is your current CGPA or academic percentage?
- What is your family's approximate annual income?
- Do you feel burdened by your course?
- Do you face any family issues?
- Do you suffer from anxiety or depression?

Importance of Financial and Academic Data

Financial and academic data were crucial in this study, particularly for identifying students falling under specific categories such as:

- Academically strong but financially challenged (e.g., high CGPA, low income)
- Financially privileged but academically struggling
- Students facing academic stress or lack of autonomy in career decisions

These dimensions were directly mapped into the ontology, enabling SPARQL queries to reason over cross-domain relationships such as financial status versus performance, or emotional well-being versus academic burden.

3.2 Methodology

The methodology for Student development model using Ontology is to gather, organize, and analyze student data. The process starts with data gathering through surveys, collecting information regarding personal information, academics and extracurricular activities. The data is cleaned and structured for uniformity before being represented in an ontology model that defines relationships between the different attributes. The knowledge base is developed using RDF (Resource Description Framework), allowing effective storage and retrieval using SPARQL queries.

The system uses data visualization methods, such as ontology graphs, bar charts, and pie charts, to represent relationships between the attributes. Ultimately for students, academic and extracurricular recommendations will be offered based on student profiles.

The model proposed here uses an ontology-based approach to capture and represent the various aspects of student development. The ontology is structured into five broad categories: (1) Personal Information (e.g., name, age, location, parental information), (2) Academic Information (e.g., school board, CGPA, career objectives), (3) Extracurricular Activities (e.g., involvement in sports and cultural activities), (4) Cultural Information (e.g., social interactions and lifestyle), and (5) SWOT analysis (Strengths, Weaknesses, Opportunities, and Threats).

Technologies used include RDF and OWL for modelling the ontology schema, SPARQL for querying the knowledge graph, and Python for implementation. Python was preferred to manual ontology editors such as Protégé to facilitate dynamic ontology creation from datasets, automatic SPARQL querying, effortless machine learning integration, and real-time data visualization.

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The deployment entailed conceptualizing student growth using a knowledge graph that connected critical academic, behavioral, and psychological variables. SPARQL queries were employed to retrieve focused insights, for example, to find financially poor but academically talented students, low CGPA but high-income students, or students with particular behavioral patterns.

3.3 System Architecture

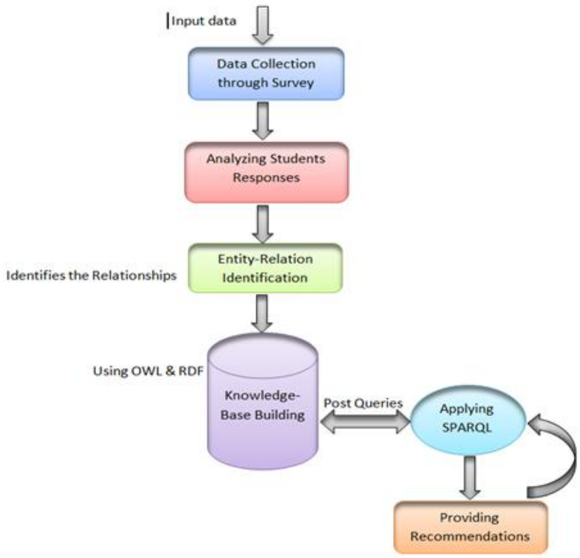

Figure 1: *The proposed System Architecture illustrating Knowledge-Base building and generating SPARQL insights*

The following are the major steps followed by the proposed system architecture as shown in Figure 1

1. Data Collection through Survey

- This initial step gathers comprehensive student data, including:
- The purpose is to create a rich base of real-world data about each student.

2. Analyzing the Survey Data

- Once data is collected, it is cleaned and standardized using Python.
- Columns are normalized, missing values handled, and entity types (e.g., numeric vs. string) are identified.

3. Entity Identification and Relationship Mapping

- This stage extracts key entities such as Student, College Name, Graduating Course, etc.
- Relationships are identified, such as:
  - attends → between Student and College Name
  - likes → for favourite food or festival
  - belongs to → for school board
- These form the backbone of the ontology.

4. Ontology Building using OWL & RDF

- An ontology is dynamically built:

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- Each student is modelled as an individual of the Student class.
- Attributes and relationships are expressed as triples (subject-predicate-object).

5. Applying SPARQL Queries

- **SPARQL** is used to filter and retrieve insights such as:
  - Financially poor but academically excellent students
  - Emotionally sensitive students needing counselling
  - Career-driven students vs. those influenced by peers
- These queries act like intelligent filters, enabling nuanced understanding.

6. Providing Recommendations

- Based on SPARQL results, the system gives personalized guidance:
  - Suggests counselling sessions
  - Recommends career paths
  - Proposes extracurricular activities to support personal development
- The recommendations are evidence-based, derived from data semantics.

Technologies Used:

- **RDF & OWL**: Semantic technologies to define the ontology schema.
- **SPARQL**: To retrieve insights from the knowledge graph.
- **Python** For ontology creation, reasoning, and query execution.

Why Use Python Instead of Protégé?

Protégé is a widely used ontology editor but has limitations.

By using **Python** we achieve:

- **Dynamic Ontology Generation:** Automatically constructing ontology from datasets instead of manual input.
- **SPARQL Query Execution:** Direct querying of knowledge graphs within Python scripts.

Table1. *Comparison of Knowledge-Based vs Traditional Database Approach*

	Knowledge-Base	Traditional Databases
Data Representation	Semantic relationships,Knowledge graphs.	Represented in tables with rows and columns.
Reasoning Ability	Supports inference and logical deductions.	Lacks reasoning.
Data Integration	Interoperable with external Knowledge sources.	Limited to structured schema.
Scalability	Supports dynamic schema updates	Schema must be predefined
Entity Relation [E.R]	Dependant Attributes with established meaningful Relations	Independent Entities/attributes
Pattern Extraction	Rule Based Matching of Query Terms	Exact matching of Query Terms/attributes

Query Processing	Rule based Query using SPARQL	Structured Query using SQL
Semantic Interpretation	Interpretations are possible	Interpretations not possible
Recommender System	Semantic recommendations can be provided	Not directly possible
AI Approaches	Knowledge Engineering approaches makes it applicable for Recommendations	Cannot be directly applicable
Results Visualization	Knowledge Graphs	Entity Relation/ Tabular Formats
Size	Applicable to unstructured data	Restricted to structured data

4. RESULTS AND DISCUSSION

The application of the ontology-based system is effective in dynamically generating, querying, and visualizing student-related information as discussed in table 1. The knowledge graph effectively depicted semantic relationships between various student attributes, including CGPA, decision-making, health conditions, and career goals.

Important SPARQL queries effectively retrieved detailed information, including:

• Students with CGPA ranging from 7 to 10 who decided on their own careers.

• Poorly funded but academically talented students.

• Academically poor students from economically affluent backgrounds.

These outputs confirmed the model's semantic reasoning and context-aware insight extraction capabilities—features not found in conventional relational databases. Additionally, ontology visualization facilitated interpretability and decision-making and made it an appropriate tool for teachers, counsellors, and academic planners.

In comparison with conventional DBMS, the approach based on knowledge provided greater reasoning, integration of data, and flexibility. Automatic ontology generation also overcame the constraints of manual input in applications such as Protégé.

Knowledge Graph

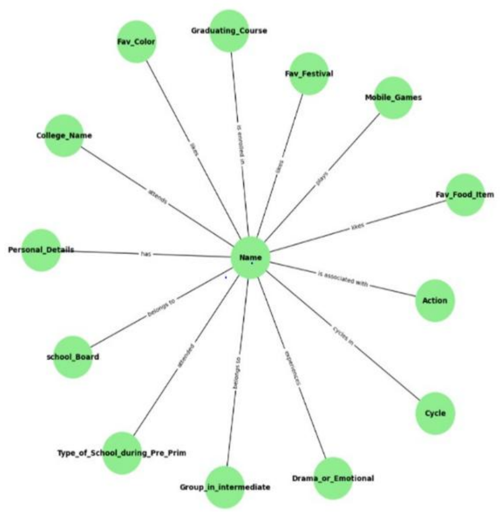

Figure 2. *Knowledge graph representing relationships among the concept and attributes*

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Description: This knowledge graph as shown in Figure 2 illustrates different details about a student, with the student's name at the center. It connects the name to information like favorite food, games, color, school background, college, and emotions. It helps us understand the student better by showing how all these things are related.

This knowledge graph is a visual representation of a knowledge base, where each student is an entity, and their attributes (like favorite color, school board, emotional traits, etc.) are stored as structured knowledge using clear relationships.

How it's related to a knowledge base:

- A knowledge base stores information in a way that both humans and machines can understand.
- This graph organizes student data into entities (nodes) and relationships (edges), making it easy to query, analyze, and reason about the student's life and behavior.
- It captures not just raw data, but meaningful connections — like what the student likes, where they studied, or how they respond emotionally — which is the essence of a semantic, ontology-based knowledge system.

So, this knowledge graph is part of a knowledge base that helps in holistic student analysis through structured, meaningful data.

Knowledge Base:

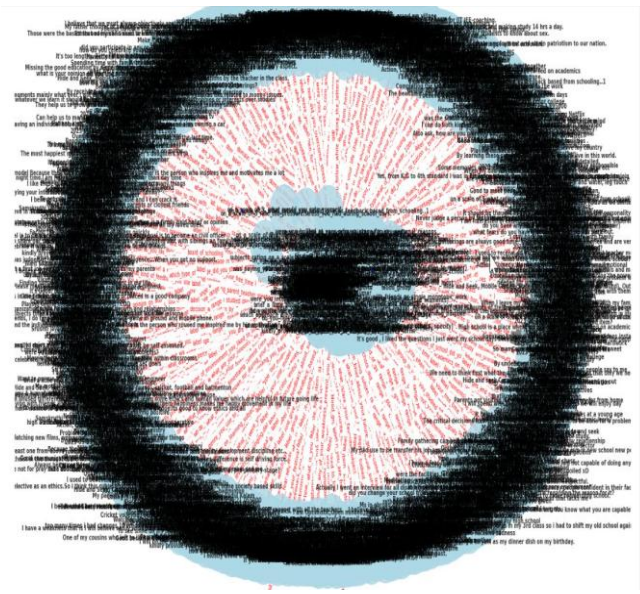

Figure 3. *Knowledge Base representing all attributes*

Description: The knowledge base as represented in Figure 3 dynamically captures and structures student data—including personal, academic, financial, and behavioral responses—into an RDF ontology using semantic web principles. It transforms raw survey responses into meaningful relationships, enabling advanced querying, reasoning, and holistic analysis of student development. Figure 4-9 represents storage and retrieval of knowledge from repositories.

SPARQL Queries:

1. Displaying names of students whose course decision was taken by parents and having cgpa < 7

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```
PREFIX ex: <http://example.org/>
SELECT ?student_name
WHERE {
?student ex:name ?student_name .
?student ex:courseDecisionByParents true .
?student ex:cgpaBelow7 true .
}
```

Result

Students Whose Course Decision Was Taken by Parents & Have CGPA < 7:

Student Name: Geetha

Student Name: M. Sharath

Student Name: Sudeshna

3. Retrieve Students Who Took Their Own Course Decision and Have CGPA Between 7 and 10

```
PREFIX ex: <http://example.org/student#>
SELECT ?name ?cgpa ?decision
WHERE {
?student a ex:Student .
?student ex:hasName ?name .
?student ex:tookDecision ?decision .
?student ex:hasCGPA ?cgpa .
FILTER(?cgpa > 7 && ?cgpa < 10 &&
?decision = "Self")
}
```

📊 Students Who Took Their Own Course Decision & Have CGPA Between 7 and 10:

	S.No	Name	CGPA	Decision
0	1	B Kumkum	9.1	Self
1	2	Alampally Anuradha	9.7	Self
2	3	Jatin Lekkala	9.5	Self
3	4	Nenavath Madhu	9.7	Self
4	5	Rathod Sai Giridhar Prasad	9.3	Self
5	6	Akshitha Reddy	9	Self
6	7	E Prathap goud	9.2	Self
7	8	Sande Ramakrishna	7.3	Self
8	9	B. Shruthi	7.5	Self
9	10	Arra Hrushitha Reddy	9.8	Self
10	11	Madanaboina Srinidhi	9.7	Self
11	12	D. Madhavi	7.7	Self
12	13	Kamati Manish	8.3	Self
13	14	Amrutha varshini	8.7	Self
14	15	Shriya Golla	8.7	Self
15	16	Samreen	8.7	Self
16	17	Ashwini Hamsini	9.3	Self
17	18	S.Jayasri	8.8	Self
18	19	K.Sreenidhi Reddy	9.2	Self

Figure4: *Students who took their course decision and their CGPA between 7 and 10*

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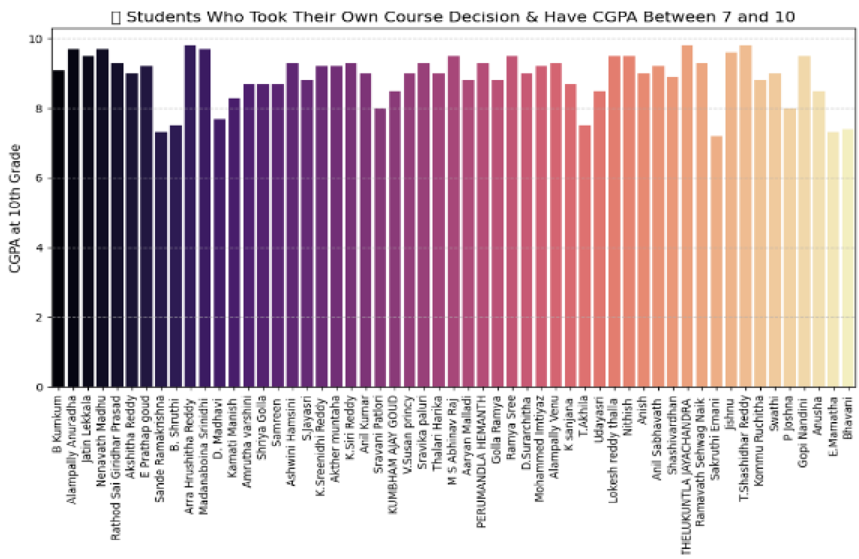

Figure 5. barchart representing students who took their own cource decision & have CGPA between 7 and 10

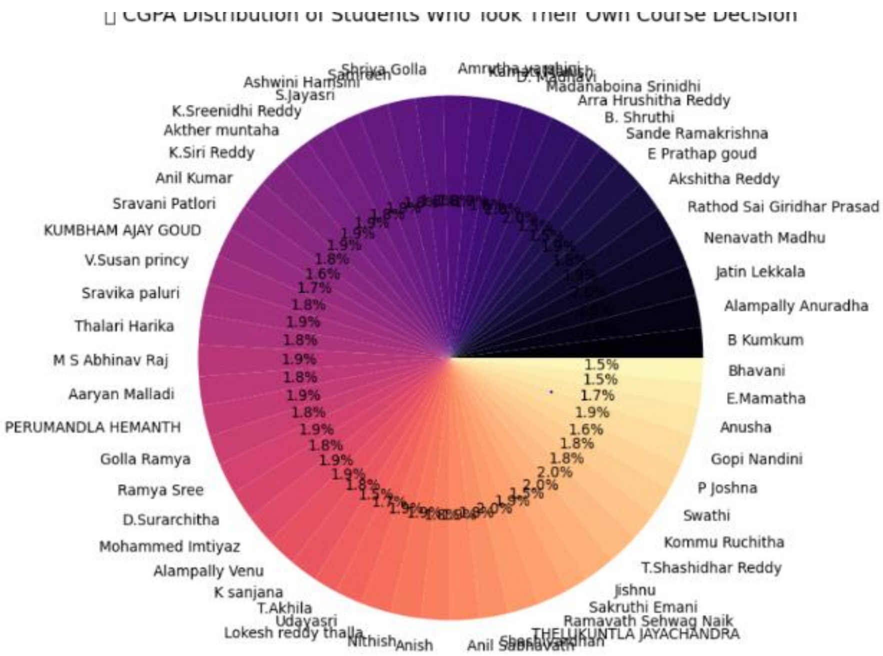

Figure 6. Pie chart representing CGPA distribution of students who took their own course decision

4. Financially Poor but Academically Good Students

```
PREFIX ex: <http://example.org/student#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
SELECT ?name ?percentage ?income
WHERE {
 ?student a ex:Student ;
 ex:name ?name ;
ex:academic_percentage ?percentage ;
ex:annual_income ?income .
 FILTER (?income < 500000 &&
?percentage > 65)}
```

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Result

S.No	name	academic_percentage	annual_income
1	Adari Pranitha	98	150000
2	GNANESH PULLETIKURTHI	80	300000
3	Sunanda Rathod	82	300000
4	RICKY DEEVEN VEERABALLI	100	150000
5	Kamati Manish	70	150000
6	P. Jahanavi	98	150000
7	Trishul Reddy	70	300000
8	Samreen	87	150000
9	Geethanjali	70	300000
10	Akther muntaha	90	300000
11	K.supriya	87	150000
12	Anil Kumar	85	150000
13	V.Susan princy	80	150000
14	Ramyasree	80	300000
15	Siri	70	300000
16	PERUMANDLA HEMANTH	90	150000
17	Alampally Venu	80	300000
18	T.Akhila	90	150000
19	Lokesh reddy thalla	80	150000
20	Nithish	95	300000
21	Shashi Kumar	90	300000
22	Anish	95	300000
23	Sakruthi Emani	80	300000
24	Guda Pavaneeshwar Reddy	87	150000
25	Arra Poojitha	97	300000
26	NARAM PRANAYKUMAR	98	300000
27	Swathi	90	300000
28	Gopi Nandini	90	150000
29	E.Mamatha	85	150000
30	Bhavani	70	150000

Figure 7: Table representing student data of Financially Poor but Academically Good Students

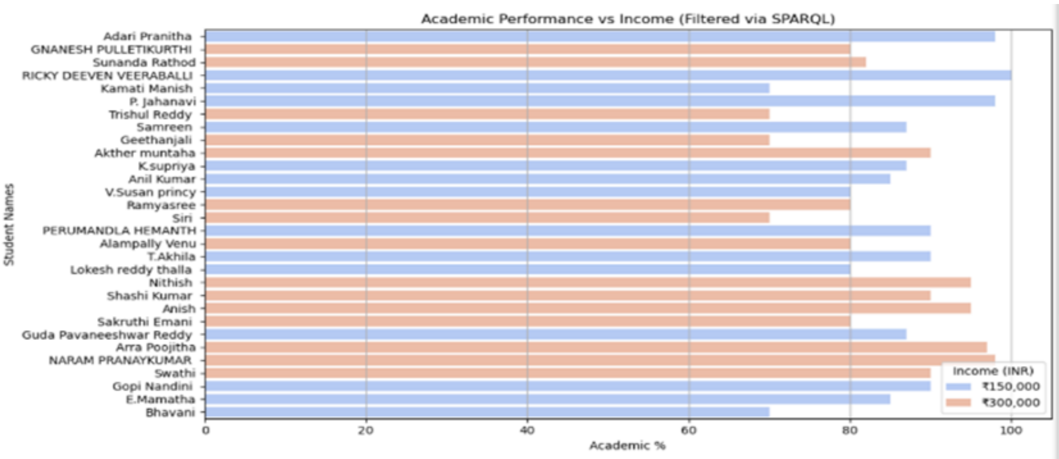

Figure 8: *Bar chart representing student data of Financially Poor but Academically Good Students*

5. ACADEMICALLY LOW AND FINANCIALLY RICH

```
PREFIX ex: <http://example.org/student#>
SELECT ?name ?income ?cgpa
WHERE {
 ?s a ex:Student ;
 ex:name ?name ;
 ex:annual_income ?income ;
ex:cgpa ?cgpa .
 FILTER (?income >= 1000000 && ?cgpa <
7)
}
```

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Result

S.No	name	annual_income	cgpa
1	Mandalapu Akhil	1000000	6.7
2	Geetha	1000000	5.8

6. Displaying student names who prefers calm surroundings and was bullied

```
PREFIX ex: <http://example.org/>
SELECT ?student_name
WHERE {
 ?student ex:name ?student_name .
 ?student ex:prefersCalmSurroundings true .
 ?student ex:wasBullied true .
}
```

Result:

Students Who Prefer Calm Surroundings & Were Bullied:

Student Name: GNANESH PULLETIKURTHI

Student Name: Kamati Manish

Student Name: Arra Poojitha

7. Family annual income < 800000

```
PREFIX ex: <http://example.org/>
SELECT ?student_name ?annual_income
WHERE {
?student ex:name ?student_name .
?student ex:annualIncome ?annual_income
.
FILTER (?annual_income < 800000)
}
```

Result:

Students Whose Family Annual Income is Less Than ₹8,00,000:

Student Name: Alampally Anuradha, Family Annual Income: ₹300,000

Student Name: M. Sharath, Family Annual Income: ₹300,000

Student Name: Akshitha Reddy, Family Annual Income: ₹300,000

Student Name: GNANESH PULLETIKURTHI, Family Annual Income: ₹300,000

Student Name: Sunanda Rathod, Family Annual Income: ₹300,000

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Student Name: D. Madhavi, Family Annual Income: ₹300,000

Student Name: Amrutha varshini, Family Annual Income: ₹300,000

Student Name: Trishul Reddy, Family Annual Income: ₹300,000

Student Name: Japala Prashanthi, Family Annual Income: ₹300,000

Student Name: Geethanjali, Family Annual Income: ₹300,000

Student Name: Thalari Harika, Family Annual Income: ₹150,000

Student Name: PERUMANDLA HEMANTH, Family Annual Income: ₹150,000

Student Name: Rathod Subash, Family Annual Income: ₹150,000

Student Name: Neha Golla, Family Annual Income: ₹150,000

Student Name: Preethi, Family Annual Income: ₹150,000

Student Name: Sindhuja, Family Annual Income: ₹150,000

Student Name: T.Akhila, Family Annual Income: ₹150,000

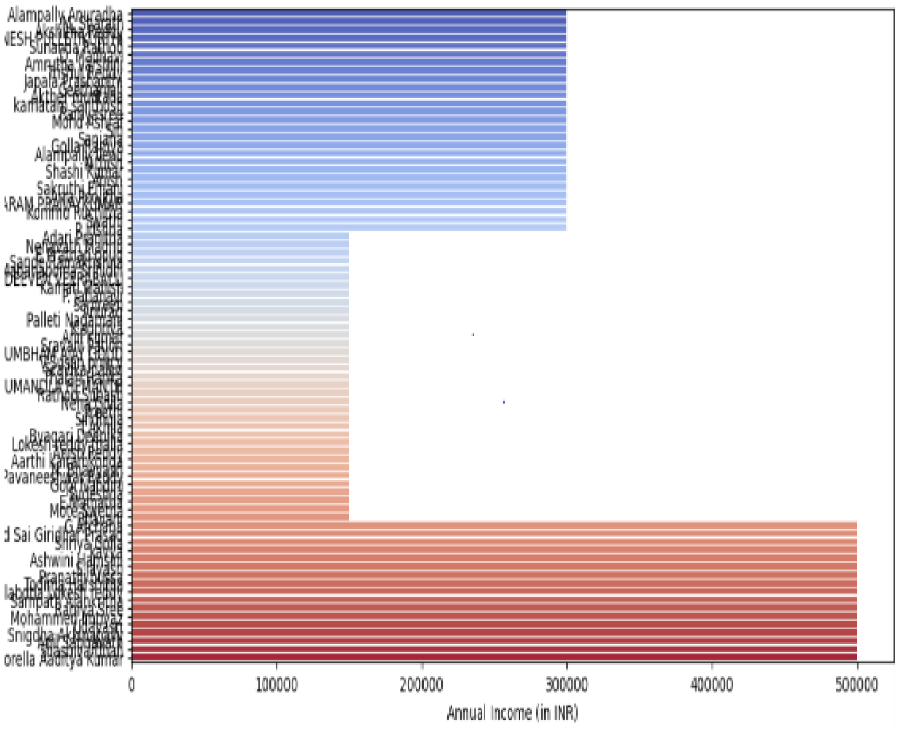

Figure 9: *bar chart representing student data whose Family annual income < 800000*

6. CONCLUSION

This research presents a dynamic, ontology-driven model that effectively captures and analyzes student development across academic, personal, behavioral, and financial dimensions. By utilizing semantic web technologies such as RDF, OWL, and SPARQL, the system transforms raw survey responses into a structured and interoperable knowledge base. The integration of real-time student data—including SWOT (Strengths, Weaknesses, Opportunities, and Threats) attributes—enables educators to uncover hidden patterns, such as financial-academic correlations, self-driven career decisions, and emotional well-being indicators.Unlike traditional database systems, this model supports intelligent reasoning, scalable schema evolution, and advanced querying capabilities, all made possible through the use of knowledge graphs. The implementation using programmatic ontology generation significantly reduces manual effort, enhances adaptability, and supports real-time updates—offering a practical solution for modern educational planning.The results obtained through SPARQL queries and visual knowledge graphs validate the model's ability to provide meaningful insights and personalized student guidance. Ultimately, this approach serves as a powerful decision-support tool for educators, counsellors, and institutions aiming to foster holistic student growth in a data-driven and scalable manner.

REFERENCE:

[1] Tkachenko, K., Tkachenko, O., Mazur, N., & Mashkina, I. (2024). Ontological Approach in Modern Educational Processes. *Cybersecurity Providing in Information and Telecommunication Systems 2024*, *3654*, 88-97.
[2] A B. Reddy, K. Akhil, A. Anuradha, G. Shriya, K. Bainee and R. S. G. Prasad, "Building A Student Knowledge Based Ontology Approach Using Web Ontology Language," 2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2023, pp. 66-74, doi: 10.1109/ICAC3N60023.2023.10541668.
[3] Wątróbski, J. (2020). Ontology learning methods from text - an extensive knowledge-based approach. Procedia Computer Science, 176, 3356–3368. https://doi.org/10.1016/j.procs.2020.09.061
[4] Konys, A., & Drążek, Z. (2020). Ontology learning approaches to provide domain-specific knowledge base. Procedia Computer Science, 176, 3324-3334.
[5] Clemente, J., Corral, H. Y., De Pedro-Carracedo, J., & Bueno, F. J. (2022). A proposal for an adaptive Recommender System based on competences and ontologies. Expert Systems With Applications, 208, 118171. https://doi.org/10.1016/j.eswa.2022.118171.
[6] Ibrahim, M., Yang, Y., Ndzi, D., Yang, G., & Al-Maliki, M. (2019). Ontology-Based Personalized Recommendation Framework. IEEE Access, 7, 5180-5199. https://doi.org/10.1109/access.2018.2889635.
[7] Rejeb, Abderahman & Simske, Steven & Fosso Wamba, Samuel & Smart, Edward & Breslin, John & yapa, kosala & Ospina, Angela & Bradau, Horia & Crowley, Bridgette & Desaraju, Sowmya & Liu, Kelly & Thakur, Subhasis & Martingale, Wayne & Keogh, John. (2022). Charting Past, Present, and Future Research in the Semantic Web and Interoperability. Future Internet. 14. 10.3390/fi14060161.
[8] Chang, M., D′Aniello, G., Sampson, D. G., & Simonelli, C. (2020). Building Ontology-Driven tutoring models for intelligent tutoring systems using data mining. IEEEAccess, 8, 48151–48162. https://doi.org/10.1109/access.2020.2979281
[9] Duran, C. G., & Ramírez, C. M. (2021b). Integration of open educational resources using semantic platform. IEEE Access, 9, 93079–93088. https://doi.org/10.1109/access.2021.3092315.
[10] Alsobhi, Aisha & Khan, Nawaz & Rahanu, Harjinder. (2015). Personalised Learning Materials Based on Dyslexia Types: Ontological Approach. Procedia Computer Science. 60. 113-121. 10.1016/j.procs.2015.08.110
[11] Butt, M., Sharunova, A., Štorga, M., Khan, Y. I., & Qureshi, A. J. (2018b). Transdisciplinary Engineering DesignEducation: Ontologyfor ageneric product designprocess. Procedia CIRP, 70,338–343. https://doi.org/10.1016/j.procir.2018.02.019
[12] Karim, N., Latif, K., Ahmed, N., Fatima, M., & Mumtaz, A. (2013). Mapping Natural Language Questions to SPARQL Queries for Job Search. 2013 IEEE International Conference on Semantic Computing, 150-153
[13] Gröschner, A. (2023). Promoting video-based research in teacher education and professionaldevelopment:Acommentaryonontological,methodologicalandepistemologicaladvances.Learning,CultureandSocialInteraction,39,100701.https://doi.org/10.1016/j.lcsi.2023.100701
[14] Rahayu, N. W., Ferdiana, R., &Kusumawardani, S. S. (2022). A systematic review ofontology use in ELearning recommender system. Computers & Education: Artificial Intelligence, 3, 100047. https://doi.org/10.1016/j.caeai.2022.100047 48
[15] J. M. Almendros-Jiménez, A. Becerra-Terón and G. Moreno, "A fuzzy extension of SPARQL based on fuzzy sets and aggregators," 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Naples, Italy, 2017, pp. 1-6, doi: 10.1109/FUZZ-IEEE.2017.8015411
[16] H. Kang, S. Hong, K. Lee, N. Park and S. Kwon, "On Integrating Knowledge Graph Embedding into SPARQL Query Processing," 2018 IEEE International Conference on Web Services (ICWS), San Francisco, CA, USA, 2018, pp. 371-374, doi: 10.1109/ICWS.2018.00064.
[17] Meenachi, N. M., & Baba, M. S. (2012). A survey on usage of ontology in different domains. International Journal of Applied Information Systems, 4(2), 46-55.

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2025, 10(41s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[18] Stancin, K., Poscic, P., & Jaksic, D. (2020). Ontologies in education–state of the art. Education and Information Technologies, 25(6), 5301-5320.

[19] Slimani, T. (2015). Ontology development: A comparing study on tools, languages, and formalisms. Indian Journal of Science and Technology, 8(24), 1-12.

[20] Liang, K., Wang, C., Zhang, Y., & Zou, W. (2018). Knowledge aggregation and intelligent guidance for fragmented learning. *Procedia computer science*, *131*, 656-664.

[21] Palombi, O., Jouanot, F., Nziengam, N., Omidvar-Tehrani, B., Rousset, M. C., & Sanchez, A. (2019). OntoSIDES: Ontology-based student progress monitoring on the national evaluation system of French Medical Schools. *Artificial intelligence in medicine*, *96*, 59-67.

[22] Chen, Y. H., Lu, E. J. L., & Lin, Y. Y. (2022). Efficient SPARQL queries generator for question answering systems. *IEEE Access*, *10*, 99850-99860.

[23] Chen, J., Zhang, F., & Zou, L. (2018, August). SPARQL Multi-Query Optimization. In *2018 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications/12th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE)* (pp. 1419-1425). IEEE.

[24] Banane, M., Erraissi, A., El Khalyly, B., Belangour, A., & Azzouazi, M. (2021, February). ScalSPARQL: A New Scalable system for the mapping of SPARQL Queries to NoSQL languages Based on MDE approach. In *2021 6th International Conference on Renewable Energy: Generation and Applications (ICREGA)* (pp. 101-105). IEEE.

[25] Zhang, Y., & Xu, F. (2018, May). A SPARQL extension with spatial-temporal quantitative query. In *2018 13th IEEE conference on industrial electronics and applications (ICIEA)* (pp. 554-559). IEEE.

[26] Vcelak, P., Kryl, M., & Kleckova, J. (2018, October). SPARQL query-builder for medical temporal data. In *2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)* (pp. 1-9). IEEE.

[27] Gupta, R., & Malik, S. K. (2011, June). SPARQL Semantics and execution analysis in Semantic Web using various tools. In *2011 International Conference on Communication Systems and Network Technologies* (pp. 278-282). IEEE.

[28] Ferru, D. S., & Atzori, M. (2016, February). Write-Once Run-Anywhere Custom SPARQL Functions. In *2016 IEEE Tenth International Conference on Semantic Computing (ICSC)* (pp. 176-178). IEEE.

[29] Fujino, T., & Fukuta, N. (2012, September). A SPARQL query rewriting approach on heterogeneous ontologies with mapping reliability. In *2012 IIAI International Conference on Advanced Applied Informatics* (pp. 230-235). IEEE.

[30] Kyu, K. M., & Oo, A. N. (2020, November). Enhancement of query execution time in sparql query processing. In *2020 international conference on advanced information technologies (ICAIT)* (pp. 153-158). IEEE.