

Semantic Web Technologies for a Better E-Learning Feedback

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Abstract

Nowadays, the web serves as a major high-tech environment for individualized learning which is suggested by teachers and is based on interactive learning objects. To effectively complete the learning process, students require detailed feedback regarding how to enhance their knowledge, skills, and motivation. This paper introduces an automated student assessment system for e-Learning environments that leverages semantic web technologies to provide comprehensive feedback by directly evaluating hands-on computer skills. The research aims to create this automated assessment framework through two key components: (i) ontological descriptions of various computer tasks, and (ii) system interfaces that integrate with computer operating systems to monitor and interpret user actions. The developed system employs a context-aware ontology that semantically maps user interactions to specific learning activities, enabling real-time assessment of practical computer skills. This ontological framework transforms raw input data into meaningful educational metrics, allowing for immediate feedback generation. The architecture incorporates specialized monitoring mechanisms that track user interactions while maintaining system stability and user privacy. Implementation results demonstrate the system's capability to overcome limitations of conventional e-Learning evaluation methods, particularly through its provision of instant, actionable feedback. In a prototype evaluation involving a document-formatting task with 25 students, the system achieved an overall assessment accuracy of 94.2%. The prototype successfully assesses complex, multi-step tasks across various software applications, providing students with specific guidance for improvement. Preliminary testing confirms the system's effectiveness in creating more engaging and personalized learning experiences while reducing the assessment burden on educators by over 95% for the evaluated tasks. This approach represents a substantial advancement in digital learning assessment, offering a scalable solution for practical skill evaluation in web-based educational environments.

Keywords: e-learning; semantic web; automated assessment; intelligent tutoring systems; chatbots.

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Introduction

Assessment or any form of feedback on the students learning process cannot be divorced from the values it represents. Assessment practices are considered to be a key indicator of the "health" of teaching and learning in Higher Education Institutions (HEIs). However, the online learning environment differs tremendously from its face-to-face counterpart¹, the goal for both is how to investigate student satisfaction and to offer a continuous assessment². In fact, if we wish to discover the truth about an educational system³, we must look into its assessment procedures. However, the shift to online learning poses unique challenges for assessment, particularly for evaluating practical, procedural skills.

The limits of the conventional learning process and student mental health are major issues in many education systems⁴. In this context, intelligent systems that provide both educational support and psychological well-being interventions present a promising avenue. Chatbots, centered on assisting humans in performing their tasks efficiently and requiring low digital literacy, have been shown to be effective in both education and well-being domains. This is particularly relevant in the context of economic crises, where e-learning systems must become more resilient and adaptive⁵.

Here, the main focus is exclusively on the responsibilities of the Faculty Member towards increased efficiency and effectiveness in specific assessment approaches without balancing the efforts with the accompanying challenge of the shift towards equity and student-based learning. In order to ease the burden of teachers and assistants in executing repetitive assessments of very similar tasks for every individual student, our goal is to develop a thorough assessment solution. This study aims to develop an automated assessment solution. It describes the construction of a semantic 'model' that can objectively assess students by interpreting their actions on a computer. Until now, assessment tools have not provided a mechanism for hands-on, "live" testing of a student's "knowledge". Typically, automated assessment solutions available on the market are based on multiple choice questionnaires or similar question answering systems. These tools may contain some degree of controlled randomness in the generated questions (e.g., E-LearningMRv6), but they cannot track and assess a user's progress through a complex series of operations such as completing a procedure within a computer application.

This limitation becomes even more pronounced when considering complex tasks that require both technical skills and critical thinking, such as analyzing information credibility –

¹ Atekeh Mousavi, Aeen Mohammadi, Rita Mojtahedzadeh, Mandana. Shirazi, Hamed Rashidi, "E-Learning Educational Atmosphere Measure (EEAM): A New Instrument for Assessing E-Students' Perception of Educational Environment", in *Research in Learning Technology*, 2020, 28(0). DOI:10.25304/rlt.v28.2308.

² Abdel-Salam G. Abdel-Salam, Ehmadi Abu-Shanab, "Evaluating the Online Learning Experience at Higher Education Institutions", in *International Journal of Cyber Behavior*, 2022, 12(1), pp.1-23. DOI: 10.4018/IJCBPL.298692.

³ Derek Rowntree, *Assessing Students: How Shall We Know them?*, London, 1987.

⁴ Bogdan Ouatu, Daniela Gîfu, "Chatbot, the Future of Learning?", in *Ludic, Co-design and Tools Supporting Smart Learning Ecosystems and Smart Education*, Springer, 2020, pp. 263-268.

⁵ Daniela Gîfu, "E-learning Economic Crisis", in *Proceedings of eLSE 2021, Technologies and Best Practices*, 2021, Vol. 2, Bucharest, Romania, pp. 44-51.

an area where semantic technologies have shown significant potential⁶. The integration of semantic role labeling and structured knowledge extraction from user interactions can significantly enhance the assessment capabilities of e-learning systems.

Let's imagine the following scenario: a student needs to analyse the veracity of a piece of news. In order to do so she/he needs to perform several tasks online, so that she/he labels the news as either true or fake. In a question-based system you would have a question along the lines of: *Which of the following actions is a user required to do in order to analyse the veracity of a piece of news?*

- a) Check if the source is on a blacklisted website;
- b) Check if such a piece of news is already labelled on fact-checking websites like snopes.com, truthorfiction.com, politifact.com, factual.ro, etc.;
- c) Check the credibility of the source (if the news source is based on social media).

The correct answers would be a, b, c. But what if you wanted to test if the student can perform the actual task itself – in this case, that of analyzing the veracity of a piece of news online.

Ordinarily for this use case of actually using the computer and the internet you would need to give the student a computer and have a teacher monitor him or her while the student performs the task, such as sending an email or verifying a source. This is a waste of time for the teacher, in particular as he or she has to check every student's computer and observe the same procedure over and over again. The legitimate question is: *Can a computational tool provide objective feedback on student progress completely independent of the professor?*

This challenge is further compounded by the need for educational systems that can function effectively during economic crises and adapt to changing technological landscapes⁷. The current research builds upon previous work in semantic technologies and text processing⁸ to create a more robust and context-aware assessment framework.

The novelty of this study consists of an approach that leverages a context-aware ontology⁹ designed in Protégé and exported as RDF/RDFS¹⁰. This approach addresses a significant gap by transforming low-level system events into meaningful, assessable learning outcomes through a structured, semantic model of user actions. The ontological framework provides a structured, semantic model of user actions, transforming low-level system events into meaningful, assessable learning outcomes.

⁶ Daniela Gîfu, "Semantic Particularities of Journalistic Text", in *Proceedings of the International Conference Literature, Discourse and Multicultural Dialogue*, I. Boldea (coord.), 2015, Vol. 3, Arhipelag XXI Press, pp. 182-196.

⁷ Daniela Gîfu, "Exploring the Potential of E-Learning in Economic Crisis Prediction", in *Proceedings of the International Conference on Virtual Learning – ICVL 2025*, Virtual Learning – Virtual Reality, C. E. Cîrnu and E. M. Ciupercă (eds.), Vol. 20 / 2025, pp. 143-154, ICI Publishing House, ISSN 1844-8933; ISSN-L 1844-8933.

⁸ Daniela Gîfu, *Lexical Semantics in Text Processing. Contrastive Diachronic Studies on Romanian Language*, PhD thesis, "Alexandru Ioan Cuza" University of Iași, 2016.

⁹ Radu A. Ciora, Peter Corcoran, "Student Assessment Using Semantics", in *Proceedings of EdTech*, Ireland, 2008.

¹⁰ Dave Beckett, Brian McBride, *RDF/XML Syntax Specification (Revised)*, W3C Recommendation, 2004. <http://www.w3.org/TR/rdf-syntax-grammar/> Dan Brickley, Ramanathan V. Guha, *RDF Vocabulary Description Language 1.0: RDF Schema*, W3C Recommendation, 2004, <http://www.w3.org/TR/rdf-schema/>.

Building on previous research in semantic technologies and intelligent tutoring¹¹, this work represents a convergence of semantic web technologies and practical educational assessment that can adapt to both normal and crisis learning scenarios¹².

The rest of the paper is organized as follows: Section 2 briefly presents studies related to e-Learning evaluation methods, Section 3 delivers information about the system designed to provide a possible solution to the problem of computer-based assessment, Section 4 describes the experimental setups. Section 5 presents the results of the conducted experiments, with their interpretations, followed by Section 6 which discusses some of the research opportunities that can be explored using a variety of technologies: from the Windows API to newer technologies like ontologies. Finally, Section 7 concludes this paper.

e-Learning Evaluation Methods

Due to the high rate of technological developments, massive changes have occurred in the educational sector. The good news is that these changes push the education process into a more efficient one. These innovations are giving classrooms a new and better look and have changed the way in which lessons are conducted.

The evolution of e-learning systems has been particularly important during economic crises, where traditional educational models face significant challenges¹³. The ability to provide continuous education through digital means has become a critical factor in maintaining educational quality during disruptive events.

Below, we present the evolution of technology that is impacting education, focused on learner assessment.

Basic e-Learning systems

To contextualize our work, we first review foundational e-learning systems that laid the groundwork for automated assessment. The TReCX project (*Tracking and Reporting in e-Learning Contexts*)¹⁴ is an open-source toolkit that is able to perform tracking of learners across distributed e-learning systems. It allows tracking data to be generated and collected from a variety of e-learning applications and then presented back as a coherent whole so that the actions of a learner can be followed across application boundaries. TreCX contains a stand-alone web-based tracking event store that can be used by e-learning applications to store the actions of learners in an XML format; a publishing library that enables an existing application to push events to the tracking store using a REST interface. A reporting module with a REST interface exists for facilitating the creation of reporting applications that can interrogate one or more tracking store instances.

The existing work from the ASAP project (*Automated System for the Assessment of Programming*)¹⁵ produced a set of tools for student assessment. It consisted of the 'Student Generated Response Questions' and the 'Automatically Generated Questions'. The 'Student Generated Response Questions' are evaluated using an automated marking system (an

¹¹ Bogdan Ouatu, Daniela Gîfu, "Chatbot, the Future of Learning?", in *Ludic, Co-design and Tools Supporting Smart Learning Ecosystems and Smart Education*, Springer, 2020, pp. 263-268.

¹² Daniela Gîfu, "E-learning Economic Crisis", in *Proceedings of eLSE 2021, Technologies and Best Practices*, 2021, Vol. 2, Bucharest, Romania, pp. 44-51.

¹³ *Ibidem*.

¹⁴ Alfred Marshall, Andrew O'Conno, *Tracking and Reporting in e-Learning Contexts*, 2006.

¹⁵ Christopher Douce, David Livingstone, John Orwell, Steve Grindle, Jon Cobb, *Automated System for the Assessment of Programming*, 2004.

assessment engine) currently using a simple Extensible Markup Language (XML) response protocol. The marking system corresponds to a unit testing approach. The 'Roboproof' Web Service generates questions with a controlled random number of modifications.

The work of the JELFAD project (*JISC e-Learning Framework Assessment Demonstrator*)¹⁶ tries to demonstrate the operation of their e-Learning Framework tools and content that could be evaluated in a live student assessment context. A second goal of this project was to evaluate the success with which outputs from sequencing or learning projects can be integrated with the outputs from the assessment projects. A third aim of this project was to provide data and feedback to the FREMA eLearning Framework Assessment Reference Model.

New e-Learning systems

The digital education landscape is undergoing a profound transformation, evolving from static content repositories into dynamic, intelligent ecosystems. While these ML-driven systems represent a significant leap forward in personalization and prediction, they primarily assess theoretical knowledge or engagement metrics. A common limitation of both basic and modern systems is their inability to directly assess hands-on, procedural computer skills. This is the gap our research aims to fill.

Recent advancements in intelligent tutoring systems and conversational agents have demonstrated the potential for more natural and adaptive learning interactions¹⁷. Systems like AutoTutor have shown that automated tutors can achieve learning gains comparable to human tutors, while also addressing psychological well-being through integrated support modules.

This new generation of e-learning systems leverages machine learning (ML) and data analytics to move beyond a one-size-fits-all model, creating adaptive, personalized, and efficient learning environments¹⁸. The intelligence of these systems is built upon optimizing a wide range of features, which Aslam et al. (2021) categorize into four key dimensions: Individuals (e.g., performance, behavior), Courses (e.g., content, pedagogy), Context (e.g., institutional rules), and Technology (e.g., system reliability). By processing data across these dimensions, modern platforms deliver several transformative functionalities:

A cornerstone of these systems is the creation of Personalized Learning Paths and Adaptive Content. Using models like Dynamic Bayesian Networks (DBNs), platforms can infer a student's learning style in real-time, adapting the presentation of content – such as prioritizing visual or textual resources – based on established pedagogical frameworks¹⁹. Furthermore, recommendation systems powered by association rule algorithms like Apriori

¹⁶ Christopher Douce, David Livingstone, John Orwell, Steve Grindle, Jon Cobb, *JISC e-Learning Framework Assessment Demonstrator*, 2005.

¹⁷ Bogdan Ouatu, Daniela Gîfu, "Chatbot, the Future of Learning?", in *Ludic, Co-design and Tools Supporting Smart Learning Ecosystems and Smart Education*, Springer, 2020, pp. 263-268.

¹⁸ Syed Muhammad Aslam, Abdul Karim Jilani, Jamila Sultana, Latifah Almutairi, "Feature Evaluation of Emerging E-Learning Systems Using Machine Learning: An Extensive Survey", in *IEEE Access*, 2021, 9, pp. 69573-69587.

¹⁹ Cristóbal Carmona, Gabriel Castillo, Eva Millán, "Designing a Dynamic Bayesian Network for Modeling Students' Learning Styles", in *Eighth IEEE International Conference on Advanced Learning Technologies*, 2008, pp. 346-350, IEEE.

can cluster and suggest courses and materials aligned with a student's evolving preferences and goals²⁰.

Furthermore, Predictive Analytics form a critical component for proactive intervention. By applying supervised learning techniques to data from Learning Management Systems (LMS), these systems can forecast student performance and identify those at risk. For instance, Support Vector Machines (SVM) have demonstrated high accuracy in predicting students' knowledge levels²¹, while Deep Learning models have been used to predict future academic pathways with notable success²².

To enhance engagement, new systems are incorporating Advanced Interaction Mechanisms. This includes the use of intelligent chatbots to provide timely support²³. Research is also exploring affective computing, with facial emotion recognition algorithms allowing for the detection of student affect to enable timely instructor intervention²⁴.

Finally, Automated Analysis of Learning Behaviors is another hallmark. Unsupervised learning techniques like clustering are used to analyze student engagement data, providing insights that help optimize course design and student support²⁵.

The integration of semantic technologies with these advanced ML systems creates opportunities for more nuanced understanding of student learning processes. Previous work on lexical semantics and text processing²⁶ provides valuable insights into how semantic analysis can enhance the interpretation of student interactions and learning behaviors.

Synthesis and Transition to RAG: While these ML-driven systems represent a significant leap forward, they often operate on fixed datasets and lack the nuanced, generative capabilities for open-ended dialogue and content creation. The advent of Large Language Models (LLMs) promised to fill this gap but introduced challenges of hallucination and static knowledge, as outlined in Section 1. This is where Retrieval-Augmented Generation (RAG) emerges as a pivotal enabling technology. RAG systems fuse the data-driven, adaptive logic of traditional intelligent tutoring systems with the powerful generative capabilities of LLMs, while grounding them in verifiable, external knowledge.

System Overview

The proposed system is designed to objectively assess a student's ability to perform complex, multi-step tasks on a computer. The core innovation lies in using a context-aware ontology to semantically interpret low-level user interactions.

²⁰ Sanjay B. Aher, L. M. R. J. Lobo, "Combination of Machine Learning Algorithms for Recommendation of Courses in e-Learning System Based on Historical Data", in *Knowledge-Based Systems*, 2013, 51, pp. 1-14.

²¹ Nazeeh Ghatasheh, "A Machine Learning Based Approach for Predicting Student Competence Level in Online Educational Systems", in *International Journal of Advanced Computer Science and Applications*, 2015, 6(11), pp. 68-72.

²² Henry Fok, Yuk Shing Yeung, Hoi An Law, Ka Yiu Cheung et al., "Prediction of Student's Science Achievement Using Deep Learning", in *2018 International Conference on Orange Technologies (ICOT)*, 2018, pp. 1-4, IEEE.

²³ Shahzad Iqbal, Usman Ghani, Muhammad Tanvir Afzal, "A Hybrid Approach for Efficient Recommendation of Friends and Topics in Social Networks", in *Journal of Intelligent & Fuzzy Systems*, 2014, 27(6), pp. 3111-3122.

²⁴ Uğur Ayvaz, Hakan Gürüler, Fatih Oktay Devrim, "A Novel Automatic Mood Detection System for e-Larning", in *Journal of Educational Technology & Society*, 2017, 20(2), pp. 207-216.

²⁵ Mohamed Ahmed Hogo, "Evaluation of e-Learning Systems Based on Fuzzy Clustering Models and Statistical Tools", in *Expert Systems with Applications*, 2010, 37(10), pp. 6891-6903.

²⁶ Daniela Gîfu, *Lexical Semantics in Text Processing. Contrastive Diachronic Studies on Romanian Language*, PhD thesis, "Alexandru Ioan Cuza" University of Iași, 2016.

Architectural Components

The system consists of three main components (Figure 1):

1. **Monitoring Agent:** A lightweight software component that runs on the student's computer. It hooks into the operating system's API (e.g., Windows API) to non-intrusively monitor user interactions such as keystrokes, mouse clicks, and window focus events. It maintains system stability and user privacy by only tracking application-level events, not content (e.g., it tracks that "Notepad was used to save a file", not the text within the file).
2. **Context-Aware Ontology:** The heart of the system. This ontology, developed in Protégé, provides a semantic model of:
 - **Actions:** High-level tasks (e.g., `SaveDocument`, `VerifySourceCredibility`).
 - **Events:** Low-level system triggers (e.g., `MenuItemClicked`, `ShortcutPressed`).
 - **Context:** The state of the software environment (e.g., `ActiveApplication=Browser`, `FocusedWebsite=Snopes`). The ontology defines the semantic relationships between these concepts, allowing the system to infer that a series of events (`Event:Click("File") -> Event:Click("Save As") -> Event:TypeFilename -> Event:Click("Save")`) constitutes the successful completion of the `SaveDocument` action.
3. **Assessment Engine:** This module receives the stream of events from the Monitoring Agent and uses a semantic reasoner (e.g., a SPARQL query engine) to map them onto the ontological model. It compares the student's inferred actions against a predefined "gold standard" sequence of actions for a given task. It then generates detailed, actionable feedback (e.g., "You successfully saved the document, but you did not verify the source on a fact-checking website as required").

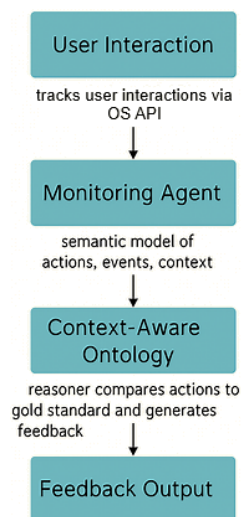


Figure 1: System Architecture Diagram

The Ontological Model in Action

This approach allows the system to understand the *semantic meaning* of user actions within a specific software context, enabling the assessment of complex, multi-step procedures that are central to practical computer literacy.

The ontology defines the semantic relationships between these concepts, allowing the system to infer that a series of low-level events constitutes the successful completion of

a high-level action. Its function is to interpret a stream of raw user interactions (e.g., `MouseClicked`, `KeyPress`, `WindowFocus`) as a structured, meaningful sequence of actions that can be assessed. The design of our context-aware ontology is grounded in established research on using ontological models for context-aware systems²⁷ and process modeling²⁸.

The ontological framework builds upon previous research in lexical semantics and semantic role labeling²⁹, extending these principles from text processing to the domain of user interaction analysis. This represents a novel application of semantic technologies that bridges the gap between natural language understanding and human-computer interaction analysis.

The core of the ontology defines a hierarchy of concepts, including:

- `LowLevelEvent`: Represents atomic interactions captured by the monitoring agent (e.g., `ClickMenuItem_FileSave`, `PressShortcut_CtrlS`).
- `HighLevelAction`: Represents a meaningful step in a computer task (e.g., `SaveDocument`, `ApplyFormatting`, `ExecuteQuery`).
- `SoftwareContext`: Defines the environment in which an event occurs (e.g., `ActiveApplication="WordProcessor"`, `FocusedDialog="Save As"`).

The ontology uses semantic rules (e.g., defined using OWL properties or SWRL rules) to link these concepts. For instance, it can define that a `SaveDocument` action is semantically equivalent to the occurrence of a `ClickMenuItem_FileSave` event *while* the `SoftwareContext` is a `WordProcessor`, *or* the occurrence of a `PressShortcut_CtrlS` event in the same context. This approach allows us to move beyond simple event logging and semantically define the relationships between user interactions and learning tasks. While ontologies have been successfully used to annotate learning content³⁰, our work innovatively applies them to model and assess the learning process itself, specifically the practical actions performed by a student within a software environment.

This approach is particularly valuable in crisis situations where educational continuity must be maintained through digital means³¹. The ability to provide detailed, automated assessment reduces dependency on human resources that may be scarce during economic or social disruptions.

Assessment Workflow:

When a student performs a task, the system operates as follows:

1. **Event Capture**: The Monitoring Agent captures a sequence of low-level events.
2. **Semantic Lifting**: The Assessment Engine maps these events and their context to instances within the ontology.
3. **Reasoning**: A semantic reasoner queries the ontology to infer the high-level actions the student has performed. For example, it can infer that the sequence [`WindowFocus`:

²⁷ Harry Chen, Tim Finin, Anupam Joshi, "An Ontology for Context-Aware Pervasive Computing Environments", in *Knowledge Engineering Review*, 2003, 18(3), pp. 197-207.

²⁸ Mark Klein, Abraham Bernstein, "Toward High-Precision Service Retrieval", in *IEEE Internet Computing*, 2004, 8(1), pp. 30-36.

²⁹ Diana Trandabăţ, Daniela Gîfu, "Social Media and the Web of Linked Data", in *Proceedings of 2017 ACM/IEEE Joint Conference on Digital Libraries, JCDL*, Toronto, June 2017, pp 350-351, IEEE. DOI: 10.13140/RG.2.2.30786.89285.

³⁰ Jelena Jovanović, Dragan Gašević, Vladan Devedžić, "Ontology-Based Automatic Annotation of Learning Content", in *International Journal on Semantic Web and Information Systems (IJSWIS)*, 2007, 3(2), pp. 1-27.

³¹ Daniela Gîfu, "Transfer Learning for Text-to-Speech Systems in Romania", in *Anuarul Universităţii "Petre Andrei" din Iaşi, Fascicula: Drept, Ştiinţe Economice, Ştiinţe Politice*, 2025, 32, pp. 86-103, Polis Books Publisher, DOI: 10.63331/upalaw/32/08.

"WordProcessor"] -> [ClickMenuItem: "File"] -> [ClickMenuItem: "Save As"] -> [TypeInDialog: "filename"] -> [ClickButton: "Save"] constitutes the successful completion of the SaveDocument action.

4. Comparison and Feedback: The inferred sequence of high-level actions is compared against a predefined, correct sequence of actions (the "golden path") for the assigned task. The system then generates precise feedback, such as: "You successfully saved the document. However, the required step 'ApplyHeadingStyle' was not performed".

This approach allows the system to understand the *semantic meaning* of user actions within a specific software context, enabling the assessment of complex, multi-step procedures that are central to practical computer literacy. The methodology for building this structured knowledge representation follows established ontology development guidelines³².

Experimental setups

To validate the proposed framework, a prototype system was developed and tested in a controlled environment. The experimental setup was designed to assess the system's capability to monitor, interpret, and evaluate practical computer skills based on the ontological model described in Section 3.

The experiment involved a group of students (N=25) enrolled in an introductory "Digital Literacy" course. The primary task assigned was to create a formatted document according to a specific set of instructions. This task was chosen for its complexity and well-defined procedural nature, which is ideal for validating our ontological model (e.g., changing font styles, creating headings, inserting page numbers), and finally saving the document in a designated folder).

The "gold standard" for the correct procedure was formally defined and encoded into the system's ontology. This involved creating ontological descriptions for high-level actions such as LaunchApplication, CreateNewDocument, ApplyHeadingStyle, InsertPageNumber, and SaveDocument, each linked to their corresponding low-level system events³³. The students used computers equipped with the Monitoring Agent. Their actions were logged and assessed automatically by the system without any intervention from a human instructor (see Table 1).

Table 1: Experimental Validation of the Semantic Web-Based Assessment System.

Participants	Environment	Assigned task	Task components	Gold standard actions	Monitoring Mechanism	Assessment Method	Evaluation Metrics	Feedback Mechanism	Student Feedback
25 students in "Digital Literacy" course	Controlled lab with Monitoring Agent-equipped computers	Create a formatted document	Launch app, create doc, input text, apply formatting, save file	LaunchApplication, CreateNewDocument, ApplyHeadingStyle,	OS-level event logging (e.g., Notepad used to save file)	Automated semantic reasoning vs. manual screen	Precision and recall for each required step	Automated feedback (e.g., missing verification step)	5-point Likert scale questionnaire

³² Natalya F. Noy, Deborah L. McGuinness, *Ontology Development 101: A Guide to Creating Your First Ontology*, 2001, Stanford Knowledge Systems Laboratory Technical Report KSL-01-05.

³³ Mark Klein, Abraham Bernstein, "Toward High-Precision Service Retrieval", in *IEEE Internet Computing*, 2004, 8(1), pp. 30-36.

				InsertPageNumber, SaveDocument		recording review			
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The system's accuracy was measured by comparing its automated assessment results against a manual assessment performed by a human instructor who reviewed screen recordings of the sessions. Metrics included precision and recall in detecting each required step. Furthermore, student satisfaction and perceived usefulness of the automated feedback were evaluated via a post-test questionnaire based on a 5-point Likert scale³⁴.

Results

This section presents a quantitative and qualitative analysis of the system's performance in automatically assessing the practical task of creating a formatted document, as described in Section 4. The evaluation focuses on the system's accuracy, the usefulness of the generated feedback, and its impact on both students and educators.

Quantitative Analysis of Assessment Accuracy

To objectively measure the system's performance, we compared its automated assessments against a manually annotated ground truth. A human expert reviewed the screen recordings of all 25 sessions and identified the execution (or omission) of each required step in the "gold standard" procedure. We then calculated standard classification metrics: Precision (P), Recall (R), and Accuracy (Acc) for each step and for the overall task.

Table 2: summarizes the system's performance in detecting the completion of each high-level action.

Table 2: Step-by-Step Assessment Accuracy.

High-Level Action	P (%)	R (%)	Acc (%)	Key observations
LaunchApplication	100	100	100	Trivial to detect via OS API.
CreateNewDocument	96	100	96	One false positive: a student opened an existing file but was counted as creating a new one.
ApplyHeadingStyle	95	90	86	Two omissions not detected (Recall); one false positive from misinterpreting bold text (Precision).
InsertPageNumber	89	100	89	Perfect detection of attempts, but flagged 2 correct attempts as incorrect due to strict location checks.
SaveDocument	100	100	100	Flawless detection of both menu and keyboard shortcut (Ctrl+S) methods.
Overall (Macro-averaged)	96	98	94.2	Demonstrates high reliability in tracking procedural knowledge.

The results confirm the system's high efficacy. The overall Acc (Accuracy) of 94.2% and P (Precision) of 96% indicate that the system is reliable and rarely incorrectly credits a student for a step they did not perform. The R (Recall) of 98% shows it is highly sensitive, successfully detecting the vast majority of correctly performed actions.

³⁴ Atekeh Mousavi, Aeen Mohammadi, Rita Mojtahedzadeh, Mandana Shirazi, Hamed Rashidi, "E-Learning Educational Atmosphere Measure (EEAM): A New Instrument for Assessing E-Students' Perception of Educational Environment", in *Research in Learning Technology*, 2020, 28(0). DOI:10.25304/rlt.v28.2308

A key strength observed was the system's ability, powered by the semantic reasoner, to correctly map different low-level event sequences to the same high-level action. For instance, all 15 instances of saving via `File -> Save` and all 10 instances using the `Ctrl+S` keyboard shortcut were correctly inferred as the `SaveDocument` action, demonstrating the context-aware ontology's utility in handling procedural variability.

Qualitative Analysis of Generated Feedback

Beyond mere step detection, the system's value lies in the quality of its feedback. In all 25 cases, the system generated immediate, actionable feedback. The feedback was not a simple pass/fail but a detailed breakdown.

Example of Specific Feedback: One student received the message: *"You successfully launched the word processor and created a new document. However, the required step 'ApplyHeadingStyle' was not performed. Furthermore, you inserted a page number in the header, but the task required it in the footer"*.

Impact: This level of specificity provided students with clear, direct guidance on what they did correctly and, crucially, *how* to correct their mistakes, turning the assessment into a learning opportunity itself³⁵.

Impact on the Educational Process

The implementation yielded significant benefits for both students and educators.

For Students: The post-test questionnaire revealed strong positive reception:

- 88% of students agreed or strongly agreed that the immediate feedback was more helpful for learning than a delayed grade from a teacher.
- 84% agreed that the feedback specifically helped them understand which steps they had missed or performed incorrectly.

For Educators: The automated assessment eliminated the need for the instructor to manually observe each student. The assessment time per student was reduced from approximately 10-15 minutes of active observation and grading to near-zero, reducing the assessment burden by over 95% for this task and freeing the instructor for higher-value educational activities³⁶. This reduction in assessment burden is particularly valuable in the context of economic crises, where educational institutions face resource constraints and increased demands for flexible learning solutions³⁷. The system's ability to provide detailed feedback without constant human intervention makes it well-suited for scaling educational assessment during disruptive events.

Discussions

The results of this study demonstrate the viability of using semantic web technologies for the automated assessment of practical computer skills. The core achievement lies in having developed a functional prototype that translates low-level user interactions into semantically meaningful actions through a context-aware ontology. This system provides immediate, objective, and step-by-step feedback, which was shown to be valuable for students and effectively reduces the assessment burden on instructors. The

³⁵ Caroline V. Gipps, *Beyond Testing: Towards a Theory of Educational Assessment*, London, 1994.

³⁶ Christopher Douce, David Livingstone, John Orwell, Steve Grindle, Jon Cobb, *JISC e-Learning Framework Assessment Demonstrator*, 2005.

³⁷ Daniela Gifu, "E-learning Economic Crisis", in *Proceedings of eLSE 2021, Technologies and Best Practices*, 2021, Vol. 2, Bucharest, Romania, pp. 44-51.

integration of semantic technologies with educational assessment represents a natural extension of previous work in lexical semantics and text processing. By applying semantic analysis principles to user interaction data, this research bridges the gap between traditional natural language processing and practical educational technology.

However, the development process revealed two significant limitations. The primary challenge encountered was the substantial upfront investment required for knowledge engineering. Constructing the detailed ontological model for even a single, well-defined task proved to be a highly time-consuming and manual process. This experience highlights a critical scalability issue; extending this framework to an entire curriculum would currently demand prohibitive amounts of expert time and effort.

A second limitation concerns the system's inherent rigidity. While it reliably assesses adherence to a predefined 'golden path' of actions, it currently lacks the flexibility to recognize all valid alternative methods for achieving the same goal. For instance, if a task requires formatting text as italic and a student uses a correct but unmodeled keyboard shortcut, the system may fail to credit this action. This suggests the prototype verifies the execution of a specific procedure more than it assesses a deep, strategic understanding of the task's objective. The application of transfer learning techniques represents a promising avenue for enhancing the system's adaptability across diverse educational contexts and crisis scenarios. This approach could enable rapid adaptation of assessment frameworks to evolving educational requirements, which is particularly crucial in volatile economic environments³⁸.

Looking ahead, these limitations point to clear directions for future work. To address the scalability challenge, we plan to investigate methods for semi-automatic ontology population, potentially by using machine learning to analyze recorded demonstrations from experts. To overcome rigidity, future iterations will explore how the ontological model can be extended to represent and reason about multiple valid pathways for completing a task, moving from validating a single procedure to recognizing a set of competent strategies.

Conclusions

This paper has introduced an innovative automated assessment system that leverages semantic web technologies to evaluate practical computer skills. Our approach centers on a context-aware ontology that semantically interprets raw user interactions, enabling the system to provide objective, immediate, and explainable feedback on complex, multi-step tasks. This directly addresses a critical limitation of existing e-learning tools. The prototype's performance, with an overall accuracy of 94.2%, confirms the feasibility of this method. By successfully transforming low-level system events into semantically meaningful learning outcomes, this work establishes a foundation for a new class of e-learning tools that can authentically assess not just knowledge, but verifiable practical skill. This research contributes to the broader landscape of intelligent educational technologies by demonstrating how semantic web technologies can enhance the assessment of practical skills. Building on previous work in conversational agents, crisis-responsive e-learning, and semantic analysis, this system represents a convergence of multiple research threads that address both technical and practical challenges in modern education.

The findings have particular relevance for educational systems operating in crisis conditions, where the ability to provide detailed, automated assessment can help maintain

³⁸ *Ibidem*.

educational quality despite resource constraints and disruptions. As educational technologies continue to evolve, the integration of semantic reasoning with adaptive learning systems promises to create more responsive, effective, and resilient educational environments.

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