CADIKA Journal: Master Journal of Future Education.
Volume 2, Issue 1, pp.27-42, (2025): Oktober

Comprehensive Review: Transforming Self-Education through Automatic Question Generation Technology

Erry Fuadillah[1], Lala Septem Riza[2], Rani Megasari[3]

[1] *Universitas Islam Negeri Sunan Gunung Djati Bandung*
[2,3] *Universitas Pendidikan Indonesia*

Abstract – *Automatic question generator (AQG) technology is a system developed to create questions automatically from input in the form of text, images, and videos. AQG has been developed using various approaches such as natural language processing (NLP), statistical approaches, and other machine approaches. AQG has a very important role in the world of education, especially in independent education, because it can be used as a good evaluation medium for students. Utilizing AQG in independent education gives students full control to determine their learning. AQG turns learning into a more interactive experience by generating questions that can trigger critical thinking and problem-solving skills. AQG technology developed in independent learning will encourage students to respond actively to the material and understand concepts more deeply. Approximately 60% of research related to AQG has been conducted for assessment, 18% for knowledge acquisition, and the remainder for validation and other purposes. This research was conducted by conducting a comprehensive review of 63 articles related to AQG in education.*

Keywords – automatic question generator (AQG), independent education, comprehensive review.

DOI: https://doi.org/10.63461/cadikajournal.v21.296

Corresponding author: Erry Fuadillah,
Universitas Islam Negeri Sunan Gunung Djati Bandung

E-mail: *erryfuadillah@uinsgd.ac.id*

Received : July 11, 2025
Revised : September 22, 2025
Accepted : October 15, 2025
Published : October 31, 2025

The article is published with Open Access at https://journals.literaindo.com/cadika

ISSN 3110-8385

How to cite:
Fuadillah, E., Riza, L.S., & Megasari, R. . (2025). Comprehensive Review: Transforming Self-Education through Automatic Question Generation Technology. *Master Journal of Future Education*, *2*(1), 27-42. https://doi.org/10.63461/cadikajournal.v21.296

I. Introduction

The Covid-19 pandemic has been successfully overcome, this tragedy has spread throughout the world and has had an impact on everyone due to social restrictions. The COVID-19 pandemic has increased the need for a more independent and creative educational transformation. In independent education, each student is required to take the initiative in learning, seeking information and learning resources by developing various necessary skills. Independent education will encourage students to think creatively. It will also encourage them to generate new ideas. And it will encourage them to solve problems in innovative ways. The development of technology makes it easier for students to search and collect information independently (Nguyen et al., 2022). The success of participants in carrying out educational activities independently is measured through evaluation (Suardipa & Primayana, 2020).

Evaluation activities in the world of education describe the interaction between teachers and students (Kalman et al., 2020) that occurs during the learning process. The most common evaluation done is by asking questions or questions (Susanti et al., 2015). The more questions you work on, the better your students' abilities will be. However, a problem arises that producing a good set of questions requires special skills (Kurdi et al., 2020). Apart from that, the question sets obtained from books and other sources are not relevant to students (Soni et al., 2019). This results in the limited opportunity to get questions with good quality to be limited. The utilization of automatic question generation (AQG) technology (Riza et al., 2019) becomes relevant to continue to be developed to support educational activities (Tsai et al., 2021) independently.

AQG is a system that can generate questions based on topics following natural human language (Mulla & Gharpure, 2023). AQG has experienced an increase in popularity recently with many systems supporting artificial intelligence technology for processing text

(Araki et al., 2016)(V. Kumar et al., 2019) and pictures. AQG has been used for various needs such as machine understanding, conversational machines, and even education (Mulla & Gharpure, 2023). AQG has been developed for various needs, such as to help students extract information from an article by changing the article into a question form with a more concise presentation of the topic (Liu et al., 2010). There are two main domains in AQG, namely being able to produce syntactically correct questions (syntactically) and meaningfully understandable (semantically) (Mulla & Gharpure, 2023). AQG is one of the main products of natural language processing (NLP) methods. It is defined as the task of how a machine can create questions that can be understood by humans.

Natural language processing (NLP) is used to make machines understand language and what it means (Soni et al., 2019)(Riza et al., 2019). NLP has two main focuses, namely question answering (QA) and question generation (QG) (Thotad et al., 2022). NLP has enormous potential, especially in the field of education (Zhu et al., 2021) because it can change the approach to learning evaluation and also a deep transformation of independent education. NLP originally used statistical and probabilistic mechanisms (Young et al., 2018) that can only process text in terms of sentence structure which has been transformed with a combination of machine learning and can recognize sentences in meaning. This is a solution to answer the challenge of providing unlimited learning content.

Seeing the phenomena that occur in the current era. This research focuses on presenting articles that support the transformation of independent education with AQG technology. The research was carried out by collecting articles from 2018 to 2023 about AQG to then extract information about the technology used in the AQG system. Finally, the researcher carried out a manual classification to determine groups of articles that were considered relevant to the theme raised.

II. Related Work

The notion of autonomous learning engenders an environment conducive to the maximisation of students' potential by empowering them to align their interests and aptitudes (Sarnoto et al., 2022)(Ishak, 2021). In Indonesia, the concept of independent learning, or what is often called independent learning has become a policy that has been passed since 2022. This is a polemic that still needs a lot of improvement (Ishak, 2021). Independent learning is influenced by various factors, one of which is gender. The gender factor shows that women have a better tendency (78.2%) in learning activities (62.4%) (Mawardi et al., 2020). Another factor that also influences the success of independent learning activities is the source of learning content data or information, communication, and technology (ICT), namely around 100% of teachers use ICT in the learning process. However, 40% of students were greatly helped in independent learning even though the learning process was still under teacher supervision (Rarasati et al., 2016).

Independent learning must be supported by appropriate evaluation methods to measure the success of the learning process. At least, working on questions is a conventional method that is often used by teachers to see the success of learning. Creating quality questions requires skill and also takes a lot of time. In 2001 Cotton revealed that teachers spend as much as 20% -50% of questions. Studies show that the availability of questions that students can access independently has a value of 3 on a scale of 5 (Susanti et al., 2015). The lack of ability to create questions makes evaluation activities bad (Kurdi et al., 2020).

The AQG system has become a hot topic of discussion for creating consistent evaluation questions. AQG has been successfully developed to create TOEFL questions (Susanti et al., 2015) for the vocabulary question type with an average score of 3 on a scale of 5, this shows that half of the questions created can be used for English language tests. Other research was conducted on error identification question types (Riza et al., 2020) and sentence completion (Riza et al., 2019) producing an accuracy of around 82.0% stated by experts. In the 5W+1H question type using the T5 method, it produces the highest scores of 60.44% and 72.78% (Pandraju & Mahalingam, 2021). AQG has succeeded in becoming a solution to meet the need for information regarding learning evaluation in the form of a system that can produce questions consistently, with content that is relevant to students and in unlimited quantities.

III. Research Methodology

The research method used was based on a systematic literature review (SLR). PRISMA was used. PRISMA is Preferred Reporting Items for Systematic Reviews and Meta-analyses. (Abelha et al., 2020). This method is a method that is quite relevant in carrying out SLR. Research methodology is a method used to obtain results from the problem to be solved. Thus, each stage carried out is completed systematically to obtain accurate results. Figure 1 shows the research methods carried out.

1.1. Data Sources and Search Strategies

Researchers collect a database in the form of research articles from websites that are considered to provide articles with good credibility. Such as Google Scholar, IEEE Explorer, Springer, and Arvix. Researchers also conducted searches directly without going through the official website (hand searched) to complete database requirements. Articles are determined from 2018 to 2023. This is a range of years that is quite relevant in one research period. In general, researchers identified articles in English and Indonesian. In expanding the search range, researchers used terms commonly used in automatic question generator technology such as "AGQ, question generator, automatic question generator for education" and so on.

Figure 1. Systematic Literature Review

1.2. Selection of Studies

This stage aims to identify titles and abstracts that are relevant to the research theme being conducted. Researchers use supporting applications to make data searching easier. There are special criteria that must appear in the articles used, namely "automatic question generator for education".

1.3. Data Extraction Process and Quality Assessment

Data extraction is a quite complicated stage because care is required in selecting the articles to be used. At this stage, there may still be many errors due to the large number of articles identified. This stage refers to taking information from the research methods and objectives in the article that is considered relevant to the research objectives.

1.4. Eligibility Criteria

According to (Abelha et al., 2020) three stages can be used to carry out eligibility criteria. Eligibility criteria are carried out to answer the research being conducted. So some articles that do not explain the research including the development process and results are not considered relevant articles to the theme "automatic question generator for education". Researchers hope that several previous studies will explicitly reveal the phenomenon of the transformation of independent education with automatic question-generator technology.

1.5. Constitution of the Corpus of Analysis

Articles that are considered relevant to the research theme being conducted and listed as previous research are arranged based on data source, year of publication and alphabetical order. This analysis refers to the article analysis technique developed by Bardin in 2011.

Searches based on keywords with inclusion criteria produced a total of 102 articles. Articles that are found are then marked with an ID to make research easier. As seen in **Table 1**.

Table 1. Initial Findings

No	Source	Initial Findings	Exclusion Criteria
1	IEEE	7	5
2	ARXIV	47	43
3	Google Schoolar	22	20
4	Hand Searched	22	16
5	Springer	4	4
	Ammount	**102**	**88**

Search results based on the keyword: "Automatic Question Generator, AQG, Automatic Question Generator for Education, Question Generator" succeeded in finding 88 articles that met the exclusion criteria. Researchers then narrowed the number to 63 articles that were considered relevant to the research objectives.

Error! Reference source not found. shows that identification refers to the general research theme by determining the keywords used. Reporting is carried out using the PRISMA approach (Abelha et al., 2020) with four main stages

.

1.6. Characteristics of Included Studies

In some cases, references in a study that is quite relevant are 5 years ago from the year the research was conducted. So, research conducted in 2023 used references from 2019. However, researchers found that 2018 was one of the years with a fairly high number of scientific publications with the AGQ theme (Kurdi et al., 2020). This is the basis for decision-making for the range of articles used from 2018 to 2023 Figure 2.

Increases occur almost every year, this shows that the AQG research trend is still relevant. Various factors greatly influence the research trends carried out, such as during the 2020 – 2022 Covid-19 pandemic. This results in independent education by students becoming one of the solutions to remaining able to attend school. In 2022, the highest number of publications about AQG will be 26. Based on the inclusion and exclusion criteria, the total number of articles collected is 88. In the process of searching for articles related to automatic question generators (AQG), researchers use articles that are related to the world of education. In total, 63 articles are considered related to the research objectives being carried out. As seen in **Error! Reference source not found.**, The blue color indicates articles provided with research objectives while the orange color is the number of initial findings according to exclusion filtration.

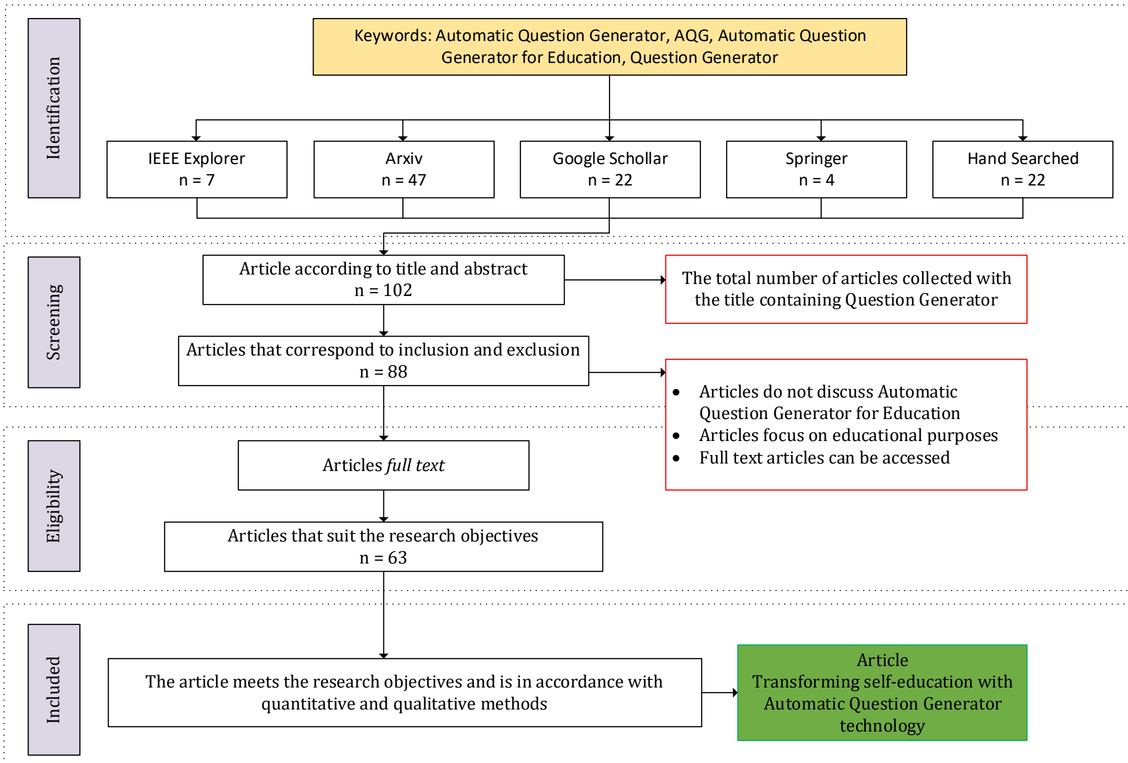

Figure 2. Scientific Reporting for comprehensive review research with PRISMA

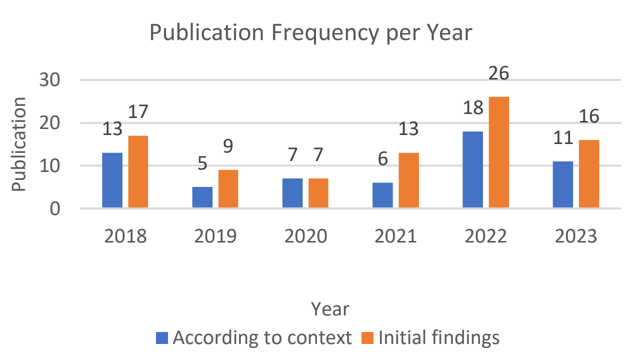

Figure 3 Publication Frequency per Year

1.7. Strengths and Limitations

This research seeks to provide an overview of efforts to increase the transformation of independent education by utilizing AQG technology. This research uses the PRISMA method. We tried to identify as many articles related to AQG as possible by expanding the keywords. Despite researchers' efforts to improve research quality, researchers limited their search to the 2018-2023 range of databases with reliable credibility. Researchers prioritize articles that provide research objectives so that the articles considered relevant are 63 articles taken from five commonly used database sources. The search results still contain deficiencies both contextually and technically, making it possible that many articles were not included in the research.

IV. Result and Discussion

The findings that the researchers obtained generally focused on summary results based on the literature review theory that Alsubait wrote in the article (Kurdi et al., 2020) because this is considered the most relevant. The research found various trends and highlighted various conditions underlying research on AQG with various speculations made. Alsubait wrote several main components in the literature review environment such as dimensions 1. QG research objectives, 2. domain, 3. knowledge sources, 4. methods, 5. types of questions, 6. question formats, and 7. evaluation. As seen in **Table *2***.

Researchers have succeeded in finding several dimensions of Alsubait's approach. There are many limitations for researchers in making assumptions from the articles used. This means that there may still be many shortcomings in the grouping that has been done.

Table 2. Research Dimensions Based on Categories

Dimensions	Category	Number of Articles	Presentation
Purpose	Assessment	40	61%
	Knowledge acquisition	12	18%
	Validation	10	15%
Domain	General	4	6%
	Domain-specific	47	76%
	Generic	15	24%
Knowledge source	Text	60	92%
	Ontologies	3	5%
	Other	2	3%
Generation Method	Syntax based	22	28%
	Semantic based	29	37%
	Template based	16	21%
	Other	11	14%
Question Type	Factual wh-questions	37	55%
	Fill-in-the-blank questions	11	16%
	Math word problems	1	1%
	Other	18	27%
Reponse Format	Free response	42	66%
	Multiple choice	19	30%
	True/false	3	5%
Evaluation	Expert-centred	20	29%
	Student-centred	2	3%
	Other / Sistem Evaluation	33	48%
	None	14	20%

The description given in **Table *2*** regarding dimensions and categories in the context of AQG can help detail the elements contained in the main tasks of AQG and in efforts to evaluate the resulting questions. **The purpose** dimension includes the purpose for which the questions produced are used. The questions generated in the AQG case can be used in various ways such as Assessment is used to measure understanding, knowledge, or skills such as English language skills (Firdaus & Riza, 2020). Assessment in English has standards that have been developed internationally such as TOEFL (Giovani, 2021)(Pertiwi et al., 2018)(Putera & Riza, 2019) and IELTS (Firdaus & Riza, 2020)(Ferlanda et al., 2022)(Firdaus & Riza, 2020). In this case, assessment is the category most frequently carried out, namely around 60%. This shows that the need for an unlimited number of questions is the basis for improving the quality of education (Kurdi et al., 2020). This also supports efforts to realize independent learning (Elkins et al., 2023) better.

Domain, this dimension refers to a field of knowledge related to AQG technology. According to Alsubait, domains are divided into two large groups, namely specific domains and general. AQG technology supports general question creation. However, to create good quality questions, technology is sometimes needed that tends to be more specific, such as AQG for Arabic (Alhashedi et al., 2022), Indonesia (Kusuma & Alhamri, 2018), and China (T. Zhang et al., 2018). The domain is also closely related to knowledge source because it refers to the source of knowledge or database from which questions are generated. The more resources that can be identified, the broader the research domain. Text is still the dominant source of knowledge with a percentage of 92% as in **Error! Reference source not found.**. This allows future research to develop by recognizing sources of knowledge in the form of images (T. Zhang et al., 2018), sound, or video.

Generation Method is the main dimension that includes the methods, approaches, and techniques used in AQG. The methods chosen tend to be adjusted to the availability of data sources and emerging trends. The commonly used method is machine learning including transforms (Raina & Gales, 2022)(C. Zhang & Wang, 2022), deep learning (Indrihapsari et al., 2023)(Chen et al., 2019), Text Mining (Last & Danon, 2020)and many more. generation method includes basic capabilities such as generators based on syntax (paying attention to grammar and sentence structure) 28%, semantics (questions created based on meaning) 37%, template base (question structure created based on predetermined templates or role models) 21% and other 14% for the oher approach. The following section contains all the information about each article. **Table *3***.

Table 3. Details of the Approach Classification of Understanding Levels and Types of Questions

No	Article	Level of Understanding Approach				Question type			
		Syntax	*Semantic*	*Template*	*Other*	*Factual wh*	*Fill-in-the-blank*	*Math word*	*Other*
1	(Chen et al., 2019)		✓						✓
2	(Indrihapsari et al., 2023)		✓			✓			
3	(Patra & Saha, 2018a)		✓			✓			
4	(Alshboul & Baksa-Varga, 2022)				✓	✓			
5	(Flor & Riordan, 2018)		✓			✓			
6	(Kurdi et al., 2020)				✓				✓
7	(Guin & Lefevre, 2022)		✓			✓	✓		
8	(Alhashedi et al., 2022)	✓		✓		✓	✓		
9	(Akyön et al., 2022)	✓							✓
10	(Chakankar et al., 2023)	✓					✓		
11	(Das et al., 2019)	✓					✓		
12	(Park et al., 2018)	✓		✓			✓		
13	(Patra & Saha, 2018b)		✓			✓			
14	(Rodríguez Rocha & Faron Zucker, 2018)				✓				✓
15	(Silva et al., 2019)				✓				✓
16	(Last & Danon, 2020)				✓	✓			
17	(Shimmei & Matsuda, 2022)				✓	✓			
18	(Tsai et al., 2021)	✓	✓			✓			
19	(Lee et al., 2018)	✓				✓			
20	(Kusuma et al., 2020)	✓				✓			
21	(Vincentio & Suhartono, 2022)		✓			✓			
22	(Fung et al., 2020)		✓	✓		✓	✓		
23	(Thotad et al., 2022)	✓	✓			✓			
24	(Zou et al., 2022)		✓						✓
25	(Dong et al., 2023)			✓		✓			
26	(Scharpf et al., 2022)				✓			✓	
27	(T. Zhang et al., 2018)	✓	✓			✓			
28	(Steuer et al., 2022)		✓			✓			
29	(Zhao et al., 2022)	✓		✓					✓
30	(Wu et al., 2022)				✓				✓
31	(L. Zhang & VanLehn, 2021)				✓				✓
32	(Oh et al., 2023)	✓	✓			✓			
33	(Kulshreshtha et al., 2022)	✓				✓			
34	(Kusuma & Alhamri, 2018)			✓		✓			
35	(Elkins et al., 2023)	✓							✓
36	(Steuer et al., 2021)		✓			✓			
37	(Chan et al., 2021)		✓	✓		✓			
38	(N. A. Kumar et al., 2023)		✓			✓			
39	(Sun et al., 2023)		✓	✓		✓			

No	Article	Level of Understanding Approach				Question type			
		Syntax	***Semantic***	***Template***	***Other***	***Factual wh***	***Fill-in-the-blank***	***Math word***	***Other***
40	(Marrese-Taylor et al., 2018)	✓					✓		
41	(Duong et al., 2022)		✓	✓		✓			
42	(Bitew et al., 2022)		✓	✓		✓	✓		
43	(Raina & Gales, 2022)	✓					✓		
44	(Z. Wang & Baraniuk, 2023)		✓	✓		✓			
45	(Riza et al., 2020)	✓							✓
46	(Surana et al., 2019)			✓					✓
47	(Muse et al., 2023)			✓		✓			
48	(Srivastava & Goodman, 2021)		✓			✓			
49	(Riza et al., 2019)	✓					✓		
50	(Gupta et al., 2020)		✓			✓			
51	(Bulathwela et al., 2023)		✓	✓		✓			
52	(Yuan et al., 2022)			✓		✓			
53	(Papasalouros & Chatzigiannakou, 2018)				✓				✓
54	(Bi et al., 2021)		✓	✓		✓			
55	(X. Wang et al., 2023)		✓			✓			
56	(C. Zhang & Wang, 2022)	✓				✓			
57	(Rodrigues et al., 2023)		✓			✓			
58	(Firdaus & Riza, 2020)	✓	✓			✓	✓		✓
59	(Anwar et al., 2018)	✓							✓
60	(Giovani, 2021)		✓				✓		
61	(Pertiwi et al., 2018)	✓					✓		
62	(Ferlanda et al., 2022)		✓				✓		
63	(Putera & Riza, 2019)		✓				✓		

The next dimension in AQG is **Question Type**, which includes several commonly used types of question in assessments. Factual wh-questions are the most frequently used type of question, namely 55%. This type is very flexible for use in various domains, such as education (Firdaus & Riza, 2020) (Rodríguez Rocha & Faron Zucker, 2018) (Alshboul & Baksa-Varga, 2022) as well as in other fields. Because this type of question contains question words such as "what", "when", "where" and so on. Questions of this type also usually have various **response formats** such as free responses (Kurdi et al., 2020). Factual wh-questions will give students the freedom to answer without being fixated on the answer choices provided. Meanwhile, the type of fill-in the blank questions usually depends on the form of the sentence produced (Riza et al., 2019) (Das et al., 2019). This type of question is not very widely developed with a percentage of 16% because it does not have the flexibility of the wh-question type. However, in the case of improving grammar skills, fill-in the blank type questions can be a pretty good choice (Riza et al., 2019) (Pertiwi et al., 2018). In other cases, the fill-in-the-blank question type is often combined with a multiple-choice answer format (Das et al., 2019).

Lastly is the **Evaluation** dimension, in the case of AQG the evaluation describes who is responsible for evaluating the resulting questions. The evaluation process involves gathering the data and information needed to determine how well the AQG has been implemented. The evaluation results can be used as the data needed to maximize the desired results. evaluation carried out directly by the system using an appropriate approach is the main choice with a percentage of 48%. An approach like transformers (Akyön et al., 2022) (Muse et al., 2023) and deep learning (Bitew et al., 2022) (Marrese-Taylor et al., 2018) have different approaches to evaluating the resulting questions. Meanwhile, expert-centered entrusts someone who is considered an expert with a judgment test to determine the extent to which the system can be used.

1.8. AQG Research Objectives in Education

AQG has a very close relationship with the world of education (Kurdi et al., 2020) (Zhao et al., 2022). The aim of AQG research was initially to help someone create questions in a short time (Rodríguez Rocha & Faron Zucker, 2018). This research was conducted to provide an overview of the transformation of independent education using AGQ technology using a comprehensive review method. The research was conducted by collecting 63 articles related to AQG. **Table 4** indicates the general aim of research on AQG.

In the educational context, assessment is a process for measuring students' abilities, progress, achievements, and understanding of the material being studied (Kusuma et al., 2020) (Marrese-Taylor et al., 2018). The purpose of assessment is to collect data and information to evaluate the extent to which students achieve learning goals (Silva et al., 2019)

Table 4. AQG Research Objectives with the Theme of Education

Objective	Number of articles
Assessment (evaluation)	40
Education in a wider environment	14
Independent Learning and self-assessment	10
Supporting Media	3
Tutoring system	5
Exercise	40
Question Generating Information System	4
Active Learning (active learning)	7

1.9. General Stages AQG

The AQG system development stages are summarized into three main stages utama (Kurdi et al., 2020), this refers to the activities of the articles that are referenced in the research carried out. Each AQG task is different for each case study that has been developed. In general, however, they have various similarities that can be grouped together to help the reader understand them more easily. The stages explained are preprocessing, question construction, and post-processing. Figure 4 shows the general stages of the AQG system.

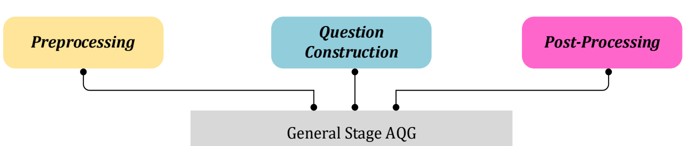

Figure 4 General Stage AQG

Preprocessing

Preprocessing involves a series of activities carried out initially to prepare data for use in analysis or modelling. (Pertiwi et al., 2018). The primary objective of preprocessing is to convert data into a format that is appropriate for utilisation and aligned with the requirements of the analysis. (Wu et al., 2022). In the case of AGQ, there are two groups of preprocessing which are the main standards, namely: **1) general standards**, namely standards using natural language processing (NLP), namely regex processing (cleaning text from unnecessary punctuation) (Riza et al., 2019) (Pertiwi et al., 2018), tokenization (changing sentence text into words(Giovani, 2021) (Flor & Riordan, 2018), lemmatization (returns the word to its basic form) (Ferlanda et al., 2022), part of speech (groups tokens into headings representing each type of speech(Gumaste et al., 2020) (Chakankar et al., 2023). **2) special standards**, namely the steps carried out in several articles that have been found. Specific standard objectives focus on customizing data in hopes of producing better output.

- *Sentence simplification*: This is the stage for changing sentences into simpler forms (Flor & Riordan, 2018). In many cases, the text used is often of high complexity. However, in reality questions do not require sentences that are too long (Kurdi et al., 2020). Sentence simplification refers to the process of simplifying sentences to make questions more accurate (Last & Danon, 2020). Previous research shows that there is a rule for simplifying sentences by choosing feelings that are considered important in a sentence (Patra & Saha, 2018a). Choosing good sentences is the main key in the AQG system (Duong et al., 2022).
- *Sentence classification*. It has a role in determining the categories of questions to be developed (Papasalouros & Chatzigiannakou, 2018). This stage has a role in identifying the type of sentence as a data source. So that questions can be generated that are more appropriate based on the sentences used (Kurdi et al., 2020). In general, sentence classification applies the NLP approach as part of the preprocessing stage in the AQG environment. In several AQG articles, sentence classification is used to determine the position of blanks in fill-in the blank question types (Riza et al., 2019) (Firdaus & Riza, 2020). In other cases, sentence classification is used to determine the pattern of a question template (Kusuma & Alhamri, 2018) (Dong et al., 2023).
- *Content selection.* Content selection is a stage for reducing sentences in a collection of chapters into sub-chapters that are considered the most important

(Steuer et al., 2021). In the case of AQG, content selection starts from the aim of creating limited questions, so it is necessary to select sentences that are considered to have content that suits AQG's objectives (Kurdi et al., 2020). content selection is done with statistics (Chakankar et al., 2023), summarizing (Chen et al., 2019) and text classification.

Question construction

Question construction is one of the important stages in the AQG case. This stage aims to produce relevant and meaningful questions based on sources in the form of text (Riza et al., 2020) (Z. Wang & Baraniuk, 2023), pictures (Surana et al., 2019), and videos in certain contexts. Question construction is the main stage but has a different process for each type of question produced (Kurdi et al., 2020), both from the form of the question and the form of the answer. Several stages in question construction have been carried out in several previous studies.

- *Question and correct answer generation*. This is a process carried out to create questions and answers which are usually done simultaneously. This stage is carried out using a syntax approach (sentence structure) (Riza et al., 2019), semantic (meaning) (Srivastava & Goodman, 2021), templates (Bulathwela et al., 2023), or statistical approach. The answers developed must be accurate, relevant, and appropriate to the questions asked. This will show how good the quality of the questions produced is.
    - Changing assertive sentences, namely sentences those express facts, statements, or opinions, into interrogative sentences (question sentences). The way the process is carried out is by using question words (Wh-words) (Sung, 2019) (X. Wang et al., 2023), changing word order, and using interrogative particles (whether).
    - Determining the type of question, there are types of questions that can be developed in AQG such as filling in the blank (Pertiwi et al., 2018), 5W+1H (L. Zhang & VanLehn, 2021), multiple choices and math questions (Scharpf et al., 2022).
    - Determine the empty position or wrong position, this usually appears in question types that do not alter the fundamental structure of the sentence. But only determine the sentence then one of the words is removed (sentence completion) (Riza et al., 2019).
- *Incorrect options (distractor) generation.* This is a very important stage because it will greatly affect the quality of the questions. Making distractors has many challenges because making distractors requires good precision. A good distractor is a collection of words that make sense so students have to think to determine the correct answer (L. Zhang & VanLehn, 2021). Various strategies are used to create a good distractor, including using keywords (Bitew et al., 2022) (Patra & Saha, 2018a), the closeness of word structure (Riza et al., 2019), part-of-speech conformity (Pertiwi et al., 2018), and with other approaches.
    - The keyword approach is a collection of words according to categories or themes. For example, a collection of words on a biology theme.
    - The word structure suitability approach, namely calculating the closeness of a word to other words, for example, "write" and "wrote".
    - A part-of-speech congruence is usually a group of congruent words having the same part-of-speech type.

  Distractor creation is adjusted to the type of question that arises, such as grammar and vocabulary questions (Sun et al., 2023) will produce a different approach to making distractors even with the same type of question, namely multiple choices (Patra & Saha, 2018b). This type of vocabulary question tends to require distractors that are antonyms and synonyms (Sun et al., 2023) which are taken from the correct answer, while grammar questions tend to require distractors from word changes (Riza et al., 2020). This is the basis that distractor creation is greatly influenced by the purpose of creating the question (Guin & Lefevre, 2022).
- Feedback generation is a stage to provide feedback to students, whether the answers to questions that have been completed are correct or wrong. Good feedback generation can provide benefits for students because they can carry out evaluations independently (Rodrigues et al., 2023). In more real cases such as the use of AQG in Intelligent Tutoring System (ITS) technology, feedback will provide students with an idea of the progress of students' abilities independently (Kulshreshtha et al., 2022). There are several roles and functions of a good feedback generator in the AQG system.
    - Providing clarification and explanation, the resulting feedback can explain the correct answer and the wrong answer.
    - Directing students, feedback can direct students to study material that is considered not yet mastered based on how many questions cannot be answered (Lee et al., 2018).

- Personalization, in several AQG systems that are connected to ITS can be personalized based on student performance (Kulshreshtha et al., 2022). For example, if students often experience errors in certain concepts, then the feedback given will focus on that concept.
- Increased understanding and feedback can help students improve their understanding of topics that appear as a set of questions. This is an important aspect of the independent learning process.

The existence of feedback generation in the AQG system helps students to learn better, improves understanding, and identifies areas that need improvement.

- Controlling difficulties is a stage that functions to determine how easy or difficult a question is. Difficulty is a fundamental component of a question. One method used to determine the level of difficulty is statistical calculations (L. Zhang & VanLehn, 2021) (The more students answer correctly, the more questions are considered too easy, and vice versa) (Kurdi et al., 2020). Controlling difficulty will produce questions that are by the learning objectives. Research in the AQG field has developed rapidly recently. However, there is not much research focusing on the control of adversity (Chan et al., 2021). So sometimes systems that are successfully developed are not relevant when evaluations are carried out together with students. Questions with a good level of difficulty require a long time (Kusuma & Alhamri, 2018) and large amounts of data (Zou et al., 2022). Various approaches are taken to maintain consistency of questions, one of which is an ontology-based approach (Kusuma et al., 2020) and based on Blom's taxonomy (Elkins et al., 2023) to maintain the standard of the questions.

Post-processing

Post-processing is the final stage of developing the AQG system to improve the results of the questions produced. The primary objective of the post-processing stage is to enhance the quality, relevance and suitability of the generated questions. (Flor & Riordan, 2018). This stage is carried out manually by experts (Last & Danon, 2020), therefore it is expected to produce questions of higher quality (Yuan et al., 2022). There are several actions carried out at the post-processing stage.

- *Grammar checking* is a step that needs to be done to check that the questions have correct grammatical rules. This includes gamma, word usage, and punctuation. One approach commonly used for verbalization is to focus on the quality of the grammar in the question. This approach also focuses on linguistic issues (Kurdi et al., 2020) which is considered to influence the quality of the questions produced.
- *Elimination of redundancy*, in the case of AQG sometimes the questions generated may contain redundant or redundant information. At this stage, information that is deemed unnecessary can be deleted to produce more concise and clear questions.
- *Selection of irrelevant questions*, this is the stage carried out for ranking or filtering questions. Previous research used an "*over-generate and rank*" approach (Kurdi et al., 2020) where the resulting number of questions are then ranked and filtered to prioritize high-quality questions.

1.10. AQG's Role in Supporting Independent Education

The concept of learning is influenced by a number of factors, including behaviour, motivation and aspects of the learning environment. This concept is known as independent education. (Daar, 2020). In implementing independent learning, students can take the initiative in planning, organizing, and directing their learning without depending on direct teaching from the teacher or instructor (Sarnoto et al., 2022)(Ishak, 2021). Independent learning gives full control to students during the learning process thereby giving them responsibility for achieving their own learning goals. So far, independent learning has become a hot topic of discussion in the world of adaptive education (Srivastava & Goodman, 2021) because it applies learning strategies according to the learning styles and preferences of individual students. The use of automatic question generator (AQG) technology has a positive impact on learning methods (Last & Danon, 2020) (Marrese-Taylor et al., 2018) and personal learning by providing opportunities for students to continue to develop themselves by carrying out continuous evaluations without having to have a teacher to meet the needs of questions (Silva et al., 2019). Providing questions that are relevant to the learning material being studied. AQG has an important role in supporting independent learning seen in Figure 5.

- *Interactive learning media*. Interactive learning media is media that can produce many interactive questions from text (Park et al., 2018), pictures (Surana et al., 2019), or videos. This makes learning material more interesting and allows students to be more active than just reading (C. Zhang & Wang, 2022)(X. Wang et al., 2023) or listening. AQG can generate questions that can be answered directly and can make students engage in critical thinking.

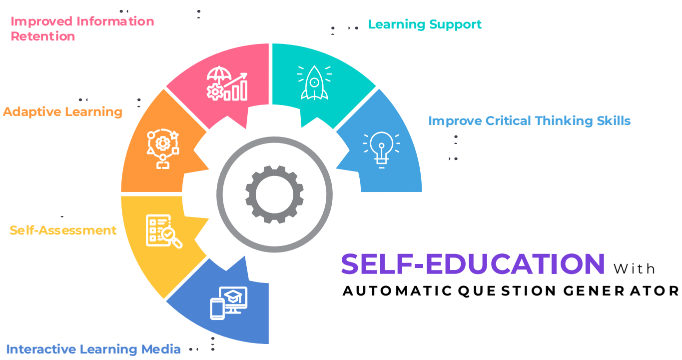

Figure 5 The Role of AQG Technology in Self-Education

- *Self-Assessment.* Self-Assessment this was probably the original goal of the development of all AQG systems. The resulting questions can be used by individual students as a self-evaluation tool (Muse et al., 2023). Self-assessment is used to improve students' abilities for various content being studied such as English (Ferlanda et al., 2022), Arabic (Alhashedi et al., 2022), Indonesian (Vincentio & Suhartono, 2022), biology (L. Zhang & VanLehn, 2021) and even mathematics (Scharpf et al., 2022). Self-assessment makes it easier for teachers to encourage students to carry out evaluations independently so that teachers can focus on the pedagogical process and in-depth discussions. From the teacher's side, this may be indirectly supportive. Texts that circulate unofficially can be accessed directly but without direct supervision will be another problem for students. With the AQG system, participants will independently receive more targeted information (Steuer et al., 2022).
- *Adaptive learning,* Adaptive learning allows for more personalized learning strategies and can help participants from different backgrounds (Kurdi et al., 2020) (Srivastava & Goodman, 2021). AGQ technology explores creating questions that are determined directly as part of the control that can be carried out by students or what is usually called independent learning. AQG technology is convenient (Chakankar et al., 2023) for students because students can determine for themselves which material will be evaluated without having to wait for the schedule given by the teacher. In several studies, the AQG system does not have high flexibility to be able to model all student models as a media to support adaptive learning (Marrese-Taylor et al., 2018). Therefore, the development of the AQG system based on NLP and deep learning (Shimmei & Matsuda, 2022) is one solution to build a more flexible AQG system.
- *Increased Information Retention*, namely doing lots of questions can help increase information retention. Active thinking activities in answering questions can help remember various information better than just reading (Fung et al., 2020) and listening. One type of question that can support active learning activities is the multiple-choice question type (Patra & Saha, 2018a). Repetition of information will cause various keywords that need to be remembered to be stored in memory for a long time.
- *Learning Support.* Learning Support this case AQG can be used in various educational contexts (Gupta et al., 2020), such as intelligence tutoring systems (Kulshreshtha et al., 2022), self-paced training, and digital platforms (Muse et al., 2023). It will continue to be available and enable learners to learn and develop their skills. Learning Support shows the role of technology such as AQG in helping teachers and students are involved in the learning process. (N. A. Kumar et al., 2023) carried out in a structured or independent manner.
- *Improve Critical Thinking Skills*. An answering questions generated by the AQG system. This will encourage students to think critically and analyze information carefully. Good critical thinking skills will be very useful for students in the independent learning process, where students must take the initiative in their learning.

V. Conclusion

After the completion of the Covid-19 pandemic, the need for technology has increased in all aspects of life, one of which is education. Automatic question generator (AQG) technology is a technology that has been widely developed recently. AQG has a very important role in supporting independent education. In today's era where all information can be accessed easily, AQG allows students to build critical thinking skills in independent education. AQG stimulates students to have active thinking, characteristic thinking, and problem analysis skills by solving the questions given. One educational concept that is deemed suitable is adaptive education using AQG technology. This research succeeded in collecting 63 articles related to AQG in the field of education from 2018 to 2023. In general, AQG technology was developed for assessment, which is around 61% of the total research found. This shows the potential for AQG to continue to be developed, especially in the education sector.

VI. References

Abelha, M., Fernandes, S., Mesquita, D., Seabra, F., & Ferreira-oliveira, A. T. (2020). Graduate Employability and Competence Development in Higher Education — A Systematic Literature Review Using PRISMA. *Sustainability*, *12*. https://doi.org/doi:10.3390/su12155900

Akyön, F. Ç., Çavuşoğlu, D., Cengiz, C., Altinuç, S. O., & Temizel, A. (2022). Automated question generation and question answering from Turkish texts. *Turkish Journal of Electrical Engineering and Computer Sciences*, *30*(5), 1931–1940. https://doi.org/10.55730/1300-0632.3914

Alhashedi, S., Suaib, N. M., & Bakri, A. (2022). *Arabic Automatic Question Generation Using Transformer Model*.

Alshboul, J., & Baksa-Varga, E. (2022). A Review of Automatic Question Generation in Teaching Programming. *(IJACSA) International Journal of Advanced Computer Science and Applications*, *13*(10), 45–51. https://doi.org/10.14569/IJACSA.2022.0131006

Anwar, F. S., Riza, L. S., & Rahman, E. F. (2018). *Implementasi Levenshtein Distance untuk Sistem Penghasil Soal Error Identification dalam Toefl*.

Araki, J., Rajagopal, D., Sankaranarayanan, S., Holm, S., Yamakawa, Y., & Mitamura, T. (2016). Generating questions and multiple-choice answers using semantic analysis of texts. *COLING 2016 - 26th International Conference on Computational Linguistics, Proceedings of COLING 2016: Technical Papers*, 1125–1136.

Bi, S., Cheng, X., Fang Li, Y., Qu, L., Shen, S., Qi, G., Pan, L., & Jiang, Y. (2021). Simple or Complex? Complexity-Controllable Question Generation with Soft Templates and Deep Mixture of Experts Model. *Findings of the Association for Computational Linguistics, Findings of ACL: EMNLP 2021*, 4645–4654. https://doi.org/10.18653/v1/2021.findings-emnlp.397

Bitew, S. K., Hadifar, A., Sterckx, L., Deleu, J., Develder, C., & Demeester, T. (2022). Learning to Reuse Distractors to Support Multiple Choice Question Generation in Education. *IEEE Transactions on Learning Technologies*, 1–24. https://doi.org/10.1109/TLT.2022.3226523

Bulathwela, S., Muse, H., & Yilmaz, E. (2023). *Scalable Educational Question Generation with Pre-trained Language Models*. 327–339. https://doi.org/10.1007/978-3-031-36272-9_27

Chakankar, T., Shinkar, T., Waghdhare, S., Waichal, S., & Phadtare, Mrs. M. M. (2023). Automated Question Generator using NLP. *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, *11*(3), 216–221. https://doi.org/10.22214/ijraset.2023.49390

Chan, Y.-H., Chung, H.-L., & Fan, Y.-C. (2021). *Improving Controllability of Educational Question Generation by Keyword Provision*.

Chen, G., Yang, J., & Gasevic, D. (2019). A Comparative Study on Question-Worthy Sentence Selection Strategies for Educational Question Generation. *AIED*, *1*, 59–70. https://doi.org/10.1007/978-3-030-23204-7

Daar, G. F. (2020). Students' independent learning implementation during learning from home period (a study at Unika Santu Paulus Ruteng, Flores). *Journal of Applied Studies in Language*, *4*(2), 313–320. https://doi.org/10.31940/jasl.v4i2.2164

Das, B., Majumder, M., Phadikar, S., & Sekh, A. A. (2019). Automatic generation of fill-in-the-blank question with corpus-based distractors for e-assessment to enhance learning. In *Computer Applications in Engineering Education* (Vol. 27, Issue 6, pp. 1485–1495). https://doi.org/10.1002/cae.22163

Dong, X., Lu, J., Wang, J., & Caverlee, J. (2023). Closed-book Question Generation via Contrastive Learning. *EACL 2023 - 17th Conference of the European Chapter of the Association for Computational Linguistics, Proceedings of the Conference*, 3142–3154.

Duong, D. H. T., Son, N. H., Le, H., & Nguyen, M.-T. (2022). *Learning to Generate Questions by Enhancing Text Generation with Sentence Selection*.

Elkins, S., Kochmar, E., Serban, I., & Cheung, J. C. K. (2023). *How Useful Are Educational Questions*

Generated by Large Language Models? 536–542. https://doi.org/10.1007/978-3-031-36336-8_83

Ferlanda, M. R., Wahyudin, & Riza, L. S. (2022). *Automatic Question Generation Jenis Summary Completion Untuk Calon Partisipan Ielts Menggunakan Metode Natural Language Processing Dan Deep Learning*.

Firdaus, Y., & Riza, L. S. (2020). *Automatic Generate Question untuk Short-Answer Question di Reading Comprehension IELTS Menggunakan Metode Natural Language Processing dan Algoritma K-Nearest Neighbor*.

Flor, M., & Riordan, B. (2018). A semantic role-based approach to open-domain automatic question generation. *Proceedings of the 13th Workshop on Innovative Use of NLP for Building Educational Applications, BEA 2018 at the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HTL 2018*, *2012*, 254–263. https://doi.org/10.18653/v1/w18-0530

Fung, Y., Kwok, J. C., Lee, L., & Chui, K. T. (2020). Automatic Question Generation System for English Reading Comprehension. *ICTE 2020*, *1*, 136–146.

Giovani, R. P. (2021). *Automatoc Question Generation untuk Soal Vocabulary pada Reading Comprehension TOEFL Menggunakan Algoritma Learning Vector Quantization*.

Guin, N., & Lefevre, M. (2022). An Authoring Tool based on Semi-automatic Generators for Creating Self-assessment Exercises. *International Conference on Computer Supported Education, CSEDU - Proceedings*, *1*(Csedu), 181–188. https://doi.org/10.5220/0010996100003182

Gumaste, P., Joshi, S., Khadpekar, S., & Mali, S. (2020). Automated Question Generator System Using NLP Libraries. *International Research Journal of Engineering and Technology (IRJET)*, *7*(6), 4568–4572.

Gupta, D., Chauhan, H., Tej, A. R., Ekbal, A., & Bhattacharyya, P. (2020). Reinforced Multi-task Approach for Multi-hop Question Generation. *COLING 2020 - 28th International Conference on Computational Linguistics, Proceedings of the Conference*, 2760–2775. https://doi.org/10.18653/v1/2020.coling-main.249

Indrihapsari, Y., Jati, H., Wardani, R., & Setialana, P. (2023). A Comparison of OpenNMT Sequence Model for Indonesian Automatic Question Generation. *ELINVO (Electronics, Informatics, and Vocational Education)*, *8*(1), 55–63. https://doi.org/https://doi.org/10.21831/elinvo.v8i1.56491 A

Ishak, D. (2021). Mechanism , Implementation , and Challenges in Independent Campus Education Policy in Indonesia. *International Journal of Science and Society*, *3*(4), 52–63.

Kalman, R., MacIas Esparza, M., & Weston, C. (2020). Student views of the online learning process during the covid-19 pandemic: A comparison of upper-level and entry-level undergraduate perspectives. *Journal of Chemical Education*, *97*(9), 3353–3357. https://doi.org/10.1021/acs.jchemed.0c00712

Kulshreshtha, D., Shayan, M., Belfer, R., Reddy, S., Serban, I. V., & Kochmar, E. (2022). Few-Shot Question Generation for Personalized Feedback in Intelligent Tutoring Systems. *Frontiers in Artificial Intelligence and Applications*, *351*(May), 17–30. https://doi.org/10.3233/FAIA220062

Kumar, N. A., Fernandez, N., Wang, Z., & Lan, A. (2023). *Improving Reading Comprehension Question Generation with Data Augmentation and Overgenerate-and-rank*.

Kumar, V., Chaki, R., Talluri, S. T., Ramakrishnan, G., Li, Y.-F., & Haffari, G. (2019). Question Generation from Paragraphs: A Tale of Two Hierarchical Models. *Computation and Language (Cs.CL)*.

Kurdi, G., Leo, J., Parsia, B., Sattler, U., & Al-Emari, S. (2020). A Systematic Review of Automatic Question Generation for Educational Purposes. *International Journal of Artificial Intelligence in Education*, *30*(1), 121–204. https://doi.org/10.1007/s40593-019-00186-y

Kusuma, S. F., & Alhamri, R. Z. (2018). Generating Indonesian Question Automatically Based on BloGenerating Indonesian Question Automatically Based on Bloom's Taxonomy Using Template Based Methodom's Taxonomy Using Template

Based Method. *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, *3*(2), 145–152. https://doi.org/10.22219/kinetik.v3i2.650

Kusuma, S. F., Siahaan, D. O., & Fatichah, C. (2020). Automatic Question Generation in Education Domain Based on Ontology. *CENIM 2020 - Proceeding: International Conference on Computer Engineering, Network, and Intelligent Multimedia 2020*, 251–256. https://doi.org/10.1109/CENIM51130.2020.9297991

Last, M., & Danon, G. (2020). Automatic question generation. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(6), 1–11. https://doi.org/10.1002/widm.1382

Lee, C. H., Chen, T. Y., Chen, L. P., Yang, P. C., & Tsai, R. T. H. (2018). Automatic question generation from children's stories for companion chatbot. *Proceedings - 2018 IEEE 19th International Conference on Information Reuse and Integration for Data Science, IRI 2018*, 491–494. https://doi.org/10.1109/IRI.2018.00078

Liu, M., Calvo, R. A., & Rus, V. (2010). Automatic Question Generation for Literature Review Writing Support. *Artificial Intelligence and Lecture Notes in Bioinformatics*.

Marrese-Taylor, E., Nakajima, A., Matsuo, Y., & Yuichi, O. (2018). Learning to Automatically Generate Fill-In-The-Blank Quizzes. *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, 152–156. https://doi.org/10.18653/v1/w18-3722

Mawardi, Agustin, & Atalya. (2020). Open Access Dominant Factor Analysis of Independent Learning as a Key Success Factors of Student Learning. *American Journal of Humanities and Social Sciences Research (AJHSSR)*, *9*, 229–235.

Mulla, N., & Gharpure, P. (2023). Automatic question generation: a review of methodologies, datasets, evaluation metrics, and applications. *Progress in Artificial Intelligence*, *12*(1), 1–32. https://doi.org/10.1007/s13748-023-00295-9

Muse, H., Bulathwela, S., & Yilmaz, E. (2023). Pre-training with Scientific Text Improves Educational Question Generation (Student Abstract). *Proceedings of the AAAI Conference on Artificial Intelligence*, *37*(13), 16288–16289. https://doi.org/10.1609/aaai.v37i13.27004

Nguyen, H. A., Bhat, S., Moore, S., Bier, N., & Stamper, J. (2022). *Towards Generalized Methods for Automatic Question Generation in Educational Domains*. Springer International Publishing. https://doi.org/10.1007/978-3-031-16290-9

Oh, S., Go, H., Moon, H., Lee, Y., Jeong, M., Lee, H. S., & Choi, S. (2023). *Evaluation of Question Generation Needs More References*.

Pandraju, S., & Mahalingam, S. G. (2021). Answer-Aware Question Generation from Tabular and Textual Data using T5. *International Journal of Emerging Technologies in Learning*, *16*(18), 256–267. https://doi.org/10.3991/ijet.v16i18.25121

Papasalouros, A., & Chatzigiannakou, M. (2018). Semantic web and question generation: An overview of the state of the art. *MCCSIS 2018 - Multi Conference on Computer Science and Information Systems; Proceedings of the International Conferences on e-Learning 2018*, *2018-July*, 189–192.

Park, J., Cho, H., & Lee, S. goo. (2018). Automatic generation of multiple-choice fill-in-the-blank question using document embedding. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 10948 LNAI*. Springer International Publishing. https://doi.org/10.1007/978-3-319-93846-2_48

Patra, R., & Saha, S. K. (2018a). A hybrid approach for automatic generation of named entity distractors for multiple choice questions. *Education and Information Technologies*, *24*(2), 973–993. https://doi.org/10.1007/s10639-018-9814-3

Patra, R., & Saha, S. K. (2018b). Automatic generation of named entity distractors of multiple choice questions using web information. In *Advances in Intelligent Systems and Computing* (Vol. 710). Springer Singapore. https://doi.org/10.1007/978-981-10-7871-2_49

Pertiwi, A. D., Riza, L. S., Rahman, E. F., & Abdullah, C. U. (2018). *Sistem Penghasil Soal Sentence Completion dalam TOEFL menggunakan Metode K-Nearest Neighbor dan Natural Language Processing*.

Putera, G. S. A., & Riza, L. S. (2019). *Automatic Question Generation untuk Pronoun Reference Question di Reading Comprehension untuk Toefl Menggunakan Metode Natural Language Processing, Tree Processing, dan Heuristik*.

Raina, V., & Gales, M. (2022). *Multiple-Choice Question Generation: Towards an Automated Assessment Framework*.

Rarasati, Y., Tiyas, I., & Febriyanti, S. (2016). The Use of Ict To Increase Learners' Independece. *International Seminar on English Language Teaching (ISELT 2016)*, *Iselt 2016*, 251–260.

Riza, L. S., Pertiwi, A. D., Rahman, E. F., Munir, & Abdullah, C. U. (2019). Question generator system of sentence completion in TOEFL using NLP and K-nearest Neighbor. *Indonesian Journal of Science and Technology*, *4*(2), 294–311. https://doi.org/10.17509/ijost.v4i2.18202

Riza, L. S., Syaiful Anwar, F., Rahman, E. F., Abdullah, C. U., & Nazir, S. (2020). Natural Language Processing and Levenshtein Distance for Generating Error Identification Typed Questions on TOEFL. *Journal of Computers for Society*, *1*(1), 1–23.

Rodrigues, H., Nyberg, E., & Coheur, L. (2023). *Using Implicit Feedback to Improve Question Generation*.

Rodríguez Rocha, O., & Faron Zucker, C. (2018). Automatic Generation of Quizzes from DBpedia According to Educational Standards. *The Web Conference 2018 - Companion of the World Wide Web Conference, WWW 2018*, 1035–1041. https://doi.org/10.1145/3184558.3191534

Sarnoto, A. Z., Sastradiharja, E. E. J., & Mansur, A. (2022). Prospects And Challenges Of Implementation Of Independent Learning-Independent Campus In Higher Education During The Covid-19 Pandemic. *Webology*, *19*(2), 3343–3358.

Scharpf, P., Schubotz, M., Spitz, A., Greiner-Petter, A., & Gipp, B. (2022). Collaborative and AI-aided Exam Question Generation using Wikidata in Education. *CEUR Workshop Proceedings*, *3262*(Wikidata), 1–16. https://doi.org/10.13140/RG.2.2.30988.18568

Shimmei, M., & Matsuda, N. (2022). *Automatic Question Generation for Evidence-based*. 1–8.

Silva, V. A., Bittencourt, I. I., & Maldonado, J. C. (2019). Automatic Question Classifiers: A Systematic Review. *IEEE Transactions on Learning Technologies*, *12*(4), 485–502. https://doi.org/10.1109/TLT.2018.2878447

Soni, S., Kumar, P., & Saha, A. (2019). Automatic Question Generation: A Systematic Review. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3403926

Srivastava, M., & Goodman, N. (2021). Question Generation for Adaptive Education. *ACL-IJCNLP 2021 - 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, Proceedings of the Conference*, *2*, 692–701. https://doi.org/10.18653/v1/2021.acl-short.88

Steuer, T., Filighera, A., Meuser, T., & Rensing, C. (2021). I Do Not Understand What I Cannot Define: Automatic Question Generation With Pedagogically-Driven Content Selection. *IEEE TRANSACTIONS ON LEARNING TECHNOLOGIES*, *XX*(X), 1–14.

Steuer, T., Filighera, A., Tregel, T., & Miede, A. (2022). Educational Automatic Question Generation Improves Reading Comprehension in Non-native Speakers: A Learner-Centric Case Study. *Frontiers in Artificial Intelligence*, *5*(June), 1–14. https://doi.org/10.3389/frai.2022.900304

Suardipa, I. P., & Primayana, K. H. (2020). Peran Desain Evaluasi Pembelajaran Untuk Meningkatkan Kualitas Pembelajaran. *Widyacarya*, *4*(2), 88–100.

Sun, X., Tang, H., & Xu, chengzhong. (2023). *Inflected Forms Are Redundant in Question Generation Models*.

Sung, E. (2019). Fostering Computational Thinking in Technology and Engineering Education. *Technology and Engineering Teacher*, *78*(5), 9–13.

Surana, H. M., Bhatnagar, G., Srivastava, A., & Srinivasa, G. (2019). NVR Guess: Automated Question Generation for Honing NonVerbal Reasoning Skills. *Proceedings - IEEE 10th International Conference on Technology for Education, T4E 2019*, 210–213. https://doi.org/10.1109/T4E.2019.00047

Susanti, Y., Iida, R., & Tokunaga, T. (2015). Automatic generation of english vocabulary tests. *CSEDU 2015 - 7th International Conference on Computer Supported Education, Proceedings*, *1*(October), 77–87. https://doi.org/10.5220/0005437200770087

Thotad, P., Kallur, S., & Amminabhavi, S. (2022). Automatic Question Generator Using Natural Language Processing. *Journal of Pharmaceutical Negative Results*, *13*(10), 2759–2764. https://doi.org/10.47750/pnr.2022.13.S10.330

Tsai, D. C. L., Huang, A. Y. Q., Lu, O. H. T., & Yang, S. J. H. (2021). Automatic question generation for repeated testing to improve student learning outcome. In *Proceedings - IEEE 21st International Conference on Advanced Learning Technologies, ICALT 2021* (pp. 339–341). https://doi.org/10.1109/ICALT52272.2021.00108

Vincentio, K., & Suhartono, D. (2022). Automatic Question Generation Monolingual Multilingual pre-trained Models using RNN and Transformer in Low Resource Indonesian Language. *Informatica*, *46*(7), 103–118. https://doi.org/10.31449/inf.v46i7.4236

Wang, X., Liu, B., Tang, S., & Wu, L. (2023). *SkillQG: Learning to Generate Question for Reading Comprehension Assessment*.

Wang, Z., & Baraniuk, R. (2023). *MultiQG-TI: Towards Question Generation from Multi-modal Sources*.

Wu, Z., Jia, X., Qu, F., & Wu, Y. (2022). *Enhancing Pre-trained Models with Text Structure Knowledge for Question Generation*.

Young, T., Hazarika, D., Poria, S., & Cambria, E. (2018). Recent trends in deep learning based natural language processing [Review Article]. *IEEE Computational Intelligence Magazine*, *13*(3), 55–75. https://doi.org/10.1109/MCI.2018.2840738

Yuan, X., Wang, T., Wang, Y.-H., Fine, E., Abdelghani, R., Lucas, P., Sauzéon, H., & Oudeyer, P.-Y. (2022). *Selecting Better Samples from Pre-trained LLMs: A Case Study on Question Generation*.

Zhang, C., & Wang, J. (2022). Tag-Set-Sequence Learning for Generating Question-answer Pairs. *International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, IC3K - Proceedings*, *1*, 138–147. https://doi.org/10.5220/0011586800003335

Zhang, L., & VanLehn, K. (2021). Evaluation of auto-generated distractors in multiple choice questions from a semantic network. *Interactive Learning Environments*, *29*(6), 1019–1036. https://doi.org/10.1080/10494820.2019.1619586

Zhang, T., Liu, Y., & Quan, P. (2018). Domain specific automatic Chinese multiple-type question generation. *Proceedings - 2018 IEEE International Conference on Bioinformatics and Biomedicine, BIBM 2018*, 1967–1971. https://doi.org/10.1109/BIBM.2018.8621162

Zhao, Z., Hou, Y., Wang, D., Yu, M., Liu, C., & Ma, X. (2022). Educational Question Generation of Children Storybooks via Question Type Distribution Learning and Event-Centric Summarization. *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, *1*, 5073–5085. https://doi.org/10.18653/v1/2022.acl-long.348

Zhu, F., Lei, W., Wang, C., Zheng, J., Poria, S., & Chua, T. (2021). Retrieving and Reading : A Comprehensive Survey on Open-domain Question Answering. *Arxiv, Artificial Intelligence (Cs.AI)*, 1–21. https://doi.org/arXiv:2101.00774v3

Zou, B., Li, P., Pan, L., & Aw, A. T. (2022). Automatic True/False Question Generation for Educational Purpose. *BEA 2022 - 17th Workshop on Innovative Use of NLP for Building Educational Applications, Proceedings*, *Bea*, 61–70. https://doi.org/10.18653/v1/2022.bea-1.10