algorithms

Review

Algorithms in Low-Code-No-Code for Research Applications: A Practical Review

Fahim Sufi

Monash University, School of Public Health and Preventive Medicine, Melbourne, VIC 3004, Australia; research@fahimsufi.com

Abstract: Algorithms have evolved from machine code to low-code-no-code (LCNC) in the past 20 years. Observing the growth of LCNC-based algorithm development, the CEO of GitHub mentioned that the future of coding is no coding at all. This paper systematically reviewed several of the recent studies using mainstream LCNC platforms to understand the area of research, the LCNC platforms used within these studies, and the features of LCNC used for solving individual research questions. We identified 23 research works using LCNC platforms, such as SetXRM, the vf-OS platform, Aure-BPM, CRISP-DM, and Microsoft Power Platform (MPP). About 61% of these existing studies resorted to MPP as their primary choice. The critical research problems solved by these research works were within the area of global news analysis, social media analysis, landslides, tornadoes, COVID-19, digitization of process, manufacturing, logistics, and software/app development. The main reasons identified for solving research problems with LCNC algorithms were as follows: (1) obtaining research data from multiple sources in complete automation; (2) generating artificial intelligence-driven insights without having to manually code them. In the course of describing this review, this paper also demonstrates a practical approach to implement a cyber-attack monitoring algorithm with the most popular LCNC platform.

Keywords: low-code-no-code; evolution of algorithm; low code application development; low code development platform; low code application platform; low code in research; cyber-attack monitor; cyber intelligence dashboard

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1. Introduction

Since the birth of the first computer, ENIAC (electronic numerical integrator and computer) in 1943, the way of writing algorithms has evolved from machine code towards low-code-no-code (LCNC). As seen from Fig. 1, in 1943, machine codes were written in binary which could be comprehended by early generation computers [1]. In 1949, the birth of assembly languages simplified machine code. Then, in 1952, Autocode enabled the programmers to write algorithms in low-level computer programming language, which could then be translated into machine codes [2]. Writing algorithms became much simpler with fewer lines of code, with the birth of high-level procedural languages (e.g., Fortran, Algol, COBOL) in 1957 [2,3]. Then, from 1965 onwards, the way of writing algorithms veered to be in object oriented languages with the birth of Simula and Smalltalk. In 2001, Outsystems was born with the vision of faster delivery of digital transformation [4]. In 2014, Outsystems released a free version of the LCNC platform for developers. Since 2014, there has been a trend for minimizing lines of codes and reducing upfront investment in setup, training, and deployment for software development [5]. In 2017, the CEO of GitHub mentioned that the future of coding is no coding at all [6]. After Forrester defined the terminology "Low-code development platform (LCDP)" in 2014, Gartner coined the term low-code application platform (LCAP) in 2016 [7]. Since then, industry giants, such as Microsoft, Google, Siemens, and others, started releasing popular LCNC/LCDP/LCAP platforms. For example, Microsoft released Power Platform in 2016 [8], Siemens published

Mendix [9] in 2018, and Google announced AppSheet [10], in 2020 as seen from Figure 1. Apart from terminologies, such as LCNC, LCDP and LCAP, there are several other popular notions, such as "citizen developer", "robotic process automation (RPA)", "IT-business alignment", and "business process management (BPM)" interchangeably being used to represent the concept of low-code-no-code development in recent times [11]. The COVID-19 pandemic accelerated the adoption of LCNC platforms as businesses sought to quickly pivot and adapt to the changing business environment between 2019 and 2020 [12]. In quarter two of 2020, an LCNC platform, Appian, reported subscription revenue rising a little over 12% compared to the same quarter last year [12]. In more recent times (i.e., 2022 to 2023), LCNC platforms continue to evolve and expand, offering more advanced features and capabilities to users. This includes the integration of AI and machine learning, improved user experiences, and increased integration with other tools and platforms. In 2023, global LCNC technologies are predicted to grow 20% [13].

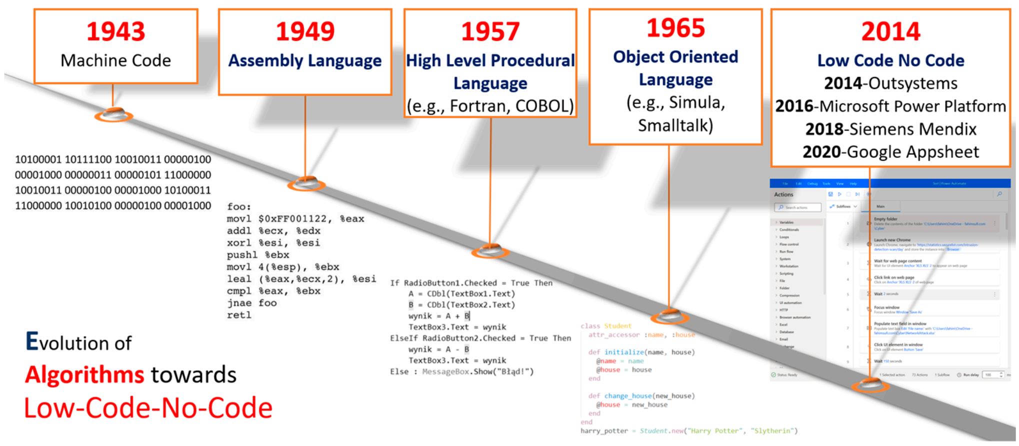

Figure 1. Evolution of algorithms from machine code to low-code-no-code.

Modern LCNC platforms realize several benefits over previous generations of manually writing lengthy lines of codes with low-level or high-level languages. These benefits include faster development with cloud-based environments, where anyone without coding experience can develop complex technology solutions by integrating technology components from multiple sources. These LCNC platforms provide simple cloud-based interfaces where a non-programmer scientist or researcher can drag-and-drop required algorithms to develop complex scientific solutions.

Hence, anyone without high-level coding knowledge can quickly deploy their scientific solutions and report them, as demonstrated in References [14–31]. These studies (i.e., [14–31]) represents the last 4 years developments in research problems addressed with LCNC platforms. In this review, existing scientific studies implementing algorithms using LCNC are critically reviewed to answer the following research questions:

- RQ1: What are the benefits of using LCNC platforms in general?
- RQ2: What are the limitations of using LCNC platforms in general?
- RQ3: Which features of modern LCNC platforms were used in existing studies?
- RQ4: Which LCNC platforms were mainly used in solving research problems?
- RQ5: What research problems or which area of research adopted LCNC platforms?
- RQ6: How can a researcher adopt modern LCNC platforms in solving critical research questions?

This study provides a comprehensive literature review on LCNC platforms. Moreover, this study guides researchers and scientists in adopting modern LCNC platforms for solving various research problems. Section 2 (i.e., Research Methods) provides details on the systematic literature review, covering the exclusion and inclusion criteria. Sections 3 and 4 provide the advantages and disadvantages of LCNC platforms based on the systematic literature review. Sections 3 and 4 answers research questions 1 and 2. Section 5 is the central part of this study answering research questions 3, 4, and 5. Section 5 provides an in-depth analysis on the usage of LCNC platforms for solving various research problems. Section 6 provides a demonstration on using LCNC platform to solve a research problem and answers research question 6. Finally, Section 7 provides a summary of achievements with the concluding remarks on LCNC platforms.

2. Research Methods

Within this study, an extensive literature review on topics, such as low-code, no-code, visual programming, and model-driven programming was performed. Using databases, such as IEEE Explore, Scopus, ACM Library, and Web of Science, 76 peer-reviewed articles were gathered. Using online search engines, such as Google and Microsoft Bing, a further 57 grey literatures (i.e., non-peer-reviewed online articles) were also gathered. Then, 133 articles were intensively reviewed and articles not contributing towards the 6 research questions (i.e., benefits of LCNC, limitations of LCNC, features of LCNC in research, LCNC platforms used in research, research area solved with LCNC, and demonstration of LCNC adoption in research) were filtered out. Eventually, 47 articles were carefully selected for answering the six research questions highlighted within the Introduction section. This entire methodology is depicted in Figure 2. Table 1 describes the common terminologies used within the context of this paper and how the readers should attempt to interpret these concepts. The exclusion and inclusion criteria for this study are detailed in Table 2. General tutorial papers, tutorial videos, and online discussions were omitted (as seen from Table 2), since the focus of this study was the usage of LCNC platforms on solving research problems. Since generic tutorial papers, videos, and discussion did not focus on solving research problems, the literature of this type was omitted. Short papers of less than four pages were also excluded since they did not delve into the details of using the LCNC platform.

Table 1. Consistent use of common terminologies.

Terminology	Conceptual Usage
Studies	Within this paper, “studies” refers to existing works in the literature or existing body of knowledge that are currently available in peer-reviewed or non-peer-reviewed (grey literature, such as websites or portals) sources.
Research area	Research area refers to the high-level grouping or categorizations of research topics. A research area is much broader than the scope of the research topic.
Research problem	Research problems are issues or gaps in existing studies that a researcher is willing to address. Research problems can encompass one or more research area.
Research question	It is a question that a study aims to answer. Research questions essentially turns the research problems into specific inquiries.
Algorithm	Algorithm refers to set of instructions to be followed to solve a research problem or to perform calculations on research data.
Feature	In general, the term “feature” means a distinctive attribute or aspect of something. In this paper, “feature” with respect to LCNC has been consistently used to represent the distinctive attributes of LCNC platforms.

Table 2. Inclusion and exclusion criteria for both peer-reviewed and grey literature.

Category		Criteria
Inclusion	Peer-reviewed Literature	• Four search keywords used: "Low Code", "No Code", "Visual Programming", "Model Driven Programming" • Review studies, survey/questionnaire-based qualitative or quantitative studies, original research articles • Paper indexed in popular peer-reviewed sources (i.e., IEEE Explore, ACM Library, Scopus, and Web of Science) • Papers focusing on research questions RQ 1 to RQ 6 • Studies available in English language • Studies available in full
	Grey Literature	• Websites focused on low code development platforms and their features • Indexed in popular search engines (i.e., Google and Microsoft Bing) • Articles authored by either by the LCNC vendor or third-party benchmarking company • Articles available in English language
Exclusion	Peer-reviewed Literature	• Tutorial papers • Short papers less than four pages • Poster papers, editorials, abstract (i.e., lacking detailed information)
	Grey literature	• Websites referring to the peer-reviewed literature • LCNC platforms promoted by bloggers, consultants, or third-party companies • Tutorial videos and discussions on LCNC

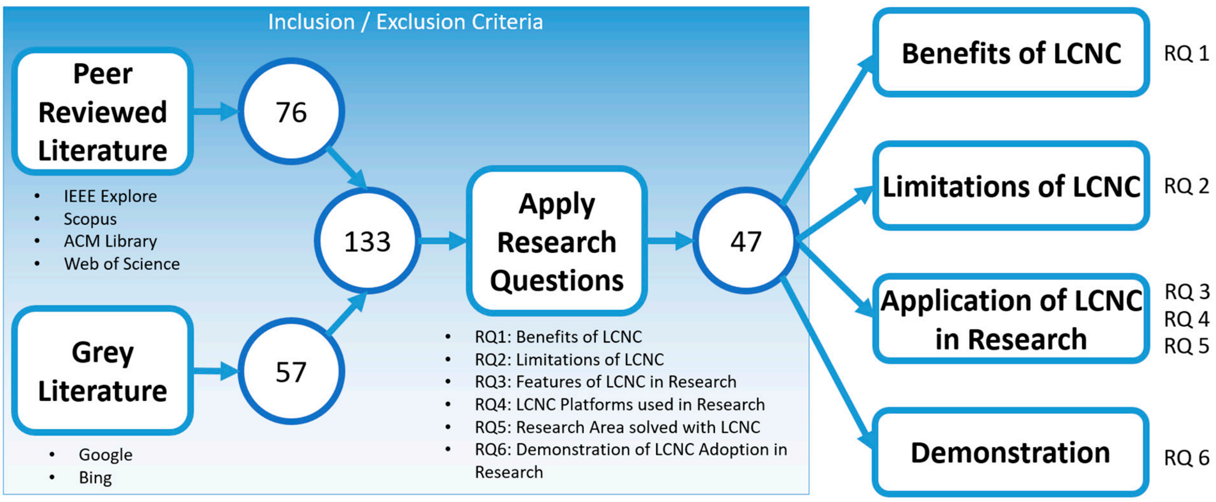

Figure 2. Methodology for reviewing the existing literature on LCNC platforms to answer research questions.

As mentioned before, the rest of the paper is organized in four different sections for answering RQ 1 to RQ 6. Section 3 deals with RQ 1. Section 4 focuses on the limitations of LCNC (i.e., RQ 2). Then, RQ 3, RQ 4, and RQ 5 are discussed within Section 5. Finally, RQ 6 is addressed within Section 6, where a demonstration of using the LCNC platform for obtaining global cyber intelligence is provided. This assemblage of the six research questions into four different high-level topics (i.e., Sections 3–6) is depicted in Figure 2.

3. Benefits of LCNC Platforms

Implementing algorithms in LCNC provides several benefits over manually coding algorithms in any low-level or high-level languages. For answering RQ 1 (i.e., benefits of LCNC platforms), 13 crucial benefits of developing algorithms using modern LCNC platforms are explored in this section.

3.1. Business-IT Alignment

Misalignment between business and IT is often the main reason for the failure of large-scale digitization projects. Often the business leaders have detailed, lengthy, and complex requirements for an organization's digital footprint in the future. However, with poor communication and a lack of domain knowledge of IT specialists, the business visions are often not translated properly into IT deliverables. Low-code-no-code platforms allow the business leaders and business analysts with in-depth domain knowledge to transform their business vision into the IT landscape. Indeed, LCNC allows the business to realize their vision without relying on IT experts. Hence, LCNC delivers business–IT alignment [32].

3.2. Address Resource Scarcity

Organizations often fail to recruit suitable IT personnel due to a shortage of qualified ones. However, LCNC allows citizen developers with domain knowledge to work on developing IT solutions, such as dashboards, applications, and databases, with ease [30]. This saves valuable time and resources for the organization, as the organization does not need to recruit additional IT personnel to conduct IT digitization tasks [30,32]. Moreover, the citizen developer can very quickly develop the required IT solutions without wasting additional time and resources to explain their idea to third-party IT specialists [33].

3.3. Cloud Forward Approach

Modern organizations are rapidly adopting cloud-based technology with their cloud migration strategy. Cloud-based technology inherently delivers flexibility, cost-effectiveness, security, mobility, disaster recovery, loss prevention, sustainability, and competitive edge, along with many other advantages compared to traditional on-premises solutions [34]. Since almost all the LCNC platforms are based in the cloud, adopting LCNC provides quick cloud migration strategies for modern organizations. "No-code supports the 'cloud-forward' approach, fostering faster and more convenient cloud migrations," said Borya Shakhnovich, CEO and co-founder of airSlate [32].

3.4. Quickly Trialling and Testing Big Ideas without Big Investment

Cost-effective LCNC solutions allow business leaders and entrepreneurs to quickly evaluate their idea without significant investments. Citizen developers can quickly develop prototypes and mock solutions [35]. Then, these fully functional IT solutions could be trialed, tested, and evaluated for their suitability. Once they are found to be suitable and profitable solutions, they could be further developed into full-fledged IT solutions. On the other hand, if these mock solutions do not realize the business benefits as promised, they would not be pursued further. According to [36], citizen developers said that more of their app development effort was devoted to innovation (i.e., big ideas) instead of maintenance, outperforming those not using low code by 5%. Thus, LCNC solutions act as a gateway process, where only profitable and worthwhile ventures are carried forward.

3.5. Speed of Development

The LCNC platforms are inherently cloud-based. Hence, the developers do not need to install multiple development tools and libraries (e.g., Visual Studio, Net Frameworks). A developer can quickly create solutions, as the learning curve is not steep as in traditional software development routes (e.g., Net, Python, C++). Using web-based drag and drop building blocks, even a naïve user can quickly create professional IT solutions [14,30]. In fact, according to [16], 66% of IT professionals prefer using LCNC for accelerating digital transformation. After the digital transformation, when it comes down to changes or updates to the solution, modern LCNC platforms, such as Outsystems, ensure faster change cycles [4].

3.6. Security by Design

By default, LCNC platform providers ensure international information security standards (ISO/IEC 27001, PCIDSS) [14]. Modern LCNC providers, such as Mendix and Microsoft Power Platform, adhere to a principle called "Security by Design" [37,38]. The Security by Design principle ensures overall security of the IT solution, taking a lot of security concerns away from the citizen developer. Hence, ensuring security becomes a crucial responsibility of the cloud-based LCNC platform [14].

3.7. Modern Patterns and Best Practices

Almost all the existing LCNC platforms support modern patterns and best practices of software development, such as responsive design, single sign-on, authentication and authorization, develop once deploy everywhere (e.g., iOS, Android, Windows), agile practice, remote access, business process modelling, app statistics and reports, etc. [17]. As a result, citizen developers were 15% more likely to deliver mobile applications in 4 months or less compared to those not using LCNC [36]. Moreover, LCNC platform users were 20% more likely to rate their agile maturity as level 3, 4, or 5 compared to those not using LCNC [36]. When citizen developers develop a solution with modern LCNC platforms, modern patterns and best practices are automatically supported by the solution.

3.8. Integration with External Services

Modern applications rarely work in isolation. Modern applications often need to communicate with third-party solutions through various modes, such as application programming interfaces (API). Existing LCNC platforms support built-in connectors through which data can be easily consumed or used [35]. For example, an application might read data from Google Drive, OneDrive, or Dropbox. The LCNC platforms support connectors to obtain data from these sources, upholding interoperability and seamless integration from third-party systems [39]. Modern LCNC platforms, such as Microsoft Power Platform, also enable researchers to consume real-time social media data from popular sources, such as Twitter, as demonstrated in [18,19].

3.9. Application Maintenance

Existing LCNC platforms also support comprehensive application maintenance procedures with AI-driven analytics and insights. For example, Microsoft Power Automate, used in [19], provided in-depth user statistics (e.g., who is using it, frequency of usage) along with AI-driven suggestions on possible improvements. Citizen developers can easily test the solution and deploy the solution, performing cloud-based maintenance of the application [39].

3.10. Protection against Technology Churn

With the evolution of IT, newer technology is always replacing older technology. Adopting mainstream LCNC platforms ensures continuous updates to the technology platform by the vendor. This minimizes the risk of technology being completely obsolete.

3.11. Easy to Learn

While traditional low- and high-level programming languages have a steep learning curve, anyone can easily learn any of the modern LCNC platforms within days [35]. This is because modern LCNC platforms provide an interactive visual interface supporting drag-and-drop actions. A citizen developer can obtain visual cues from the highly visual interface and can easily develop a complex application. This "easy to learn" feature of LCNC platforms is encouraging for non-programmer research scientists for their research data analysis.

3.12. Disaster Recovery and Loss Prevision

Analogous to cloud-hosted solutions, LCNC platforms ensure that the system is regularly backed-up. Moreover, in the case of disaster, automated recovery becomes the responsibility of the vendor (i.e., the provider of the LCNC platform). While 20% of cloud users claim disaster recovery in four hours or less, only 9% of non-cloud users could claim the same [40]. Moreover, while traditional developers using their own computers are running the risk of losing their source codes during a disaster, cloud-hosted services (e.g., LCNC Platforms) ensure data is always available [40].

3.13. AI, ML, & Deep Learning

One of the major benefits of using modern LCNC platforms is integration of AI, machine learning (ML), and deep learning (DL) technologies. Citizen developers can quite easily integrate AI-, ML-, and DL-based services within their solutions with drag and drop-based interfaces [41]. Social media analysts and researchers can quite easily obtain their required data from multiple sources, such as Tweeter, online news agencies, websites, and portals, using API or web scraping technologies, as demonstrated in [20–22]. Once they obtain their required data, AI and natural language processing (NLP) technologies would allow them process their data with language detection and translation, sentiment analysis, named entity recognition (NER), and category classification, etc., as demonstrated in [18,19,23,24].

Citizen developers, as well as researchers, can also use other ML algorithms, such as clustering, linear regression, logistic regression, and root cause analysis without writing a single line of codes, as demonstrated in [15,18–22,25–27]. Moreover, complex deep learning algorithms, such as the convolutional neural network (CNN), are also being applied using LCNC platforms to solve complex research problems [15,18,20,25,27]. For example, manual or hand-coding-based application of AI/ML technique on landslide data (as demonstrated in [42–45]) could be replaced by easier LCNC-based visual programming, as shown in [25].

4. Limitations of LCNC

There are a few limitations of existing LCNC platforms. Hence, not all algorithms are suitable for LCNC-based development [35]. Some of these limitations are explored in this section for answering RQ 2.

4.1. Creation of Shadow IT

The LCNC platforms reduce dependency towards centralized IT authority of any organization. Since each of the departments can develop their own solution without depending on the centralized IT authority, LCNC platforms create multiple shadow ITs within an organization. Multiple solutions developed by diverse groups of citizen developers within their own silos could challenge an organization with hostile competitive behavior and low morale. Citizen developer-driven solutions using LCNC platforms could become a threat to centralized governance and control of IT solutions by the designated IT authority.

4.2. Vendor Lock-In

Once citizen developers select a LCNC platform (e.g., Mendix, Outsystems, Microsoft Power Platform, etc.) and start developing their solution on the selected platform, they become locked-in to that platform [35]. If they decide at a later stage to move their solution to another LCNS platform, then they have to redesign and redevelop the entire solution on the new platform. This is due to the fact that all the existing LCNS platforms do not provide seamless integration among them (i.e., a Mendix solution could not be executed in Microsoft Power Platform) and each of these vendor specific platforms follows their own ecosystems of application development.

4.3. Lack of Flexibility

Even though the citizen developers can quickly become experts in their chosen LCNC Platforms, they are bound within the framework offered by the LCNC platform [35]. Using traditional programming languages and platforms (e.g., C# in Net), a professional developer can develop a wide variety of programs targeting desktops, mobile, and even embedded platforms. Hence, traditional programming languages and platforms offer unrestricted creativity for the professional developers. However, none of the existing LCNC platforms allow citizen developers to develop embedded software or native mobile applications. Hence, citizen developers are restricted in terms of viable options when developing their solutions under LCNC platforms.

4.4. Lack of On-Premises Support

Almost all current LCNC platforms provide a cloud forward or cloud-first approach, where the citizen developers implement their algorithms in cloud-based interfaces. Solutions that could not be maintained in the cloud (e.g., defense solutions, intelligence solutions, secret government applications, etc.) are not suitable for LCNC platforms. Even many private organizations are hosting data that could not be hosted in the cloud for privacy compliance (e.g., privacy compliant personal health information of patients). Technology solutions that deal with these types of secret or privacy compliant data are required to be offline or on-premises by design.

4.5. Unsuitable Mission Critical Systems

Mission critical systems are not suitable for most LCNC platforms. Existing LCNC platforms provide a cloud-based shared environment for thousands of developers. Even though most of the existing LCNC platforms support dedicated capacity, if the developer wants to attain higher performance, it is often not very cost effective. For example, while a Power BI per user license costs USD 10 per month, a Premium Per Capacity license can cost USD 5000 per month [46]. Mission critical systems or real-time systems work best with low-level languages, such as Assembly, or high-level languages, such as C/C++.

4.6. Ongoing Cost Commitment

Cloud-based LCNC requires ongoing operational expenses. Even though the subscription cost is meagre (e.g., USD 10 per month [46]) compared to the benefit offered by LCNC platforms, it is often not feasible for many organizations or universities located in low-income countries. Moreover, the payments are required to be made via credit card, which might not be suitable for many scientists or universities not possessing international credit cards.

5. LCNC Used in Existing Research

As seen from Section 3, there are several advantages offered by LCNC that could be useful in solving problems in all areas of research. Researchers in all areas perform critical analysis in their domain of expertise. To conduct critical analysis, scientific studies often need to apply a range of AI-based algorithms. The LCNC platforms enable scientists and researchers in all areas to easily apply AI-based algorithms on their data to find critical insight. To apply AI-based algorithms, the researchers and scientists do not need to be a programmer or data scientist. Using the drag-and-drop features of LCNC platforms, citizen developers can execute complex AI-based analysis that includes regression, clustering, CNN, decomposition analysis, and others. As seen from Table 3, existing studies in [15,18–22,25–27,31] have recently used these analytical features of LCNC platforms to solve research problems in multiple disciplines (i.e., answers RQ 3).

Table 3. Features of LCNC platforms used in solving research problems.

References	AI/ML Algorithms									NLP Algorithms				
	Linear Regression	**Logistic Regression**	**K-Means Clustering**	**Deep Learning/CNN**	**Decomposition Analysis**	**Others**	**Automated Data Acquisition**	**Data Processing & Modelling**	**Interactive Data Visualization**	**Sentiment Analysis**	**Named Entity Recognition**	**Category Classification**	**Language Detection & Translation**	**Mobile & Tablet Deployment**
[15]				•			•	•	•	•	•		•	•
[18]	•	•		•			•	•	•	•	•	•	•	•
[19]			•				•	•	•	•	•		•	•
[20]				•			•	•	•	•	•		•	•
[21]	•	•					•	•	•	•	•		•	•
[22]					•		•	•	•	•	•		•	•
[23]							•	•	•	•	•		•	•
[24]							•	•	•	•	•		•	•
[25]	•	•		•	•			•	•					•
[26]	•	•						•	•					•
[27]	•	•	•	•				•	•					•
[31]						•			•					

Similarly, researchers analyzing human behavior or perceptions of society might want to execute NLP algorithms, such as sentiment analysis, NER, category classification, language detection, and translations. Since sociologists, behavioral scientists, and political scientists are often not comfortable in hand-coding NLP algorithms, LCNC platforms allow them a quick and easy approach to analyze their data. For example, using the LCNC platform, a social scientist may analyze anti-vaccine sentiments without hand-coding NLP algorithms [23]. Likewise, a political scientist or researcher may obtain critical insights on the multidimensional geopolitical impact arising from COVID-19. as shown in [15,24].

Since data-driven multidisciplinary research has gained popularity in recent times, the studies in [20–22] automatically obtained data from several thousand sources (e.g., Twitter, CNN, the BBC, the New York Times, etc.) using AI-based data acquisition features of LCNC platforms.

Social scientists and researchers working with strategic decision-makers are often unable to create mobile apps for obtaining AI-based insights. As demonstrated in [25–27], social scientists easily created mobile apps running in iOS, Android, and Windows for evidence-based policy making using the LCNC platform. Without LCNC platforms, the researchers would need to hire expert coders for developing mobile apps or AI-based algorithms. Table 3 summarizes different features of LCNC platforms currently used by researchers, explaining RQ 3. In terms of answering RQ 4 (i.e., LCNC platforms used in research), Microsoft Power Platform is the most popular, followed by Mendix, SetXRM, the vf-OS platform, Aurea BPM, CRISP_DM, Primary AI, and others, as shown in Table 4. According to Table 4, LCNC platforms supported multidisciplinary research in the area of manufacturing, supply chain management, software development, business process automation, education, global news analysis, COVID-19, social media analysis, and even disaster management (e.g., landslides, tornadoes, etc.). Niche research topics in the area of smart cities can also benefit from adopting LCNC platforms [47]. This answers RQ 5 for the various areas of research supported by existing LCNC platforms.

Table 4. Different area of research supported by existing LCNC platforms.

Area of Research	Reference	LCNC Platforms
App creation or software development	[9,48]	Mendix
Software and application development	[14]	SetXRM
Manufacturing and logistics industry	[16]	vf-OS platform
Business process in manufacturing	[17]	Aurea BPM
Digitization of process	[28]	CRISP-DM
Landslides	[25]	Microsoft Power Platform
Tornadoes	[26,27]	Microsoft Power Platform
Social media analysis	[15,18,19]	Microsoft Power Platform
COVID-19	[15,23,24]	Microsoft Power Platform
Global news analysis	[20–22]	Microsoft Power Platform
Industrial engineering education	[29]	Unspecified/Questionaire
Supply chain management	[30]	Unspecified/Questionaire
AI education for students (grades 3–5)	[31]	PrimaryAI

It becomes evident from Table 3 that there are five crucial aspects of LCNC platforms that appeal the most towards multidisciplinary researchers (i.e., the answer to RQ3), as follows:

1. Applying AI/ML algorithms;
2. Applying NLP algorithms;
3. AI-based data collection and pre-processing;
4. Interactive data visualization;
5. Mobile and tablet deployment.

It should be mentioned that the above five features were used in [14–31] for solving research problems. These critical features of LCNC platforms answer the research question "RQ3: Which features of modern LCNC platforms were used in existing studies". These features briefly described below.

5.1. Applying AI/ML Algorithms

The AI/ML algorithms supported by modern LCNC platforms include regression, clustering, deep learning decomposition analysis, and others.

5.1.1. Regression Algorithm

Using LCNC platforms, existing studies in disaster management (e.g., landslides, tornadoes, bushfires, floods, earthquakes, etc.) and major event analysis have used both linear and logistic regression algorithms [18,21,25–27]. These researchers used drag-and-drop features of LCNC platforms (e.g., key influencer visualization of Microsoft Power BI [49]), where they did not have to code the regression algorithms. Implementation of a regression analysis automatically ranks the factors that matter, contrasts the relative importance of these factors, and displays them as key influencers for both categorical and numeric metrics. For numerical features, linear regression was performed using SDCA regression implementation from Microsoft's ML.NET [50]. On the other hand, for categorical features, logistic regression was performed using L-BFGS logistic regression from ML.NET [51,52].

5.1.2. K-Means Clustering Algorithm

Existing studies in [19] used visual features of Microsoft Power Platform (i.e., key influencer visualization of Microsoft Power BI [49]) for implementation of k-means clustering. The k-means algorithm in [19] used data pertaining to Australian tropical cyclone events to analyze almost 80 parameters. It should be mentioned that the implementation in Microsoft Power BI obviated the requirements for manually selecting the number of clusters. Moreover, AI-based automated clustering by Microsoft Power BI eliminated the requirement of manual pre-processing (e.g., normalization, data transformation, etc.) of input data [19].

5.1.3. CNN-Based Deep Learning Algorithm

The anomaly detector enhances line charts by automatically detecting anomalies within time series data. It also provides explanations for the anomalies to facilitate root cause analysis. Researchers in [15,18,20,25,27] used CNN-based deep learning using the anomaly detection feature provided by Microsoft Power BI's line chart visualization. Within [18], CNN algorithm was implemented with the LCNC platform to detect anomalies from live social media feeds on disaster events. For implementing complex CNN algorithms in [18], social media analysts and researchers did not have to manually write algorithms using any programming languages. Similarly, media analysts and political scientists can find out abnormalities in global events using a CNN algorithm by using interactive visualization or tools, as demonstrated in [20]. Geologists, who are unable to program complex CNN algorithms, can now implement CNN-based anomaly detection to automatically identify and analyze abnormalities in landslides [25] and tornadoes [27]. Moreover, the LCNC-based solution in [15] used CNN for evidence-based strategic decision-making on the COVID-19 crisis. The implementation of CNN within [15,18,20,25,27] used a saliency reduction (SR) model [53,54] and NLP-based explanations [55].

5.1.4. Decomposition Analysis Algorithm

Microsoft Power BI's decomposition tree visual is a valuable tool for ad hoc exploration and conducting root cause analysis, while allowing the user to visualize the data across multiple filter attributes [56]. Using the visual drag-and-drop interface, a non-programmer researcher or scientist can easily perform root cause analysis with a decomposition tree visual in Microsoft Power BI [49]. In [22], the researchers created threat-maps based on global events by using an interactive decomposition tree visual. On the other hand, in [25], decomposition analysis allowed the visualization of landslide casualty data over a range of landslide feature attributes, such as triggers, categories, settings, sizes, and countries.

5.2. Applying NLP Algorithms

There are several NLP algorithms supported by modern LCNC platforms, such as category classification, sentiment analysis, NER, language detection, and translation. These algorithms have been implemented by non-programmer scientists and researchers using the drag-and-drop features of modern LCNC platforms (as demonstrated in [15,18–24]).

5.2.1. Category Classification Algorithm

Without manually programming the category classification algorithm with C# or other programming languages, social media researchers in [18] used the visual interfaces of Microsoft Power Automate [57] to implement category classification. Category classification is applied to classify text inputs into categories that are suitable for a certain business cases. There are pre-built models of category classification (e.g., customer feedback) available via Microsoft's AI-builder [58] that can categorize a text input to any of the following categories:

- Issues;
- Compliment;
- Customer service;
- Documentation;
- Price and billing;
- Staff.

Other than assessing customer feedback, category classification has also been used to discover the interest or inquisitiveness of an online social media user [59].

5.2.2. Sentiment Analysis Algorithm

Research on sentiment analysis commenced early in 2002 with the publication of [60,61]. Research in [60] represented a supervised learning corpus-based machine classifier, and [61] exhibited an unsupervised classifier based on linguistic analysis. Previously, the prominence of sentiment analysis was on movie and product reviews. It spread across other domains with the advent of social media users [60–73]. Recent studies on sentiment analysis have been used for assessing customer feedback towards comprehending the political sentiment of people, specifically to predict election results [74]. Even though several existing studies used hand-coding skills of experienced data scientists, studies in [15,18–24] were implemented using visual interfaces of LCNC platforms. Studies in [15,18–24] invoked sentiment analysis algorithms through MS Power Automate [57]. Microsoft Power Automate uses drag-and-drop feature to invoke sentiment analysis with Microsoft Cognitive Services Text Analytics API [75].

5.2.3. NER Algorithm

Here, NER is an NLP-based information extraction task that seeks to locate and classify named entities mentioned in unstructured text into pre-defined categories, such as locations, person names, organizations, date/time expressions, monetary values, quantities, numerical values, and percentages. Indeed, NER has been applied in almost all domains of research for extracting crucial information from unstructured texts [69,76]. Previous research has extracted three different categories of entities (i.e., "Disease or Syndrome", "Sign or Symptom", and "Pharmacologic Substance") from health-related tweet messages [76] for discovering public health information and developing just-in-time disease outbreak prediction systems and drug interactions systems. A study in [69] applied basic NLP-based methodologies to extract entities and relationships, as well as to identify sentiment. The keywords investigated within [69] were drug abuse—cannabinoids, buprenorphine, opioids, sedatives, and stimulants. Research in [70] qualitatively evaluated posts about methylphenidate from five French patient web-forums including an analysis of information about misuse or abuse. Data were accumulated from French social networks that cited methylphenidate keywords. Text mining methods, such as NER and topic modeling, were used to analyze the chatter, including the identification of adverse reactions. Previous research in [69,70,76], did not use NER as a pre-processor for AI-based algorithms. The NER could be invoked with C# using the Microsoft Cognitive Services Text Analytics application programming interface (API) [75]. The NER algorithms could also be implemented with the drag-and-drop features of Microsoft Power Automate [57], as demonstrated in [15,18–24].

5.2.4. Language Detection and Translation Algorithm

Microsoft Cognitive Services Text Analytics API [75] enables social media analysis and researchers to implement language detection and translation using the visual interface of Microsoft Power Automate [57]. A non-programmer scientist can easily drag-and-drop appropriate language detection and translation components and perform dynamic translations, as demonstrated in [15,18–24]. These research studies demonstrated that live tweets in 110 different languages can easily be comprehended and analyzed without writing a single line of code (i.e., harnessing the power of modern LCNC platforms).

5.3. AI-Based Data Collection and Pre-Processing

Modern LCNC platforms allow researchers to obtain their research data automatically from multiple sources, such as csv files, xlsx files, pdf files, databases, social media, or even websites (with web scraping technologies). For example, research data was automatically collected using Twitter API through the visual interface of Microsoft Power Automate within [15,18–24]. On the other hand, research works in [25–27], automatically obtained data from csv, xlsx, pdf, and even NASA's global landslide databases. As demonstrated in [25], LCNC platforms also allow non-programmer researchers to perform a range of data modelling, transformation, and cleansing tasks for obtaining better AI-driven insights from their data.

5.4. Interactive Data Visualization

Current LCNC platforms, such as Outsystems, Mendix, Microsoft Power Platform, and others, provide interactive data visualization capabilities to non-programmer researchers [35]. Hence, studies in [14–28,31] could easily portray the research findings. The interactive nature of current LCNC platforms allows even younger children and teenagers (e.g., grades 3–5) to seamlessly perform AI programming using simple visual interfaces (as shown in [31]).

5.5. Mobile and Tablet Deployment

As demonstrated in Table 3, existing studies using LCNC platforms have used mobile deployment features in [15,18–27]. Without writing a single line of code, the dashboards and reports generated in LCNC platforms can be quickly deployed with the click of a button in all major mobile platforms, such as iOS, Android, and Windows.

6. Demonstration of LCNC Adoption in Modern Research

As highlighted in the Research Methods section (i.e., Section 2), this section will provide a practical insight into using modern LCNC platforms for answering modern research problems. With the rising threat of global cyber-attack, a researcher might want to develop an innovative algorithm that automatically produces cyber intelligence for strategic decision-makers. The algorithm in Alg1 provides necessary pseudocodes for this cyber intelligence solution. In an effort to answer RQ 6, this section will demonstrate how to implement Alg1 with Microsoft Power Platform [8], a leading LCNC platform.

As seen from Figure 3, a non-programmer scientist or researcher can obtain cyber-attack data from multiple sources, using Microsoft Desktop UI flow or Microsoft Power Automate, which is part of Microsoft Power Platform [8]. There were two different types of data obtained for this demonstration, as follows:

- Real-time cyber-attack data collected from anti-virus vendors (i.e., https://statistics.securelist.com/ (accessed on 3 January 2023));
- Real-time cyber-related Twitter feeds obtained using Twitter API (i.e., https://developer.twitter.com/en/portal/dashboard (accessed on 3 January 2023)).

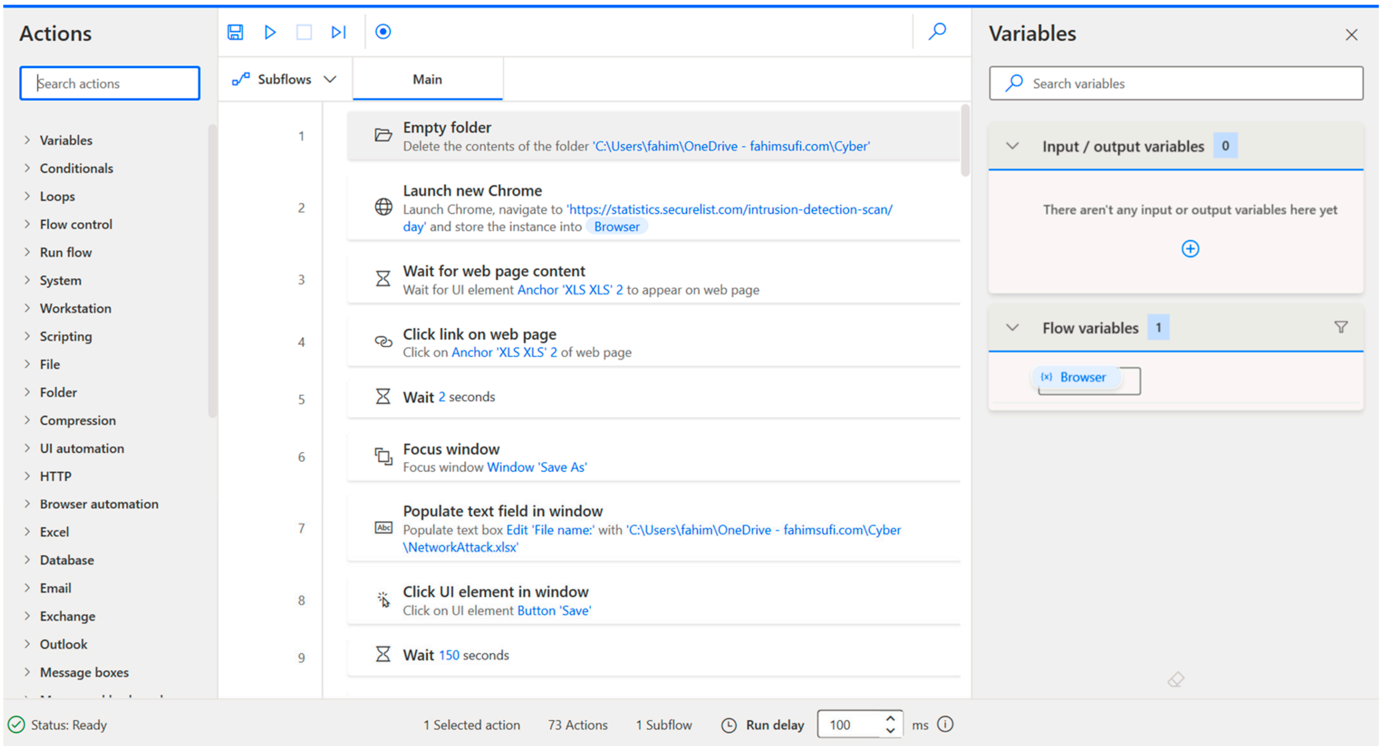

Figure 3. Aggregation of cyber-attack data from multiple sources using Microsoft Power Automate Desktop UI flow [57].

Figure 3 implements line 1 of Algorithm 1; the detailed process of obtaining data from social media, websites, and other online avenues has been demonstrated in [15,18–24].

After aggregating the cyber-attack data from multiple sources, the non-programmer scientist or researcher can apply complex artificial intelligence (AI)-based algorithms, such as sentiment analysis, NER, category classification, language translation, and others as seen from Figure 4. Figure 4 implements line 2, 3, 4, 5, 6, and 7 of Algorithm 1.

Algorithm 1. Cyber-attack Intelligence.

1: Obtain cyber-attack statistics from multiple sources including social media
2: **for each** of these messages $m_1, m_2, m_3, \ldots, m_n$, **do**
3: $\quad s_i = AI\_Translate(m_i)$
4: $\quad t_i = AI\_AnalyseSentimentScore(s_i)$
5: $\quad \{e_j, e_k\} = AI\_ClassifyEntity(s_i)$
6: $\quad c_i = AI\_ClassifyCategory(s_i)$
7: **end for**
8: Perform CNN- based Anomaly Detection for all messages $\{s_i, t_i, \{e_j, e_k\}, c_i\}$

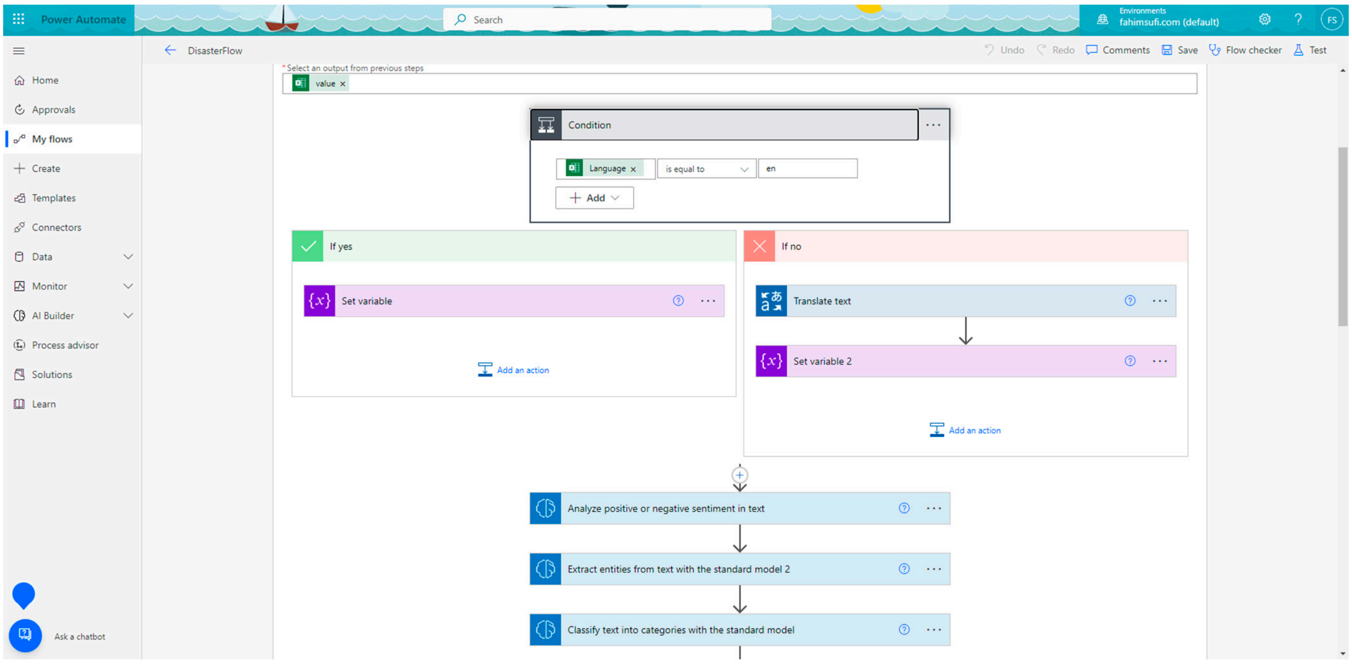

Figure 4. Implementation of complex AI-based algorithms, such as sentiment analysis, named entity recognition, category classification, language translation using Microsoft Power Automate cloud flow [57].

As seen from Figures 3 and 4, LCNC platforms, such as Microsoft Power Automate [57], allows a scientist or researcher to easily obtain data for their research from multiple sources and then perform AI-based analysis on their research data, without writing a single line of code. Figure 5 shows CNN-based anomaly detection deployed using a line-chart visual of Microsoft Power BI [49]. Without writing a single line of code, two anomalies (for 17 October 2022 and 25 October 2022) within the cyber-attack spectrum of the Republic of Palau were detected, as seen from Figure 5. Figure 5 implements line 8 of Algorithm 1.

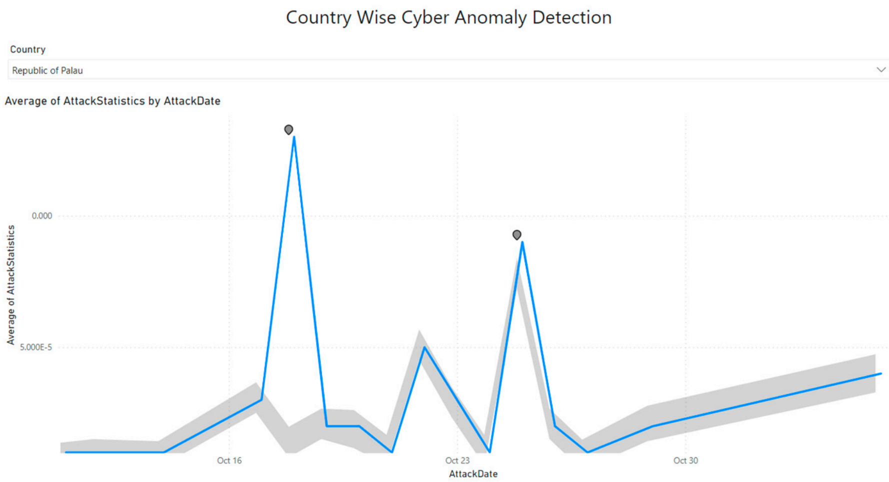

Figure 5. CNN-based deep learning Algorithm used for identifying anomalies in cyber-attacks for the Republic of Palau.

Table A1 in Appendix A demonstrates the complete result of implementing the algorithm (i.e., Alg1) on cyber data using the LCNC platform without writing any low-level or high-level codes. Data within this table represent cyber-related posts collected from live Tweets from 13 October 2022 to 13 November 2022. During this 30 days period, 6697 Tweets in 42 different languages from 5984 unique users were analyzed. These Tweets were translated into English, and sentiment analysis was performed to ascertain whether these posts were negative, positive, or neutral. Moreover, locations mentioned on these posts were extracted using NER. As previously mentioned in Section 5, Microsoft Cognitive Services Text Analytics API [75] were used for translation, sentiment analysis, and NER on these Tweets. As seen from Figures 3 and 4, only drag-and-drop features provided by the cloud-based LCNC platforms were used to collect and analyze the data. After collecting the data, they were analyzed using complex AI-based algorithms, such as CNN (as shown in Figure 5). Finally, in Figure 6, we can see the interactive dashboard visualizing the entire dataset from 11 October 2022 to 13 November 2022. The dashboard in Figure 6 shows different types of cyber-attacks, such as ransomware, exploit, spam, and others, and a user can click any of these types and the dashboard will filter itself automatically based on the selected type. Moreover, a user can click on any country and the entire dashboard will be filtered to represent data pertaining to the selected country. The global cyber-attack data collection as shown in Figure 3 and Table A1 (within Appendix A) was deployed in mobile and tablet contexts, as shown in Figures 7 and 8, respectively. In Figure 7, the solution was deployed on a Samsung Galaxy Note 10 Lite mobile. On the other hand, Figure 8 shows the deployment on an Apple iPad, 15th generation. None of this deployment required any high-level or low-level coding skills from the researchers.

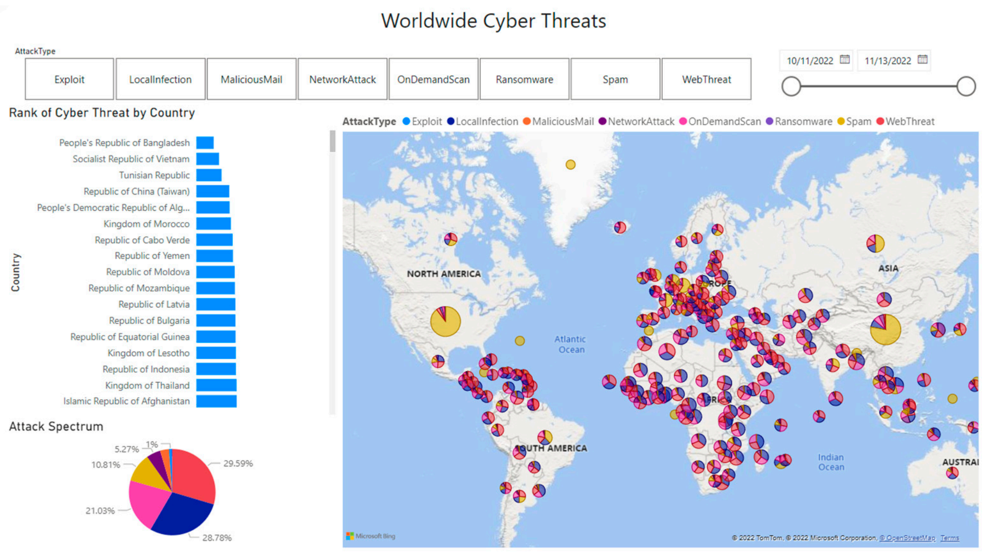

Figure 6. Visualization of cyber-attack data on Microsoft Power BI [49] without writing a single line of code.

As mentioned earlier, the cyber intelligence solution was developed using Microsoft Power Platform. All the source files (including the pbix Microsoft Power BI solution, cyber-related Tweets, etc.) are publicly available at https://github.com/DrSufi/COVID_Index_Anomaly (accessed on 3 January 2023) for the sake of research reproducibility.

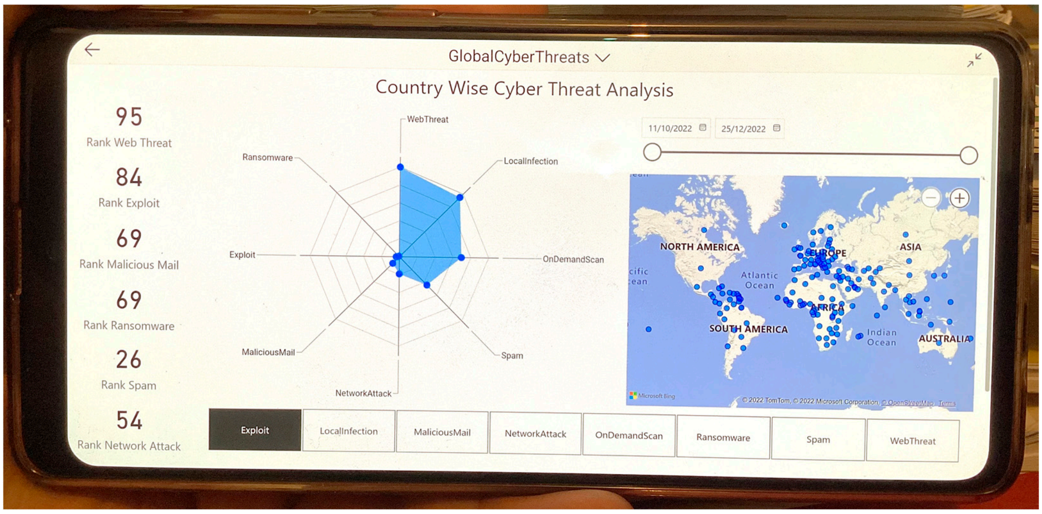

Figure 7. Global cyber-attack data of different types are demonstrated on a deployed Android app on a Samsung Galaxy Note 10 Lite Mobile.

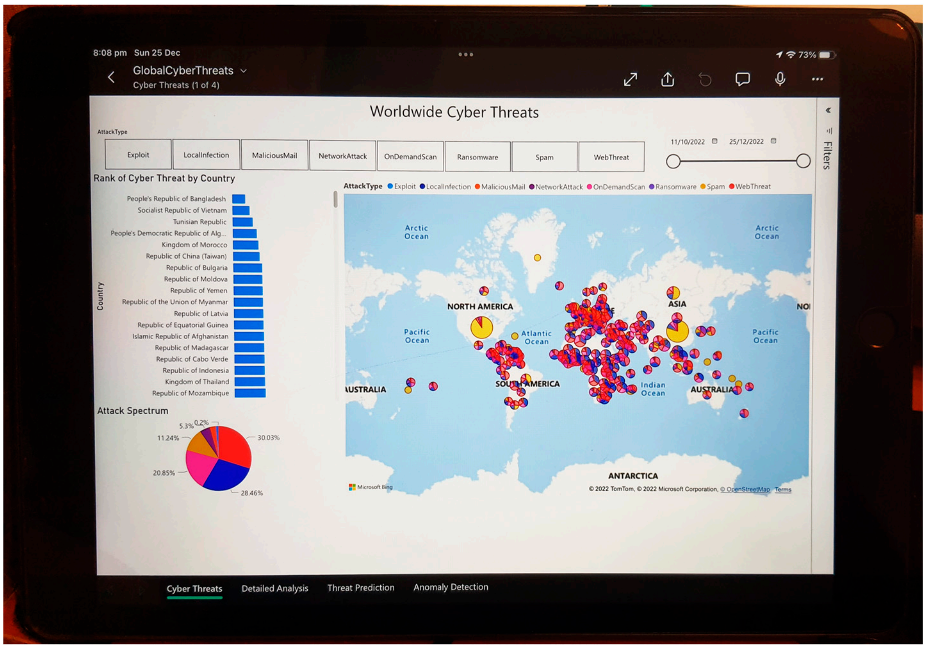

Figure 8. Global cyber-attack data along with cyber-related social media data being shown on a deployed iOS App on an Apple iPad, ninth generation.

As seen in this section, using the LCNC platform. a researcher can easily obtain data from multiple sources (e.g., social media, online news sites, online databases), and apply AI algorithms to deploy not only a cyber intelligence solution, but also political threat intelligence, COVID-19 intelligence, social cohesion intelligence, military intelligence, and many other innovative solutions.

7. Conclusions

Within this paper, several existing studies that used modern LCNC platforms were reviewed and analyzed. Since adoption of LCNC platforms for solving research questions is still at the level of infancy, only 47 studies of scientific significance were found. Among there studies, 3 were LCNC review articles, 21 were LCNC feature-related articles, and only 23 were on multidisciplinary research solving research questions with LCNC platforms. With these 23 LCNC platform related studies, researchers used 6 different LCNC platforms (e.g., SetXRM, the vf-OS platform, Aurea BPM, CRISP-DM, Primary AI, Microsoft Power Platform). A total of 61% (i.e., 14 out of 23) of these existing studies resorted to Microsoft Power Platform as their chosen LCNC platform.

These studies predominantly used 14 features of modern LCNC platforms as depicted in Table 3 to solve different research problems. These research problems were within the area of global news analysis, social media analysis, landslides, tornadoes, COVID-19, digitization of processes, manufacturing, logistics, supply chain management, AI education, industrial engineering education, and software/app development (as shown in Table 4). As shown in Table 3, the main reasons for solving research problems with LCNC were to obtain research data and generate AI-driven insights with complex algorithms (e.g., regression, clustering, deep learning, classification, sentiment analysis, entity recognition, etc.) without having to manually code them. Modern LCNC platforms have allowed non-programmer scientists and researchers to quickly obtain their research data from multiple sources and analyze their data with AI algorithms. During the course of this review study, it was also practically demonstrated how to obtain cyber-attack data (Figure 3), analyze the data with AI algorithms (Figure 4), perform CNN-based deep learning (Figure 5), visualize the information (Figure 6), and deploy the solution on mobile platforms (Figures 7 and 8) using LCNC platforms without manually writing codes in any programming languages.

In summary, this study found the following core benefits of using LCNC platform to solve research problems:

- AI-powered tools: AI is increasingly being used to enhance low-code and no-code platforms, making it easier to build applications and automate tasks. Indeed, AI can be used to generate code, suggest best practices, and improve the overall efficiency of the development process.
- Improved user experience: There has been a focus on improving the user experience of low-code and no-code platforms, making them more accessible and intuitive for users. This includes improvements in drag-and-drop interfaces, visual representations of data and workflow, and other features that simplify the development process.
- Integration with other tools: Low-code and no-code platforms are now integrating with a variety of other tools and platforms, including cloud platforms, databases, and third-party APIs. This allows users to build more complex applications and connect them with existing systems.
- Increased Adoption: Low-code and no-code technology is becoming more widely adopted, particularly among businesses. This is due in part to the ease of use and rapid development times that these platforms offer, as well as the ability to build applications that meet specific business needs.

Overall, low-code and no-code technology is continuing to evolve and expand, offering more advanced features and capabilities to users. This technology is likely to become increasingly popular and widely adopted in the coming years. Modern LCNC platforms provide competitive advantages in solving critical research questions predominantly through their AI-based data analysis and information processing capabilities. Widespread adoption of LCNC platforms within the research community will be seen once critical concerns, such as ongoing cost commitments and vendor lock-ins are addressed. However, it is unlikely that LCNC platforms will completely remove the requirement of hand-coding in future, since it is not a revolutionary technology [77].

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3 January 2023)). Because of this anonymous access to Kaspersky site, it was possible to practically demonstrate the development of a cyber-intelligence solution with Microsoft Power Platform.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Result of applying NLP algorithms on live Twitter data on a cyber-attack using the LCNC platform.

Date	Count of Twitter IDs	Count of User ID	Count of Location	Count of Tweet Language	Sum of Retweet Count	Average of Negative Sentiment	Average of Neutral Sentiment	Average of Positive Sentiment	Count of Translated Text
13 October 2022	52	51	29	7	80,707	0.40	0.42	0.18	12
14 October 2022	211	189	122	15	77,089	0.40	0.40	0.20	67
15 October 2022	219	208	116	18	408,635	0.29	0.46	0.25	74
16 October 2022	208	205	111	18	428,407	0.31	0.44	0.25	67
17 October 2022	221	208	122	14	188,791	0.30	0.46	0.24	60
18 October 2022	186	180	101	18	49,255	0.31	0.49	0.19	56
19 October 2022	226	219	133	18	132,222	0.35	0.42	0.22	55
20 October 2022	216	215	123	17	231,915	0.32	0.47	0.21	51
21 October 2022	206	204	129	17	533,082	0.43	0.41	0.15	37
22 October 2022	219	209	118	14	134,067	0.41	0.40	0.19	46
23 October 2022	223	207	116	18	34,249	0.33	0.47	0.20	69
24 October 2022	226	218	128	16	88,944	0.44	0.35	0.21	59
25 October 2022	227	219	118	20	200,700	0.43	0.40	0.16	46
26 October 2022	219	205	113	13	30,097	0.37	0.41	0.21	48
27 October 2022	222	219	121	14	175,143	0.34	0.42	0.24	47
28 October 2022	218	212	124	14	287,112	0.39	0.38	0.23	48
29 October 2022	224	215	126	14	176,450	0.41	0.36	0.23	41
30 October 2022	222	215	114	12	217,949	0.35	0.45	0.20	48
31 October 2022	209	205	113	18	252,942	0.32	0.48	0.20	55
1 November 2022	227	223	133	14	175,690	0.31	0.44	0.25	48
2 November 2022	225	216	120	19	158,510	0.37	0.45	0.18	54
3 November 2022	219	213	126	15	435,121	0.46	0.38	0.15	47
4 November 2022	227	214	114	17	178,945	0.34	0.41	0.24	48
5 November 2022	219	208	123	12	65,565	0.45	0.36	0.19	53
6 November 2022	212	205	105	16	469,544	0.36	0.41	0.23	47
7 November 2022	221	210	107	13	89,628	0.38	0.42	0.20	43
8 November 2022	226	221	117	14	115,866	0.48	0.35	0.17	47
9 November 2022	213	205	117	19	73,431	0.43	0.38	0.19	49

Table A1. *Cont.*

Date	Count of Twitter IDs	Count of User ID	Count of Location	Count of Tweet Language	Sum of Retweet Count	Average of Negative Sentiment	Average of Neutral Sentiment	Average of Positive Sentiment	Count of Translated Text
10 November 2022	212	207	124	15	90,221	0.36	0.41	0.23	42
11 November 2022	216	213	109	12	110,456	0.33	0.43	0.23	40
12 November 2022	217	213	121	14	104,071	0.46	0.36	0.17	41
13 November 2022	109	105	56	14	49,361	0.52	0.35	0.13	4
Total	6697	5984	2482	42	5,844,165	0.38	0.42	0.21	1466.00

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