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Stevan Didijer
1911-2004

EDITOR'S NOTE **VOL 12. NO. 3 (2022)**

AI-Driven Competitive Intelligence: Enhancing Business Strategy and Decision Making

In the world of business, the importance of competitive intelligence cannot be overdone. As companies compete for market share and seek to gain an edge over their competitors, understanding the market and their competition becomes increasingly critical. As artificial intelligence (AI) continues to evolve, its potential to impact competitive intelligence grows. Companies can use AI to automate data collection and analysis, allowing them to gain insights more quickly and efficiently (Krakowski et al.2022). AI can also be used to analyze competitors' online activities, including their social media presence, website traffic, and search engine rankings. This allows companies to stay up-to-date with their competition and respond quickly to changes in the market.

In this issue, authors will explore the role of competitive intelligence in an AI world, examine practitioners' thoughts on technological advances and the educational needs of their successors, and discuss the impact of artificial intelligence on the hiring process. The use of artificial intelligence and machine learning is becoming increasingly popular in competitive intelligence. These technologies can be used to automate data collection, analysis, and reporting, making the process more efficient and accurate. There is also a discussion of knowledge mapping for the study of artificial intelligence in education research, the effect of marketing intelligence adoption on enhancing profitability indicators of banks, and more intelligent trading strategies, including interacting trading strategies based on an agent-based approach.

As technological advances continue to change the competitive intelligence landscape, practitioners must keep up with the latest developments to remain effective. They must also ensure that their successors are prepared to succeed in an increasingly technology-driven world. This requires ongoing education and training in areas such as data analysis, AI, and machine learning.

AI is also changing the hiring process, allowing companies to use data-driven approaches to identify and recruit the best candidates. AI can be used to analyze resumes, evaluate candidate responses to interview questions, and even predict a candidate's future job performance. This allows companies to make more informed hiring decisions and reduce the risk of hiring the wrong person for the job.

Marketing intelligence can also play a critical role in improving a company's profitability. In the case of banks, marketing intelligence can be used to identify new opportunities for growth and optimize their marketing efforts to reach the right customers. This can help banks to increase their profitability and gain a competitive advantage in the market.

In the financial world, trading strategies are also becoming more intelligent. An agent-based approach involves using AI to create a model of the market and simulate how different trading strategies would perform in that market. This allows traders to identify the most effective strategies and improve their trading performance.

In conclusion, the impact of AI on the business world is significant and continuing to grow. Competitive intelligence, in particular, can benefit greatly from advances in AI and practitioners must stay up-to-date with the latest technological developments and ensure that their successors are prepared for an increasingly technology-driven world (Cekuls, 2022). AI is also impacting the hiring process, education research, marketing intelligence, and trading strategies, highlighting the need for ongoing education and training in these and other areas (Stroumpoulis et al, 2022). By embracing these technological advances, companies can gain a competitive advantage and improve their overall performance in the market.

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On behalf of the Editorial Board,
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Stevan Didijer
1911-2004

Competitive intelligence in an AI world: Practitioners' thoughts on technological advances and the educational needs of their successors

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ABSTRACT: Information Age trends have caused the competitive intelligence (CI) industry to flourish while changing the way CI is conducted. Universities educating CI analysts are interested in knowing what knowledge and skills are necessary for future practitioners. In 2022, *Harvard Business Review* addressed this topic's relevancy, noting increases in CI departments and growing demand for analysts to sift through unconfirmed information. This study addresses the question of what skill sets are needed for future CI analysts and how do instructors prepare them for an evolving and dynamic future in CI? Over 130 CI practitioners were surveyed about recommended skills and curriculum for the next generation. Results confirmed CI's technology evolution (e.g., faster turnarounds, greater client expectations). While tech-savvy skills are essential, soft skills consistently ranked as top requirements. Findings are applicable to other disciplines that analyze data for business strategy.

KEYWORDS: artificial intelligence, big data, competitive intelligence, pedagogy

1. INTRODUCTION

Since the pandemic, the importance of intelligence in the corporate world has hit new heights. As misleading information proliferates, so does the need for CI departments to aid companies in effective decision-making (Kolbe and Morrow, 2022). Calof *et al.*'s (2018) comparative study discovered a widespread growth of CI over the last two decades with "87% of all responding organizations had some form of formal competitive intelligence structure and many organizations had multiple intelligence or intelligence type functions in their organization" (p. 675). A sister discipline to market research, colleges have had difficulty offering CI because "most faculty members do not view the intelligence profession as a distinct discipline" (Miller, 2000, p. 65). However, university resistance to CI appears to be breaking down with the recognition of such CI activities as monitoring competitors, benchmarking, and war-gaming (Barrett, 2010).

CI skills are evolving due to technological advances. One of the most impactful is Artificial Intelligence (AI); however, the extent of its impact remains to be seen (Hoffman and Freyn, 2019). Toumi (2018) predicts, "in

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the next years, AI will change learning, teaching, and education" (p. 2). Gunderson (2019) notes that "these rapid [technological] changes require the CI field to adapt" (p. 14). Mabe *et al.* (2019) asserts on the one hand "it is important that CI skills and capabilities are well defined" to enable practitioners to "understand which skills and capabilities they should develop," but then notes "there is currently no set framework of skills and capabilities for defining the roles of CI practitioners" (p. 720). This calls into question *what* skills are necessary for CI practitioners to be proficient. To address the evolving needs of the 21st century, this study will research the following questions:

- How has technology affected the current CI environment and subsequently, the educational needs for future practitioners?
- How can educators best prepare future CI analysts?

The paper will review CI's evolution and research related to specific skills needed for the discipline. Methodology will cover survey development and distribution followed by results and further research in the field of CI pedagogy.

2. LITERATURE REVIEW

CI's evolution

The origin of CI can be traced to *Competitive Strategy* (Porter, 1980). Porter advocated both "competitor monitoring" (p. 96) and "relating a company to its environment" (p. 3). Until the mid-1990s, intelligence was portrayed as a cloak-and-dagger activity (Miller, 2000). By the late 1990's publications including *The Wall Street Journal* began to endorse intelligence drawing upon practices in the U.S. intelligence community (Miller). Former CIA analyst, Jan Herring (1999), professionalized CI by introducing the CI cycle.

Before the Information Age, "the scenery of science and technology was quite stable. Large and even small companies knew exactly their marketplace" (Dou *et al.*, 1992, p. 35). Technological developments eliminated stability, prompting the expansion of CI presence and scope. Some changes included the digitization of corporate information (Sadok *et al.*, 2019), plummeting cost of data storage (Hoffman, 2018) and corporate access to big data and AI (Ranjan and Foropon, 2021). By the start of the 21st century, 90% of the information needed by a company to monitor competitors and their industry was available in the public domain (McGonagle and Vella, 2002). A related development has been the proliferation of software designed to facilitate and expedite the work of CI practitioners (Semerkova *et al.*, 2017).

CI's evolution has seen the rise of Competitive Technical Intelligence (CTI), a branch of CI, used by companies to ensure they have "the best information possible on customer needs, technology options…and the competitive environment" (Paap, 2020, p. 41). Paap expanded CI's traditional scope from Porter's (1980) competitor focus to include *customer needs* and *technology*. In recent years, CTI has become more useful applying AI, coupled with big data, to reveal insights that were previously unattainable (Porter, 2019).

Skills—today and the future

To gain CI knowledge and skills, professionals often draw from trade organizations (e.g., SCIP: Strategic Competitive Intelligence Professionals) and academies. While universities often incorporate business, library science, and human intelligence (HUMINT) into the discipline (Hoffman and Freyn, 2019). These resources are necessary, but recent research indicates that they may be insufficient for managing the profession's demands. Applying the CI cycle as the framework (Dishman and Calof, 2008; Freyn 2017), current research will be discussed as it relates to the needs of the discipline; figure 1.

Planning

Strategic thinking is necessary to do the backward planning to conceptualize, and achieve, a desired corporate end state (Wang *et al.*, 2019); also, a key starting point for planning. Kula and Naktiyok (2021) stated, "Strategic thinking is seeing the future" (p. 54). From a CI perspective, this translates into imagining the future and having vision regarding such factors as the impact of emerging technology, the implications of competitor activities, or the effects of new regulations.

Task force approach. Collaboration is an aspect first considered during the planning stage. Paap (2020) described how CI practitioners "have expertise on data collection and analysis" and turn to the company's technical staff for expertise on technical issues (p. 44). Mabe *et al.* (2019) also stressed the importance of "relationship building (networking) skills in order to foster collaboration" (p. 724) calling them "the most required skills for CI practitioners" (p. 726).

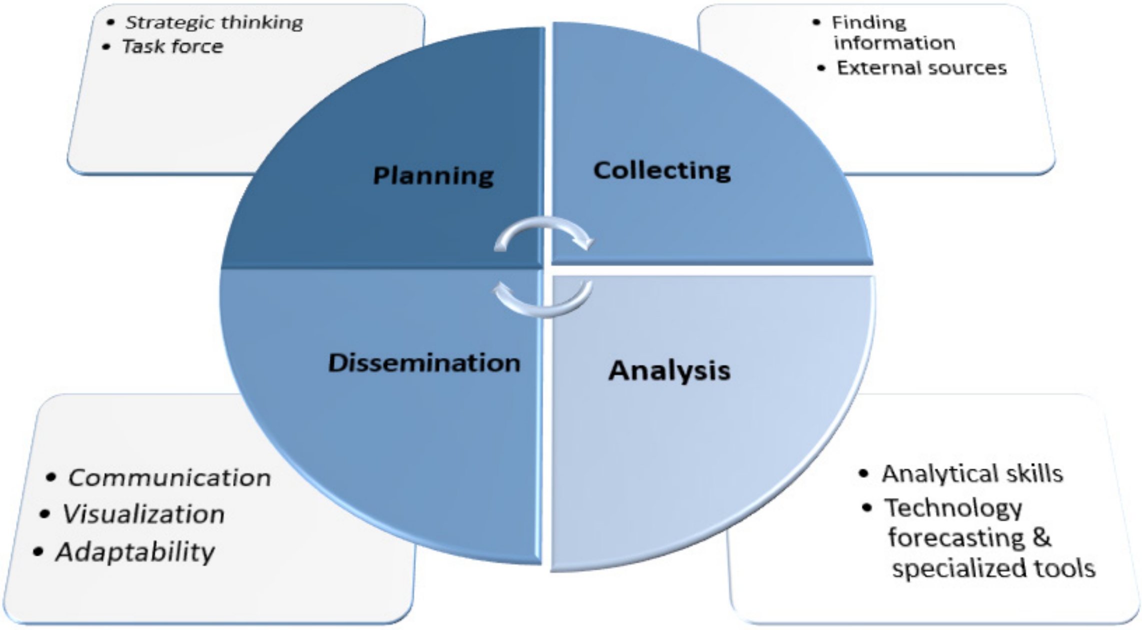

*Figure 1**. CL cucle of skills needed for future analysts.

* note this is not all encompassing but serves as a atarting point to develop the suvery and validate literature.

Collecting

Finding information. Online information that is publicly available and accessible on the *surface* web (data indexed by search engines) accounts for only four percent of what is on the Internet; far more information is available in the so-called *deep* web (Iftikhar, 2011). For CI practitioners, knowing where and how to seek information is an increasingly valuable skill.

External sources. Business intelligence practitioners access dedicated data warehouses of their company's *internal* information to provide diagnostic, prescriptive, and predictive information. CI practitioners acquire *external* information requiring a different approach because "the range of topics are too broad, and the frequency of looking at any individual area so spread out, that it is not practical to keep the database up-to-date" (Paap, 2020, p. 44). Rather than rely on databases, practitioners have "more reliance on external sources that are kept up to date by the service providers" (Paap, 2020, p. 44).

Analysis

Analytic skills. While big data may be "the new oil" (Gunderson, 2019, p. 8); like oil, data must be processed, refined, and delivered to achieve maximum value. Saddhon *et al.* (2019) asserted that, "The keys to the fortunate utilization of competitive intelligence are analysis of information and synthesis of knowledge" (p. 156). Experienced analysts strive to professionalize analytic work to "get analysts to challenge their arguments and judgments, defend analytical positions and more effectively determine between what was fact and what was their opinion" (Walsh, 2017, p. 550).

Technology forecasting encompasses future-oriented techniques developed by the U.S. Department of Defense and The RAND Corporation to assess and predict implications of future technologies (Cho and Daim, 2013). CI practitioners tasked to forecast technological developments must build expertise in these techniques (Paap, 2020, p. 49). Papp (2020) explained that a Science & Technology CI practitioner "uses tools to assess patents, scientific literature, technical trade shows, and other sources of technical information to identify the who, where, why, and how fast new technologies are being developed or used" (p. 43). CI data may be structured, unstructured, or semi-structured, with user proficiency in different software applications required to gather, store, and process that data (Gunderson, 2019, p. 9). Porter (2009) described the value of technically analyzing patent information. While, Paap (2020) also advocated it as it "can help you identify who the players are, new developments in a particular technical area" and provide "insights on development trends" (p. 50).

Dissemination

Communication is a critical skill throughout the entire CI process. Practitioners must effectively communicate with clients to understand and accurately capture information needs (Jin and Ju, 2014). Final CI projects must be successfully communicated in writing and/or orally. Maungwa and Fourie (2018) identified poor communication skills as one of the major contributors to a CI project failure. Due to the volume of data, communication through visualization has become an expectation by clients via dashboards and other graphical data presentations (Zheng, 2017). Sarica *et al.* (2019) used the example of overlaying visualization and network-based metrics for competitive intelligence analyses.

Adaptability. CI "is characterized by numerous 'one-off' intelligence efforts" seeking information from external sources (Paap, 2020, p. 44). A plethora of open-source information is now widely and equally available to all companies in any given industry. The companies that are able to rapidly identify, analyze, and turn information into actionable intelligence will likely gain competitive advantage (Gilad and Fuld, 2016). The greatest benefit of CI is its ability to quickly adapt to changing market conditions (Gilad and Fuld).

Practitioners rely on interpersonal skills to validate requirements, function as a team, obtain information from human sources, and deliver conclusions and insights to clients. At the same time, practitioners are expected to visually depict findings and otherwise leverage technology to perform their craft. These developments prompted researchers to ask CI practitioners what they believe are the educational needs of the crop of college students who will ultimately replace them.

3. METHODOLOGY

Survey design

A survey was created based on the CI cycle and respective literature to address: 1) key evolutionary trends in CI, 2) needed skills for CI and 3) respective curriculum to prepare future analysts. Several curriculum-based questions were derived from Mercyhurst University's Business & Competitive Intelligence program (established 2009). According to Kolbe and Morrow (2022) "academic institutions, such as Mercyhurst University, are producing a new generation of private-sector focused intelligence professionals" (para 5).

Expert discussions from a CI Council webinar on the topic of preparing future analysts along with the researchers' own expertise also assisted in building factors to test (Hoffman and Freyn, 2020). To increase content and face validity, questions were reviewed by CI experts and educators to ensure questions were relevant and meaningful, unambiguous, and easy to answer from the perspective of the participant (Connell, et al., 2018). The survey offered several open-ended questions for additional insights.

Sampling frame and response rate

For valid inferences from survey data, respondents' characteristics much reflect the target population (Malhotra, 2019). To achieve this, the study included members of the CI council, SCIP and Special Librarians Association, CI division. A filter question asked professional affiliation to a CI trade association. Fifty-two percent were part of SCIP, 40% Special Librarians Association and 8% were CI Fellows or on CI boards.

Using ProQuest©, 721 individuals viewed the survey, 219 responded (30.3% response rate) and 134 were fully completed (18.6%). Fulton (2016) argued that non-response is a growing issue in organizational research and noted "if there are no systematic differences between respondents and non-respondents, then the sample remains representative of the population and can provide valid inferences" (p. 4). The researchers deemed the response rate acceptable.

Managerial and higher-level positions represented 49% of the respondent pool, while researchers/analysts reflected 47%. This offers perspectives at a strategic, operational, and tactical level (Lackman and Lanasa, 2013). For experience, the distribution was roughly 1/3 representing the categories: 3 years or less, 4-6 years and 7+ years. Respondents were equally distributed in part-time and full time positions and as sole practitioner. In terms of education, 81% had a bachelor's or higher degree.

Industries represented:

• Finance, real estate, insurance	26%
• IT (hardware, software, consulting)	22%
• Consulting	18%
• Construction or building trades	8%
• Manufacturing	7%
• Other categories	< 5%

4. RESULTS

Both quantitative and qualitative feedback were assessed to address the research questions. The following section presents the current perspective of CI's evolution, the CI cycle categories related to necessary skill sets and feedback regarding curriculum development and future skills needed.

CI's evolution

To fully assess the future of the discipline, researchers first asked practitioners to rate how CI has changed over the past decade followed by an open-ended question to gather more insight. Applying research findings, respondents rated four factors based on degree of change. Based on the mean values of the Likert scale, the impact of technology represented the most change with client/customer expectations the lowest; table I.

Table I. Factors impacting the CI discipline changes*

	Mean	Standard Deviation
1. Impact of technology (N = 130)	3.87	.80
2. Doing more CI tasks in-house (N = 129)	3.52	.85
3. Nature of client taskings (N = 128)	3.52	1.04
4. Client or customer expectations (N = 129)	3.26	.79

* *Rating: 1 = no change at all, 5 = considerable change*

Open-ended responses to w*hat do you believe has been the biggest change for you in the CI field* provided more insight. Common themes were identified based on repeated terms. Key quotes are presented:

1) Technology's impact
   - *Technology's influence over how we do our jobs. We are constantly being asked to do more, and faster. Emerging platforms and existing/evolving platforms... make our lives much easier.*
   - *The use of far more automation at the expense of HUMINT, critical thinking, and analysis.*
   - *More data analytics and scraping the web for information. A lot less reliance on HUMINT.*
2) Customer expectations
   - *Customers expecting more concrete answers due to big data and analytics despite the quality of information not changing.*
   - *Managing customer/client expectations continues to be challenging. In part, this is because of technology changes elsewhere that clients feel should make work in CI similarly easy. However, the in-depth analysis and understanding as to what data is meaningful to collect and review is still not wholly understood.*
3) Nature of Tasking
   - *The increased recognition that CI can be more than just 'stick fetching' and actually contribute to the executive mindset regarding competitor's intentions.*
4) Change in perception of CI
   - *Greater acceptance of the concept of CI having a seat at the table among top level company executives for strategic insights and implications. CI must have an internal brand champion that actively finds ways to become more influential and become a trusted business advisor.*
5) In-house CI
   - *Easier for intelligence users to collect their own material.*
   - *Clients doing more CI tasks in-house; using self-service technology; using social media; using AI-driven search engine platforms to gather and disseminate information quickly.*

CI cycle and the current environment

Planning and the decision maker. Freyn (2017) noted that the planning step in the CI process is to ensure that not all possible information and data is collected, but instead identifying the specific needs of the decision maker. Planning is reliant on two primary conditions: a) an understanding of what CI provides an organization and b) actual decision maker support whether executive, manager or client (Hoffman and Freyn, 2019). Numerous studies have argued the need for leadership support in order for the discipline to grow and evolve (Herring, 1991; Freyn, 2017). A question was asked reflecting the issues faced in the planning stage. *What do you find most challenging with respect to educating your superiors and clients as to what CI can do for them? (N = 52).* Common themes (in order of response rate) were identified along with key quotes.

1) Building an understanding of what CI is and its value.
   - *Helping them realize what kind of information can be gathered. Also, helping*

them think about how to use competitive intelligence to strategic advantage.

- *To really have them understand the distinction between intelligence and information as well as the impact of bias.*
- *Show the importance of CI, what is CI, CI is beyond competitors and competition.*

2) Time and technology limitations offer challenges.
    - *The lack of understanding regarding time-consuming tasks, as well as the need for information not usually available, which makes short-term planning hard.*
    - *Combating the belief that CI knowledge and insights can be generated by technology.*
    - *Getting them to understand that better quality/reports with more depth require more time.*
3) Executive reliance on own internal resources as a trade-off to CI.
    - *Most successful business executives are their own best CI collector and analyst. Because knowledge is power, they are reluctant to share their intelligence outside the context of their own professional power base.*
    - *Many executives continue to rely on their own internal sources and traditional methods of obtaining insights. What is challenging then is breaking into the mindset that someone on their team can help them get a better sense of what is going on, in the marketplace, strategically.*

Collecting. A question regarding the collection step of the CI cycle identified resources most commonly used by practitioners. Company website information and third-party sources were most common followed by news media and trade publications. While HUMINT was used by only 10% of respondents identifying a shift to more data focused collecting; figure 2.

Analysis commonly includes using methodologies to evaluate collected data and information**.** Respondents first identified the percentage of structured analytic techniques (SAT) they used that were taught in college. There was an even distribution of responses with approximately 1/3 representing the categories of <40%, 41-60%, and >60%. Only 8% noted that they learned more than 80% of SAT in college indicating opportunities to build curriculum. Respondents also were to identify what SATs they currently use in practice; table II. SWOT analysis, competitor profiling and market research were most common, while future oriented technology forecasting ranked much lower. Ironically, the top methodologies have been part of the CI discipline for decades. This may indicate an opportunity to build CI curriculum incorporating new techniques that address the complexity of evolving technologies.

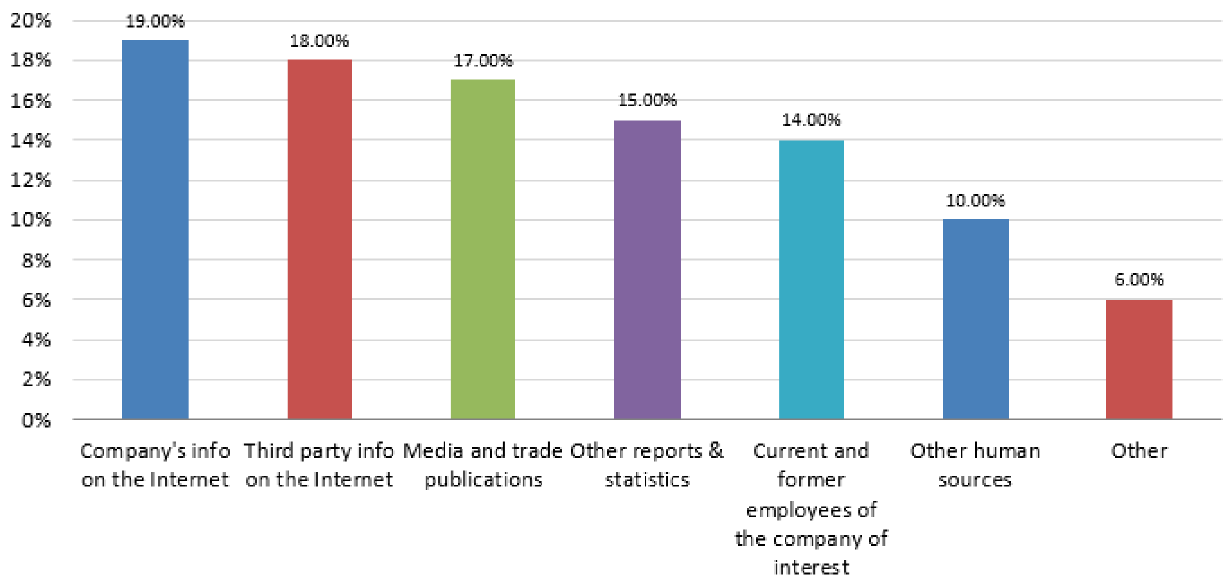

Figure 2. Common sources for research (N = 131).

Table II.. Current CI techniques used N = 130.

Structured Analytic Techniques	Total %
1. SWOT Analysis	54.6%
2. Competitor Profiling	46.9%
3. Market research & analysis	45.4%
4. Scenario planning / simulation & modeling	38.5%
5. Financial analysis	36.2%
6. Benchmarking	34.6%
7. Management profiling	33.8%
8. R&D / technology forecasting	33.1%
9. Success Factor analysis	31.5%
10. Trade show collection & analysis	29.2%
11. Win / loss	28.5%
12 Counterintelligence	23.8%
13. STEEP/PEST	23.1%
14. Other	9.2%

Table III. CI Dissemination Methods.

	Mean	SD
Frequency* (N=130)		
1. CI research reports (ad hoc tasking)	3.75	.97
2. In-depth analysis reports	3.68	.93
3. CI reports to other co. departments	3.53	.97
4. CI newsletter	3.49	1.09
5. Face-to-face presentations (N=129)	3.43	.89
6. Periodic CI reports (monthly, quarterly)	3.42	.90
7. Other	3.26	1.12
8. Online forum (N=129)	3.02	1.06
9 Electronic CI alerts	2.85	1.05
Effectiveness**		
1. Finished, written reports (N=132)	3.61	1.02
2. Face-to-face presentations (132)	3.60	1.05
3. Email to specific individuals (130)	3.53	.97
4. Phone (132)	3.52	1.12
5. Company intranet (129)	3.18	1.01
6. Email newsletter- mass (130)	3.18	.90
7. Online forum (129)	3.06	1.12
8. Printed newsletter (130)	2.97	1.03

**Rating: 1 = never; 5 = very frequently.*

***Rating: 1 = not effective at all; 5= very effective.*

Dissemination. Two questions addressed the dissemination of CI: 1) most common methods used and 2) effectiveness of methods. Based on frequency of use, project reports scored highest, while more technology based online forums and electronic alerts rated neutral or lower; table III. Traditional formats appear to be preferred; however, there may be opportunities to build curriculum expanding communication methods to incorporate more technology-based dissemination. Written reports and personal dissemination were rated as the most effective methods pointing to the importance of interpersonal skills. Mass communication tools like newsletters and forums rated neutral indicating direct dissemination as being more effective.

Necessary skills & building curriculum

Practitioners were provided skill sets based on the literature and asked to rate how critical these skills were for CI (1 = not critical at all; 10 = most critical). Cronbach's alpha was strong at 0.826 (Hair *et al.* 2010). One-sample t-tests indicated all skills were significantly greater than neutral (4.5) identifying them as critical; table IV. Note the table illustrates the top three variables as analytical, research and communication representing the key stages of the CI cycle.

Curriculum development questions were asked regarding courses and degrees. Courses were rated in terms of professional utility for the future analyst. Table V reflects the courses ranked based on means with top courses being BI/CI, market research, and data analytics being top rated over more traditional subjects.

Respondents rated desirability of degrees for new hires (1 = low desirability; 10 = high desirability); table VI. Based on means, more specific degrees in intelligence and in technology (i.e., IT) were rated as more desirable over more traditional degrees.

Finally, respondents provided invaluable recommendations and suggestions for future curriculum. The final questions asked *Given your professional experience and expertise, what comments or recommendations do you have regarding the educational preparation of future competitive intelligence practitioners?* See appendix for themes and key quotes.

Table IV. Critical skill sets for CI (N = 130) and (df = 129).

Skills	Mean	SD	t	*Sig*
1. Analytical (N = 129)	8.02	2.01	16.79	***
2. Communication Skills	7.80	1.67	15.72	***
3. Research	7.66	1.66	14.85	***
4. Human Intelligence	7.57	1.76	13.36	***
5. Adaptability	7.55	1.62	14.32	***
6. IT/Computer	7.36	1.57	13.56	***
7. Industry-specific	7.28	1.93	10.54	***
8. Presentation	7.12	1.64	11.26	***
9. Strategic	7.08	2.01	8.93	***

*** = $p < .001$

Table V. Course utility* for future professionals (N = 130) and (df = 129).

Course	Mean	SD
1. BI/CI course	3.95	1.1
2. Market Research	3.76	.79
3. Data Analytics	3.74	.78
4. Business	3.72	.57
5. Economics	3.64	.82
6. Statistics	3.61	.82
7. Human Intelligence Collection (N = 129)	3.60	1.0
8. Computer Programming	3.30	.95
9. Library Science (N = 129)	3.20	.99
10. Accounting	2.95	.79

* *Rating: 1 = negligible utility; 5 = high utility.*

Table VI. Desirability* of bachelor's degrees of new hires (N = 131).

Course	Mean	SD
1. Intelligence Studies (N = 129)	7.61	2.02
2. Business & Competitive Intelligence (130)	7.49	1.82
3. Information technology	6.74	2.33
4. Management	6.60	1.98
5. Library Science (130)	6.36	2.37
6. Math (130)	6.07	2.35
7. Accounting	4.99	2.16

* *Rating: 1 = low desirability; 10 = high desirability.*

5. DISCUSSION

The intent of this research was to address questions pertaining to CI's evolution with technology in the hopes of guiding educators to better prepare students. One common theme related to curriculum supported the incorporation of more specialized courses relevant to the discipline (i.e., BI/CI, Analytics) and gaining experiences prior to graduation. Beyond traditional business curriculum, open-ended feedback stressed liberal arts-based skills as being essential.

There needs to be more critical thinking and business writing preparation, especially for those just coming out of college. They need to be able to ask the questions: what do I see? Does it matter? What does X mean to our business?

[The] Key is to find the intellectually curious who can communicate well.

Ironically, more collection-based courses (i.e., HUMINT, librarian science) were rated lower with several comments regarding

HUMINT being replaced by data. Topics such as AI had led to unrealistic expectations of data having all the answers and situations of "a world where human analysts have been largely replaced by computers" (Hoffman and Freyn, 2019, p. 277). With research skills noted as a top competency, instructors may want to ensure that research is presented holistically stressing the synergistic value of data and HUMINT. In turn, this reinforces critical thinking and analytical skills.

Respondents stressed the need for students to be versed in SATs recommending more analytics focused courses. As noted in the literature, analysts are impacted by AI and navigating evolving technologies may require more advanced techniques (Hoffman and Freyn, 2019). Based on the lower ranking of futuristic SATs like technology forecasting, instructors may want to continue to build the curriculum with a focus on more technology-based techniques. Finally, communication skills were denoted as essential for a CI analyst's success. Popular methods of dissemination were mostly via reports or in person; future methods may need to incorporate more electronically based dissemination especially for executives (Nohria, 2021).

Themes, beyond curriculum, parallel the CI cycle (Dishman and Calof, 2008). Many comments reinforced the need of planning and having the research capabilities to know where and how to find resources (i.e., collecting).

The most valuable skill they can come away with is the ability to 1) Ask the RIGHT questions, 2) Know what data they need to answer those questions and where those data live, and 3) Know how to analyze those data and which tools to apply to which types of questions.

In addressing the evolution of CI, technology has had the biggest impact on the field from emerging platforms and big data to the automation at the expense of HUMINT and some interpersonal skills. With technology, CI professionals reinforced the idea that expectations are growing for more concrete and faster results. However, despite all the data, in-depth analysis of what it all means (especially AI) is still in pioneering stages. This may be the skills new analysts can to bring to the table. Most importantly, many noted CI as a growing field in general as more organizations recognize its value (Kolbe and Morrow, 2022).

6. CONCLUSION

This study gained valuable insight into the current CI environment, its challenges and its evolution with technological advances. Survey feedback supported the CI cycle regarding necessary skills from strategic thinking to research capabilities and analytical competencies. Communication skills were ranked as most valuable in the discipline, while courses and degrees were identified to aid in building future curriculum. Results indicate a shift to more focused degrees in intelligence studies over traditional business degrees.

An overarching finding in the research confirmed that although the presence of new technologies is evolving the discipline, softer skills like communication and analytical skills will never waiver in importance. These should remain a focus in curriculum development, as synergies will ensure not only a tech savvy analyst, but a successful one too.

This study serves as a starting point in building curriculum to prepare future CI analysts. Expanded research could build the framework and apply findings to any business discipline with the goal to evolve curriculum for the AI-enabled world. With the growing speed of technology along with rising expectations, this topic will only continue to increase in relevancy.

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The authors of this paper hereby affirm that the submission has not been previously published and has not been submitted to or is not under review by another journal or under consideration for publication elsewhere, and, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright- holder.

The authors also affirm that there is no conflict of interest.

The anonymized research data will be made available if required and if the university ethics board permits.

To the best of our knowledge there is no copyright material in this paper.

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Appendix

Practitioners' recommendations

Topic	Themes	Key Comments
Strategic thinking	**Planning**	• *Applying critical thinking skills…discerning the impact ("so what")* • *Be willing to learn and ask questions.* • *Thinking holistically and broadly.* • *Focus on strategy and how strategy helps companies combine strategy and CI methods and techniques.*
Research skills	**Collecting**	• *Information gathering education.* • *…the student who knows how build an automated collection apparatus will be able to contribute immediately.* • *It is critical that they know how to perform desktop research…where to find the most readily available, free resources.*
Analytic techniques	**Analysis**	• *Education in cutting-edge data analytics and big data techniques is useful, but don't abandon the basics.* • *Data literacy is a key item to have. A strong math/science/economics background is very good, since these draw inferences from data* • *I would recommend use structured analytic techniques…more frequently in course work.* • *Data analytics and reporting tools/languages are increasingly becoming important.* • *Focus on strategic thinking and intelligence analysis.*
CI courses & experience	**Curriculum**	• *Having a broad understanding of all business practices including accounting and marketing is…imperative to being a truly successful CI practitioner.* • *A foundation understanding of CI needs to be included in more fields of study.* • *Students need lots more time studying future sciences/foresight, practical experience in the field.* • *I need people with business acumen who also can take a problem and think about it from different angles.*

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1911-2004

Towards a digital enterprise: the impact of Artificial Intelligence on the hiring process

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ABSTRACT: In this paper, we proposed a decision support tool for recruiters to improve their hiring decisions of suitable candidates for such a vacancy post. For this purpose, we proposed the use of the Artificial Neural Network (ANN) method from Artificial Intelligence (AI), thus we used real data from a recruitment agency. However, for the adopted methodology, we used the process opted by the methods and techniques related to Data Mining.
As a result, after completing the modelling process, we were able to obtain a model capable of predicting the decision to accept or reject such a candidate for such a vacancy. However, we obtained a model with an accuracy of 99% as well as with a very low error rate.
However, our results show that Artificial Intelligence techniques can provide a better decision support tool for recruiters while minimising the cost and time of processing applications and maximising the accuracy of the decisions made.

KEYWORDS: Artificial Neural Network (ANN), Human Resources (HR), Artificial Intelligence (AI), Digital Enterprise, Recruitment

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INTRODUCTION

In the current era of globalisation and the emergence of new technologies, as well as the competition of the global business market, companies cannot afford to continue to adopt traditional methods in the various business processes. However, new methods emanating from Artificial Intelligence (AI) can improve the smooth running of the company, especially in managing the hiring process. However, the hiring process follows important steps such as the selection and appointment of suitable candidates for such a vacancy post.

Every enterprise invests a lot of money and time in recruiting persons for specific positions and wastes resources in searching for potential candidates. The total investment becomes a loss if the selected candidates do not meet the company's requirements after completing the whole hiring process. Therefore, the objective of this empirical study is to propose a decision support tool to improve the hiring process using a method from Artificial Intelligence.

In this paper, we have applied the Artificial Neural Network (ANN) method to build a predictive model of the decision in the hiring process. Our methodology consists of adopting the process applied by Data Mining techniques, starting with a pre-processing and exploratory analysis of the data, then building our model by the Artificial Neural Network method using the proportion of training data and finally evaluating the model using the proportion of test data, using the various validation metrics emanating from the confusion matrix.

1. LITERATURE REVIEW

A range of scientific papers have revealed the importance of exploiting new methods from Artificial Intelligence in several fields and disciplines.

For (S. Singh et al., 2013) compared several methods from Artificial Intelligence, in order to build a model capable of analysing the performance of students' academic records as well as to rank students according to their final grade in different classes (Excellent, Average, Poor), however the results obtained revealed the robustness of these methods.

In the employment market, and more specifically in the application of Artificial Intelligence techniques in the hiring process, several studies have been carried out in this sense in order to improve the said process.

Therefore, the study conducted by (D. Alao et Al., 2013), the authors constructed a set of rules using the decision tree method in order to build a model capable of predicting new employee attrition, however, the results obtained yielded a model with an accuracy of 74%.

For (C. E. A. Pah et al., 2020) proposed a decision support model for ranking candidates in the employee hiring process using a variety of methods from Artificial Intelligence, namely, C4.5 decision tree, Naïve Bayes, SVM and Random Forest. However, the authors achieved a maximum accuracy of 88.24% using the decision tree method.

2. HIRING PROCESS

If a company wants to select a specific employee profile and skills, it will need to introduce sound tactics into the hiring process.

Owever, the hiring process can be internal or external, therefore, it can take many forms that differ from one company to another, but remains faithful to the single purpose of choosing the best profile for such a job vacancy. However, the selection of candidates for an interview is a crucial step and represents more than 50% of the rating assigned to the pre-selected candidates.

3. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANNs), inspired by biological neural networks, represent a field of research that deals with learning and reasoning problems. As statistical classification techniques, unlike parametric techniques, ANNs are robust to misspecification (Cybenko, 1989; Funahashi, 1989; Barron, 1993).

Neural networks, as systems capable of learning, implement the principle of induction, i.e., learning from experience. By confrontation with specific situations, they infer an integrated decision system whose generic character depends on the number of learning cases encountered and their complexity in relation to the complexity of the problem to be solved.

An artificial neural network is generally composed of a succession of layers, each of which takes its inputs from the outputs of the previous layer. Each layer i is composed of N_i neurons, taking their inputs from the N_{i-1} neurons of the previous layer. The first layer is called the input layer and the last layer, composed of a single neuron, is called the output layer. The intermediate layers are called hidden layers.

3.1 Presentation of Artificial Neural Networks (ANN)

An artificial neural network is generally composed of a succession of layers, each of which takes its inputs from the outputs of the previous layer. Each layer i is composed of N_i Neurons (*nr*) taking their inputs from the neurons of the previous layer. The first layer is called the input layer and the last layer, consisting of a single neuron, is called the output layer. The intermediate layers are called hidden layers (Fig. 1).

3.2 Structure and operation of an artificial neural network

An artificial neuron is considered to be a device that receives input from other neurons and weights it with real values called synaptic coefficients or synaptic weights.

Consider the neuron j of a layer i. Let us note $x_1^i, x_2^i, \ldots, x_{N_{i-1}}^i$ the N_{i-1} inputs from the layer $i-1$ to the neuron j of the layer i. We also consider the N_{i-1} weights denoted $w_{1j}^i, w_{2j}^{i-1}, \ldots, w_{N_{i-1}j}^i$. The neuron j calculates the sum of its inputs weighted by the respective synaptic coefficients, to which it adds a constant term called the bias b_j^i. This gives the formula:

$$S_j^i = \sum_{k=1}^{N_{i-1}} w_{kj}^i x_{kj}^i + b_j^i$$

The bias is an external parameter of the neuron j. It can be integrated into the weighted sum, as the signal x_0^i which takes the value 1, weighted by the weight w_{0j}^i whose value is equal to the bias b_j^i:

$$\begin{cases} x_{0j}^i = 1 \\ b_j^i = w_{0j}^i \end{cases}$$

The sum S_j^i can thus be written as:

$$S_j^i = \sum_{k=1}^{N_{i-1}} w_{kj}^i x_{kj}^i + b_j^i$$

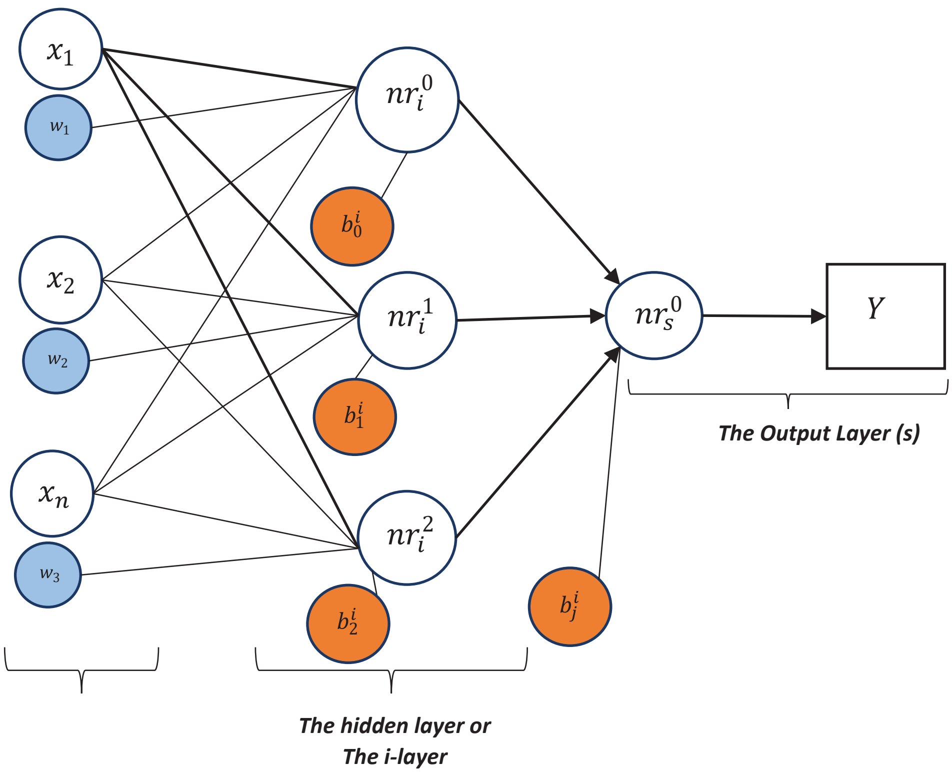


Figure 1. :Architecture of an artificial neural network (Source: Author).

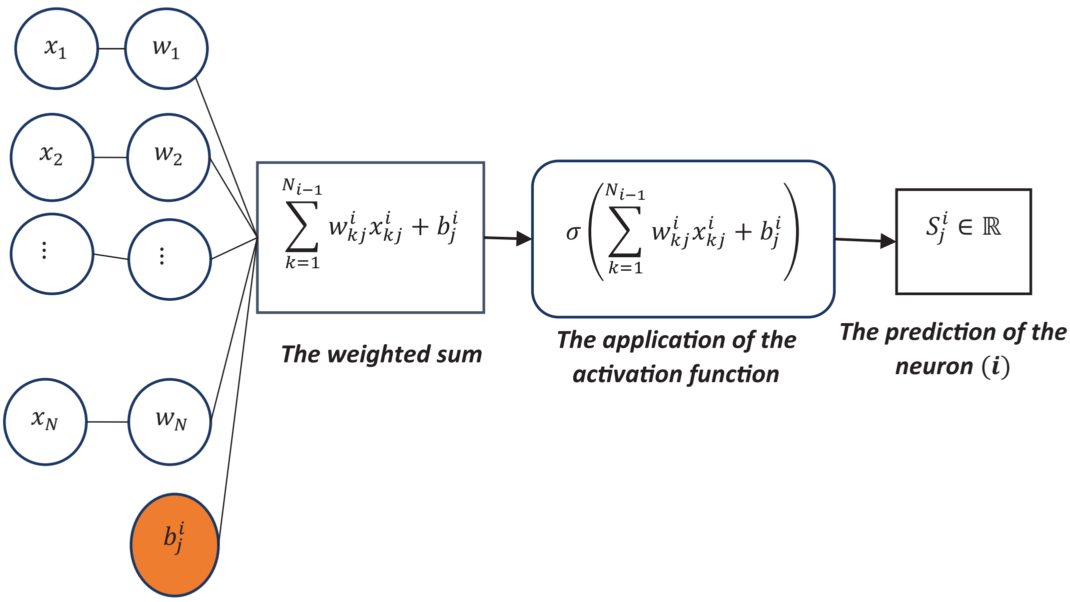


Figure 2. The mathematical formulation of an artificial neurons (Source: Author).

To this sum S_j^i the neuron applies an activation or transfer function φ to obtain an output y_j^i (Fig. 2)

$$y_j^i = \varphi(S_j^i) = \varphi\left(\sum_{k=0}^{N_{i-1}} w_{kj}^i x_k^i\right)$$

The output y_j^i (output) of the neuron j neuron in the i layer is sent to other neurons or to the outside.

3.3 Matrix writing

We consider the layer i layer composed of M_1 neurons.

For any neuron j with $1 < j < M_i$ we put:

$$X^i = \begin{pmatrix} x_0^i \\ x_1^i \\ \vdots \\ x_{N_{i-1}}^i \end{pmatrix} \quad W_j^i = \begin{pmatrix} w_{0j}^i \\ w_{1j}^i \\ \vdots \\ w_{N_{i-1}j}^i \end{pmatrix}$$

So:

$$S_j^i = \sum_{k=0}^{N_{i-1}} w_{kj}^i x_{kj}^i = \begin{pmatrix} w_{0j}^i & w_{1j}^i & \cdots & w_{N_{i-1}j}^i \end{pmatrix} \begin{pmatrix} x_0^i \\ x_1^i \\ \vdots \\ x_{N_{i-1}}^i \end{pmatrix} = {}^T W_j^i . X^i$$

We pose:

$$S^i = \begin{pmatrix} S_1^i \\ S_2^i \\ \vdots \\ S_{M_i}^i \end{pmatrix}$$

So:

$$S^i = \begin{pmatrix} S_1^i \\ S_2^i \\ \vdots \\ S_{M_i}^i \end{pmatrix} = \begin{pmatrix} w_{01}^i & w_{11}^i & \cdots & w_{N_{i-1}1}^i \\ w_{02}^i & w_{12}^i & \cdots & w_{N_{i-1}2}^i \\ & & \vdots & \\ w_{0M_i}^i & w_{1M_i}^i & \cdots & w_{N_{i-1}M_i}^i \end{pmatrix} . \begin{pmatrix} x_0^i \\ x_1^i \\ \vdots \\ x_{N_{i-1}}^i \end{pmatrix} = \begin{pmatrix} {}^T W_1^i \\ {}^T W_2^i \\ \vdots \\ {}^T W_{M_i}^i \end{pmatrix} . X^i$$

We put:

$$W^i = \begin{pmatrix} w_{01}^i & w_{02}^i & & w_{0M_i}^i \\ w_{11}^i & w_{12}^i & \cdots & w_{1M_i}^i \\ \vdots & \vdots & & \vdots \\ w_{N_{i-1}1}^i & w_{N_{i-1}2}^i & & w_{N_{i-1}M_i}^i \end{pmatrix} = \left(w_{kj}^i\right)_{\substack{0 \le k \le N_{i-1} \\ 1 \le j \le M_i}}$$

So:

$$S^i = {}^T W^i . X^i$$

The outputs of the M_i neurons of the layer are then written:

So:

$$Y^i = \begin{pmatrix} y_1^i \\ y_2^i \\ \vdots \\ y_{M_i}^i \end{pmatrix}$$

$$Y^i = \begin{pmatrix} y_1^i \\ y_2^i \\ \vdots \\ y_{M_i}^i \end{pmatrix} = \begin{pmatrix} \varphi(S_1^i) \\ \varphi(S_2^i) \\ \vdots \\ \varphi(S_{M_i}^i) \end{pmatrix} = \varphi \begin{pmatrix} S_1^i \\ S_2^i \\ \vdots \\ S_{M_i}^i \end{pmatrix} = \varphi(S^i)$$

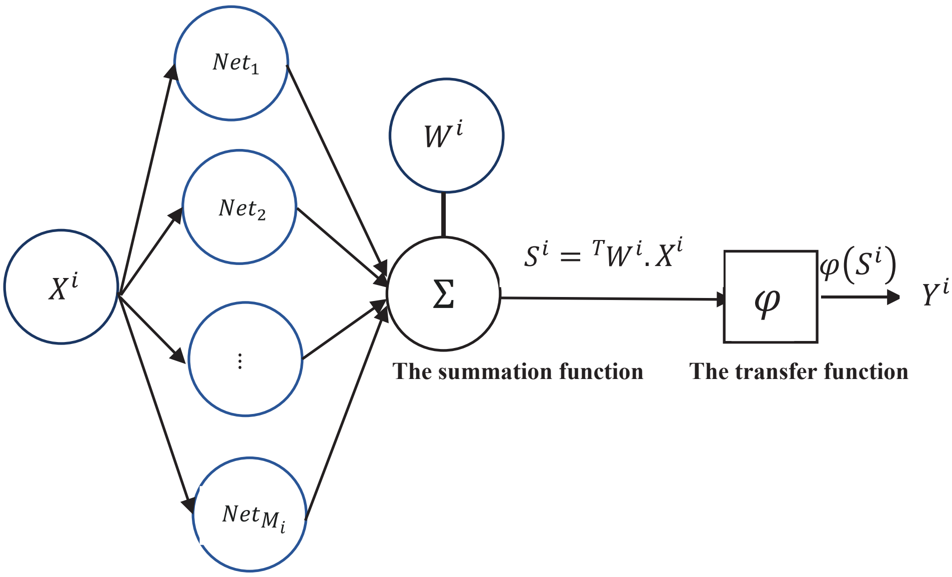
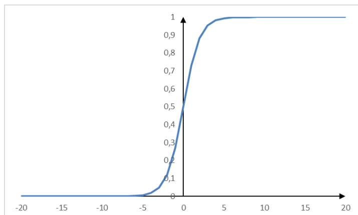
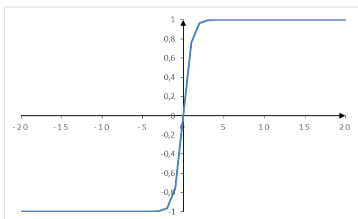
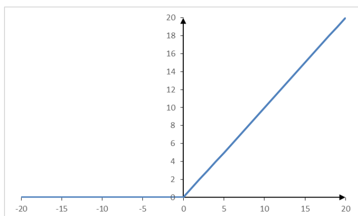


Figure. 3. Architecture and functioning of ANN (Source : Author).

Table 1. The list of activation functions (Source: Author).

The function title	The function	The Graphic Representation
Sigmoid	$\sigma(x) = \dfrac{1}{1 + e^{-x}}$	
Hyperbolic tangent	$Tanh(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$	
ReLu	$ReLu = Max(0, x)$	

3.4 Activation function

The transfer function or activation function or thresholding function, also called the activation function, is the function used to propagate information from layer to layer. The most common functions cited in the literature are listed in the following table (Table 1):

3.5 Error functions

To calculate the correct weights (parameters), the error between the expected output and the output produced by the network must be calculated. Methods for calculating the error include:

- $\boldsymbol{R-square}$:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

With:

y_i : *the exact value*

$\bar{y}$: the average of the values of y_i

$\widehat{y_i}$: *the value we have predicted*

- ***Mean Absolute Error* « *MAE* »**

***Mean Absolute Error* « *MAE* »** :

$$Error = \frac{1}{m}\sum_{i=1}^{m}|y_i - \widehat{y_i}|$$

m The number of individuals or objects to be predicted or the number of observations.

***Mean Squared Error* « *MSE* »** :

$$Error = \frac{1}{2m}\sum_{i=1}^{m}(y_i - \widehat{y_i})^2$$

3.6 Learning the artificial neural network

The vast majority of neural networks have a "training" algorithm which consists of modifying the synaptic weights according to a set of data presented as input to the network. The purpose of this training is to allow the neural network to learn from the examples. If the training is carried out correctly, the network is able to provide output responses very close to the original values of the training dataset. But the interest of neural networks lies in their ability to generalise from the test set. It is therefore possible to use a neural network to create a memory; this is known as neural memory.

Supervised learning occurs when the network is forced to converge to a specific final state as it is presented with a pattern.

In contrast, in unsupervised learning, the network is left free to converge to any final state when presented with a pattern.

ANN learning can be achieved, among other things, by:

i) Changing weights,
ii) Modification of the network structure (creation or deletion of neurons or connections, or layers),
iii) The use of appropriate attractors or other appropriate steady state points,
iv) The choice of activation functions.

Since backpropagation training is a gradient descent process, it can get stuck in local minima in this weight space. It is because of this possibility that neural network models are characterised by high variance and instability.

- **Back-propagation**

Backpropagation consists of backpropagating the error committed by a neuron to its synapses and the neurons connected to them. For neural networks, the backpropagation of the error gradient is usually used, which consists of correcting errors according to the importance of the elements that have actually participated in the making of these errors: the synaptic weights that contribute to generating a large error will be modified more significantly than the weights that have generated a marginal error.

- **How to choose the number of layers and neurons**

The number of neurons and layers directly influences the performance of an ANN in terms of prediction quality. Indeed, to determine the number of hidden layers, we can follow a process that consists in starting with a single hidden layer and adapting it to reach the ideal architecture.

So if one layer does not produce satisfactory results, then we automatically have to think about adding another until we get satisfactory results. The same goes for the number of neurons, we try to modify it until we get the desired results. The number of neurons in each layer must not exceed the number of input variables. So, you have to think about doing several tests to arrive at a relevant and powerful ANN in terms of accuracy in predicting the output variables.

On the other hand, the more layers you increase the capacity of the network, the more you risk overlearning if you exaggerate in terms of the number of layers or neurons, and the same thing if you decrease the number of layers, you risk underlearning.

To avoid the problem $d'underffiting$ and $d'overffiting$ we try to divide the data into 4 parts and try to alternate the combinations between these parts. By applying this technique, we will have a perfect test of the data since all parts will be used for the test.

4 METHODOLOGY, METRICS AND DATA

4.1 Methodology

The aim of this empirical study is to build a model that can be implemented as a decision support tool for recruiters to effectively hire suitable candidates. However, the proposed methodology (Figure 4) includes the construction of a prediction model based on Artificial

Intelligence, for which we adopted the process of data mining techniques.

This process is initially based on the preparation of the data, followed by the splitting of the data into two proportions; the first is intended to train the prediction model, while the second serves as a test proportion for the accuracy of the resulting model.

4.2 Metric

To evaluate the model obtained from the modelling process, it is necessary to define some metrics to assess the performance of the model obtained. This is done by filling in the confusion matrix using the test data set. Given that the test data set represents 25% of the overall data and the training set represents 75% of the overall data.

However, the confusion matrix (Table 2) allows us to indicate the number of correct predictions for each class and the number of incorrect predictions for each class organised according to the predicted class. Each row of the table corresponds to a predicted class, and each column corresponds to an actual class.

Table 2. Confusion matrix.

	Positive prediction	*Negative prediction*
Positive	True Positives (TP)	False positives (FP)
Negative	False Negative (FN)	True Negatives (TN)

With:

→ True Positives: items that are true and correctly classified.
→ False Positives: items that are true and are misclassified.
→ True negatives: items that are false and are correctly classified.
→ False negatives: items that are negative and misclassified.

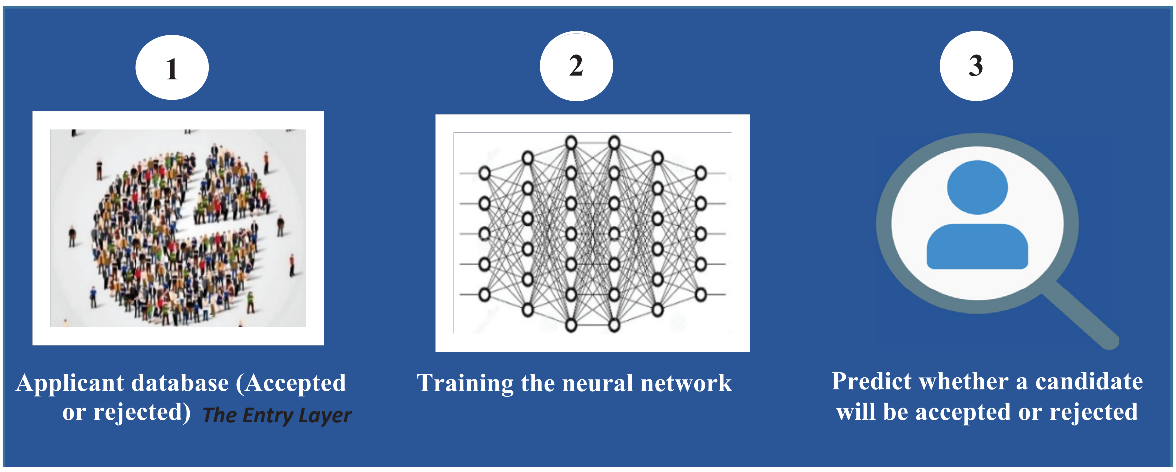


Figure 4. The modelling process using artificial neural networks (Source: Author).

From this confusion matrix the following ratios can be calculated:

$$\boldsymbol{Accuracy} = \frac{TN + TP}{TP + TN + FP + FN}$$

$$\boldsymbol{Precision} = \frac{TP}{TP + FP}$$

$$\boldsymbol{Recall} = \frac{TP}{TP + FN}$$

4.3 Data

In the data preparation stage, we used a database that includes 1000 rows of applicants from a recruitment agency. In addition, this database has 8 explanatory variables and only one dichotomous variable to be explained which takes 2 binary values (Accept / Reject), so we coded all categorical variables according to the table below (See Table 3):

5. RESULTS

After preparing the data for the modelling, we proceeded to the application of the ANN; for this we defined the number of layers and parameters to build our network (See Figure: 5)

The function *fit()* function is used to train our model over 50 iterations, allowing us to

Table 3. Coding of explanatory variable values.

Code	1	2	3	4	5
Speciality	Computer Science	Finance	Secretariat	Management	Right
Current Status	Unemployment	Assets			
French level	A1	A2	B1	B2	C1
English level	A1	A2	B1	B2	C1
Computer level	Beginner	Medium	Advanced	Excellent	
Decision	Reject (0)	Accept (1)			

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_3 (Dense)             (None, 8)                 72

 dense_4 (Dense)             (None, 6)                 54

 dense_5 (Dense)             (None, 1)                 7

=================================================================
Total params: 133
Trainable params: 133
Non-trainable params: 0
_________________________________________________________________
```

Figure 5. The architecture of our neural network.

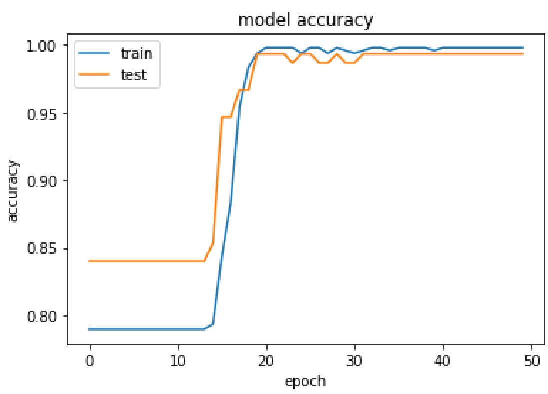


Figure 6. The evolution of the error of our model.

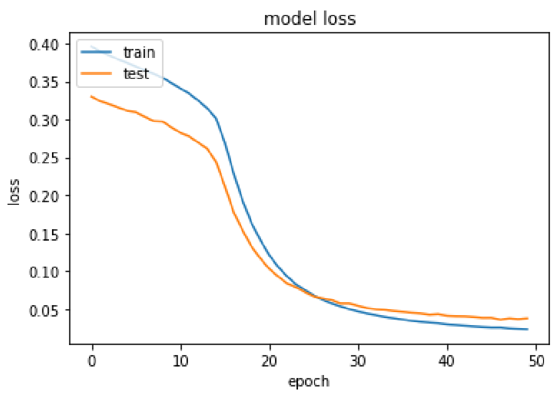


Figure 7. The evolution of the accuracy of our model.

choose the right values for the weight matrix *W*. The calculations are performed using the gradient descent method. The training data used are stored on *X_train* (starting values) and *Y_train* (expected arrival values). Figures 6 and 7 show the evolution of the accuracy and the error (loss) of the model in the training phase.

We can see from Figure 6 that the error decreases and the accuracy increase with iterations, as the training algorithm continuously updates the weights and biases in the neural network according to the training data. We can also see from Figure 7 that the accuracy curves (blue and orange) are very close for both Test and Train data sets, which means that the model has been well trained. We also notice in Figure 6 that the error (loss) curves for the Test and Train data sets decrease towards 0, which means that the model performs well.

Thus, we calculated the metric *Accuracy* for the training and test data and obtained an accuracy equal to 99,33% using the test data (see Figure 8).

Indeed, according to the value of the metric obtained, we can conclude that our model has a fairly high level of predictability, which will help us to make accurate predictions of the recruitment decision.

6. CONCLUSION

Selecting and hiring the right candidate is a daunting task for the company. Therefore, companies are looking for tools that can collect, sort and analyse a large amount of information about candidates to assess their personality and skill level, which is what Artificial Intelligence provides to improve this hiring process.

It is in this context that our paper is written, we have tried to detect the importance of using these techniques in the construction of a model capable of predicting the recruitment decision of new candidates for a company. For this purpose, we have relied on the use of the Artificial Neural Network (ANN) method, so we have exploited a database that includes a range of explanatory variables that describe the level of competence of candidates.

After following the process adopted by data mining techniques, we were able to achieve a result that reflects the performance of Artificial Intelligence techniques, and the accuracy obtained at the end of the modelling process, which exceeds 99%, reveals the robustness of the model obtained, which will improve the hiring process for companies.

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Knowledge Mapping for the Study of Artificial Intelligence in Education Research: Literature Reviews

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ABSTRACT. This study aims to provide a systematic and complete knowledge map for researchers working in the field of research on the application of artificial intelligence in education. In addition, it is designed to help researchers quickly understand author collaboration characteristics, institutional collaboration characteristics, trending research topics, evolutionary trends, and research frontiers of scholars from a library informatics perspective. In this study, a bibliometric approach was used to quantitatively analyze the retrieved literature with the help of the bibliometric analysis software CiteSpace. The analysis results are presented in tables and visual images in this paper. The results of this study indicate that collaborative relationships among scholars need to be improved and collaborative research relationships among research institutions are more fragmented. This study also points out the shortcomings of this study: Chinese educational researchers and practitioners still have a relatively vague understanding of some fundamental issues in the process of integration and development of AI and education. Therefore, this paper uses quantitative research methods such as bibliometrics

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and visualization pictures to systematically and intuitively reveal the research progress and trends on the application of artificial intelligence in education based on the published literature and to provide a reference for further research on this topic in the future.

KEYWORDS: Artificial Intelligence; Education

1. INTRODUCTION

Artificial intelligence is the science and engineering of making seeded machines that exhibit human behavioral intelligence characteristics, including reasoning, learning, goal-seeking, problem-solving, and adaptability (Monostori, 2014).Artificial intelligence, as a vital technological force for social development, has rapidly penetrated all walks of life and become a new driving force and trend for the development of various industries.In this situation, it has become a significant challenge for governments worldwide to adapt education to the needs of the intelligent era and to use innovative technologies to promote changes in teaching models and the cultivation of creative talents.The U.S. 2016 release, Preparing for the Future of Artificial Intelligence, refers to implementing AI education and expanding AI and data science curricula into developing the talent needed for AI to drive economic development (White House, 2016).The Development Plan for a New Generation of Artificial Intelligence promulgated by the Chinese State Council in July 2017 proposes to develop intelligent education, use innovative technology to accelerate the reform of talent training models as well as teaching methods, build a new education system that includes intellectual learning and interactive learning, and promote the application of artificial intelligence in teaching, management, and resource construction (Chinese State Council, 2017a).In the same year, the 13th Five-Year Plan for National Education Development promulgated by the State Council of China also proposed to “explore new models of future education and teaching by making comprehensive use of technologies such as the Internet, big data, artificial intelligence, and virtual reality” (Chinese State Council, 2017b).As can be seen, the use of AI technology to promote change and innovation in education systems has attracted a great deal of attention from countries around the world.

Although China’s education reform has made remarkable progress, there are still some outstanding problems, such as unbalanced education development, an imperfect cultivation model of innovative talents, and an unreasonable allocation of quality education resources. With the advent of the intelligent era, artificial intelligence will become a “powerful tool” to crack these educational problems, playing an essential role in innovating education and teaching models, optimizing talent training programs, developing students’ professional skills, and building a lifelong learning system to promote the change and development of education in the future.

In recent years, domestic experts and scholars in the field of education have focused on the connotation and critical technologies of educational AI (Leun et al., 2017), the connotation and target orientation of intelligent education (Zhang Jinbao et al., 2018), the promotion of AI for blended teaching (Dai Yonghui et al., 2018) and the innovative educational applications of deep learning and machine learning (Liu Yong et al., 2017; Yu Minghua et al., 2017), Etc. A preliminary discussion was conducted.However, educational researchers and practitioners still have a relatively vague understanding of some fundamental issues in the integration and development of AI and education, such as the technical framework of AI in education, application models, and development challenges.

Based on this, this study uses Citespace software to visualize and analyze the literature related to the research topic of artificial intelligence in education so that the readers can understand the current situation, research hotspots, and research trends of this research topic of artificial intelligence in education in China more clearly and intuitively, and thus provide references for further in-depth research on the research topic of artificial intelligence in education.

2. LITERATURE REVIEW

Citespace is a Java-based information visualization software developed by Professor Chaomei Chen of Drexel University, USA. It can extract scientific literature, generate corresponding visual atlases, and interpret them to understand the knowledge base, research hotspots, disciplinary frontiers, and new trends in related fields (Chen Chaomei, 2006). CiteSpace requires JRE 1. 4. 2 or higher as the runtime environment for the software authoring platform. Although CiteSpace can access many web services and other information through PubMed, etc., the Internet is unnecessary for CiteSpace to run. The data file format input to CiteSpace is the data format output by ISI. Unlike other similar information visualization software, the CiteSpace software itself comes with a data converter, which can directly convert the data format downloaded from the Internet without converting the downloaded raw literature data to the correlation matrix, which can eliminate the complex steps and processing of correlation matrix conversion, which is one of the advantages of CiteSpace software (Chen C, 2004).Before starting data processing with CiteSpace, the literature data files must be placed in the same folder. In addition, the name of each data file must begin with "download" and have ." txt" as a suffix. Before creating a new project using CiteSpace, two paths need to be specified, one for the literature data store and one for the project store. The project storage path allows researchers to find saved images and output files while CiteSpace is running, and the setup process is done from the main CiteSpace interface.

CiteSpace has the following essential features. (1) The raw data does not need to be converted into the format of the matrix, and the raw data format of databases such as WOS and CNKI can be directly imported into CiteSpace for calculation and plotting; (2) For the same data sample, multiple plots can be performed to show the evolutionary characteristics of the data from different perspectives. (3) The software clearly shows the change of literature data over time by marking nodes and connecting lines with different colors; (4) The color of nodes is represented chronologically, clearly showing the citation of different periods; (5) The color of connecting lines represents the earliest time when the co-citation frequency of that connecting line reaches the selected threshold.

CiteSpace has four essential functions: (1) Identify critical paths in the evolution of subject areas through citation network analysis. (2) Identify crucial literature for the evolution of disciplinary fields. (3) Analyzing the potential dynamic mechanisms of disciplinary evolution. (4) Predicting disciplinary frontiers.

CiteSpace software is used to detect and analyze temporal trends in disciplinary research frontiers and their relationship to the knowledge base and to discover internal connections between different research frontiers. By visually analyzing the information in the literature on the subject area, researchers can visually discover the evolutionary path of the subject frontier and the classical primary literature of the subject area.

CiteSpace software uses the cosine algorithm to calculate the strength of collaboration between researchers or institutions, and the power of connection between nodes represents the strength of association between researchers or institutions, which is calculated by the cosine distance of the angle between nodes (Chunlai Yan, Hongxia Li & Ruihui Pu, 2022). Equation (1) is as follows.

$$Cosine\,(x,y)=\frac{XY}{[X][Y]}=Cosine\,(c_{ij},s_i,s_j)\frac{C_{ij}}{\sqrt{S_iS_j}}$$

Where c_{ij} represents the number of papers published by co-authors (author i and author j), S_i and S_j represent the number of documents published by author i and author j, respectively, and the value of collaboration intensity ranges from 0 to 1.

The main principles and methods of using Citespace are as follows:

Divide and conquer principle: The idea of the divide and conquer strategy is to divide a significant problem that is difficult to solve directly into several smaller-scale identical problems and solve them separately, dividing and conquering them. The basic idea of divide and conquer is to decompose a problem of size n into k smaller subproblems that are independent of each other and identical to the original problem. The solution for each part is found, and then each part is combined into a solution for the whole problem.

Success breeds the success principle: if a paper is cited in more articles, the greater the probability of encountering it when reading the literature and, therefore, the greater the probability of citing it in an article. Barabasi and Albert (1999) showed that many real-world complex networks are not regular random networks but belong to scale-free networks and made several studies on such a class of networks' Some studies on the number of features point to two fundamental properties that determine the scale-free properties of networks such as the Internet, the World Wide

Web, and collaborative research networks of scientists: node growth and preferential connectivity.

Minimum spanning tree algorithm. Suppose G = (V, E) is an undirected connected weighted graph, and if the subgraph G' of G is a tree containing all the vertices of G, then G' is called the spanning tree of G. The sum of the weights of the edges of the spanning tree is called the consumption of the spanning tree. Among all the spanning trees of G, the spanning tree with the minor consumption is called the minimal spanning tree of G. In modern mathematical graph theory, Prim's algorithm and Kruskal's algorithm can be applied and implemented by computer programming statements.

Expectation maximization algorithm. The maximum expectation clustering method (EM clustering for short) is a basic algorithm for large likelihood estimation in statistics, i.e., the maximum likelihood estimation of parameters in distribution with hidden state variables. The algorithm is mainly applied to estimate the missing variable X from the available information Y when the data is incomplete. The E step takes the conditional expectation, and the M step takes the maximum value. This iterative optimization method is known as the EM method. Clustering is performed by distance characteristics of nodes but by specific parameters, such as year of publication, authorship, node centrality, half-life, number of citations, etc. The criteria for clustering are determined by statistical analysis using the maximum likelihood estimation of the algorithm. Clusters of nodes shown on the graph as different colors, i.e., clusters of nodes of the same color, form the same cluster. Further statistical analysis of the clusters leads to the expected results.

Word frequency analysis method. By counting the frequency of core words such as keywords, subject words, and chapter words that appear in specific academic literature, the research hotspots, knowledge structure, and development trend of that academic field can be revealed (Li Yan, 2011). Counting the frequency of subject terms appearing in a literature set can form a clustering network of these word pair associations. The proximity between nodes within the network can reflect the affinity of the subject content (Liu I, Huang Chuanhui, 2010).

Citation analysis method. The citation and cited phenomena of scientific and technical journals, papers, authors, and other analysis objects are analyzed to reveal their quantitative characteristics and internal laws.

CiteSpace generates maps with richer colors and better appearance.In addition, we can view the articles covered by the nodes, the cluster's size and content, and the cluster's average year from the visual image.Therefore, we decided to use CiteSpace to analyze the data from this study.This study allows us to derive visual images, obtain partnerships between authors and research institutions, and identify research trends in the research topic of Artificial Intelligence in Education. The subject of this study is the application of artificial intelligence in education, which belongs to the subject of education, and CNKI collected all data on this subject.With the help of CNKI data sources, this study conducted preliminary research and obtained 527 literature records using advanced search tools with the search terms artificial intelligence and education. The authors imported these 527 documents into cite space software, automatically checked the weights, eliminated non-research documents and de-weighted them, and finally identified 518 documents. The authors used word frequency analysis and citation analysis to conduct the analysis.

3. RESEARCH TRENDS

3.1 Analysis of the results of a survey of Chinese researchers

Analyzing the distribution of authors is a prerequisite to deeply grasping the research field and scientific research dynamics of a particular discipline. The study of authors with in-depth insights and scientific achievements in the related fields can effectively grasp the development process of scientific research activities in this field, which is of positive significance to the analysis of the current situation, summary, refinement, and future research of the research topic.After the data were imported into Citespace V, the node was set to Author, in 2003–2020, with a time cut of 1 year. Set Selection Criteria (top = 50, selecting the top 50 strata for each year) to get the visualization plot (as shown in Figure 1). Each circular node in the figure represents a different author of the posting; the more significant the corresponding font of the author, the more the posting volume, and the connecting line between the nodes represents the cooperation relationship between the authors, the thicker the degree of connection, the more the cooperation posting. In the figure Largest C C is 5 (2%), indicating that the largest group of AI in education research partnership has five people, respectively, Qinhua Zheng as the primary researcher and Xinfeng Gao, Li Chen, Lei Xie, and Yujuan Guo as a supplementary collaborative research team, which accounts for only 2% of the total number of researchers.

3.2 Distribution of Chinese Institutions for Research on the Application of Artificial Intelligence in Education

The node type was changed to the institution, and the software was run to obtain the visual mapping of research institutions on the application of AI in education, as shown in Figure 2. The top 10 institutions in terms of the number

Figure 1. Visualization of authors of research on the application of artificial intelligence in education.

Figure 2. Visual mapping of research institutions on the application of artificial intelligence in education.

of publications were selected to draw Table 1. According to Figure 2, it can be seen that the College of Education of Shaanxi Normal University and the College of Education Technology of Beijing Normal University, and the College of Education Science of Xinjiang Normal University are tied for first place in terms of the number of articles, with four articles; the Cunjin College of Guangdong Ocean University, the Department of Education of Beijing Normal University, the Department of Education Technology of the College of Education of Peking University, the College of Education of Tianjin University, and the Liaoning Construction Vocational College are tied for the fourth place in terms of the number of articles, with three articles; the Party School of the Communist Party of China Beijing Materials Co. and the College of Teacher Education of Zhaoqing College are tied for the ninth place in terms of the number of articles, with two articles.This suggests that these research institutions have not focused much on how AI can be applied in education and have not studied it in depth. However, upon investigation, it was found that researchers in these institutions have researched the application of AI in various fields. However, there is no specific research focusing on the application of AI to a particular field.The fragmentation of each node in the whole network mapping is more serious, which indicates that the research among institutions is still relatively independent. The cooperation is not close enough and needs to be strengthened. The nature of the institutions shows that most institutions conducting and publishing-related research are universities, indicating that the leading positions of AI in education application research are in universities, and they are credited with the rapid development of AI in education application research.

3.3 Hot spot analysis of Chinese research on the application of artificial intelligence in education

Keywords are a high-level summary of the research topic and content of the literature. Proper keyword analysis can tell the literature's actual research content, and measuring the number of keywords can determine the hot spots of disciplines, institutions, and research knowledge base in a specific period. This research set the node as Keywords, set the node threshold as Top N = 30, selected "pathfinder" to crop, and ran the software to obtain the knowledge map of AI in education application research hotspots (Figure 3). The nodes in the figure represent the keywords of the retrieved documents, the size of the circle to which the keywords belong represents their frequency of occurrence, and the connecting lines between the nodes represent the co-occurrence relationship between the keywords. The centrality is a measure of the size of the connectivity in the knowledge graph network, and a purple color at the edge of the circle indicates that the centrality value of the node is greater than or equal to 0.1.

According to the keyword co-occurrence mapping and partial keyword table of AI in education, it can be seen that the frequency and

Table 1. Top 10 research institutions in terms of the number of articles published on the application of artificial intelligence in education.

Serial number	Count	Year	Institution
1	4	2019	College of Education, Shaanxi Normal University
2	4	2006	College of Educational Technology, Beijing Normal University
3	4	2018	College of Education Science, Xinjiang Normal University
4	3	2019	Cunjin College of Guangdong Ocean University
5	3	2018	Department of Education, Beijing Normal University
6	3	2010	Department of Educational Technology, College of Education, Peking University
7	3	2018	College of Education, Tianjin University
8	3	2018	Liaoning Construction Vocational College
9	2	2019	Party School of Communist Party of Beijing Materials Co.
10	2	2019	School of Teacher Education, Zhaoqing College

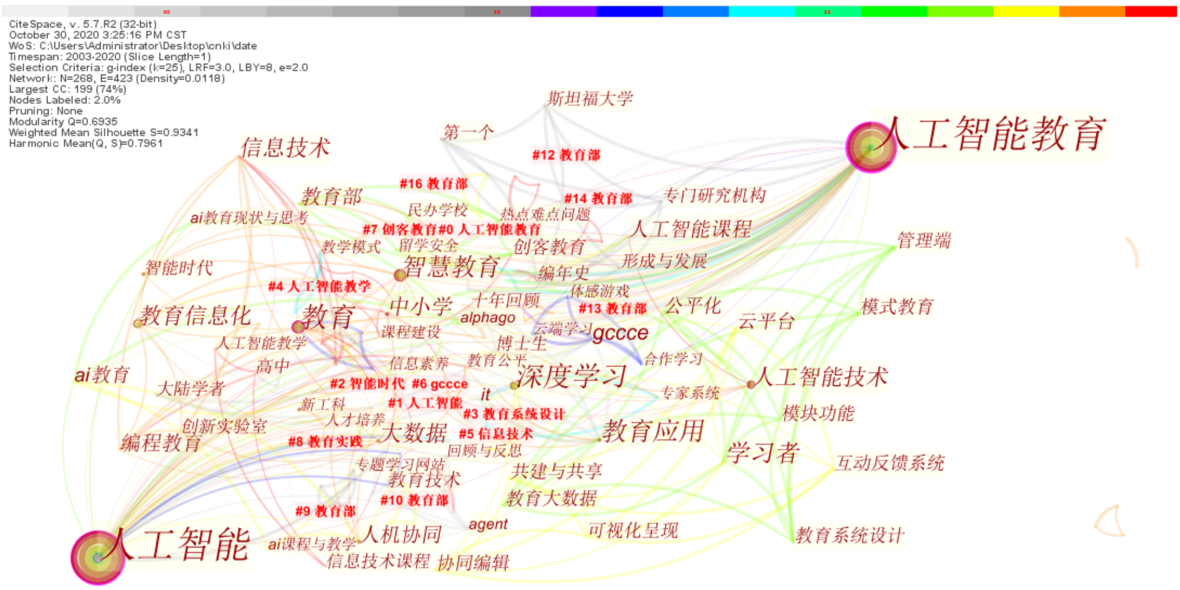

Figure 3. Keyword co-occurrence mapping of research on the application of artificial intelligence in education.

Table 2. Key words of research on the application of artificial intelligence in education.

Serial number	Count	Centrality	Key word
1	124	0.57	Artificial Intelligence
2	108	0.62	Artificial Intelligence Education
3	17	0.1	Education
4	13	0.03	Artificial Intelligence Technology
5	12	0.09	Smart Education
6	11	0.05	Education Applications
7	9	0.08	Deep Learning
8	8	0.06	Primary and Secondary Schools
9	7	0.02	Education Informatization
10	5	0	Education Technology
11	5	0.01	Artificial Intelligence Curriculum
12	5	0.04	Information Technology
13	4	0.03	Big Data
14	4	0.03	Ministry of Education
15	4	0.02	Human-Machine Collaboration
16	4	0	Information Literacy
17	4	0.02	Talent Cultivation
18	4	0.01	Programming Education
19	3	0.02	Creativity Education
20	3	0.03	Learners
21	3	0	grace
22	3	0.03	Intelligent Age
23	3	0.02	High School
24	3	0.06	Information Technology Course
25	3	0	Artificial Intelligence Era
26	3	0.01	New Engineering
27	3	0	Artificial Intelligence+
28	3	0.02	Teaching Artificial Intelligence
29	2	0.01	IT
30	2	0	Education Artificial Intelligence

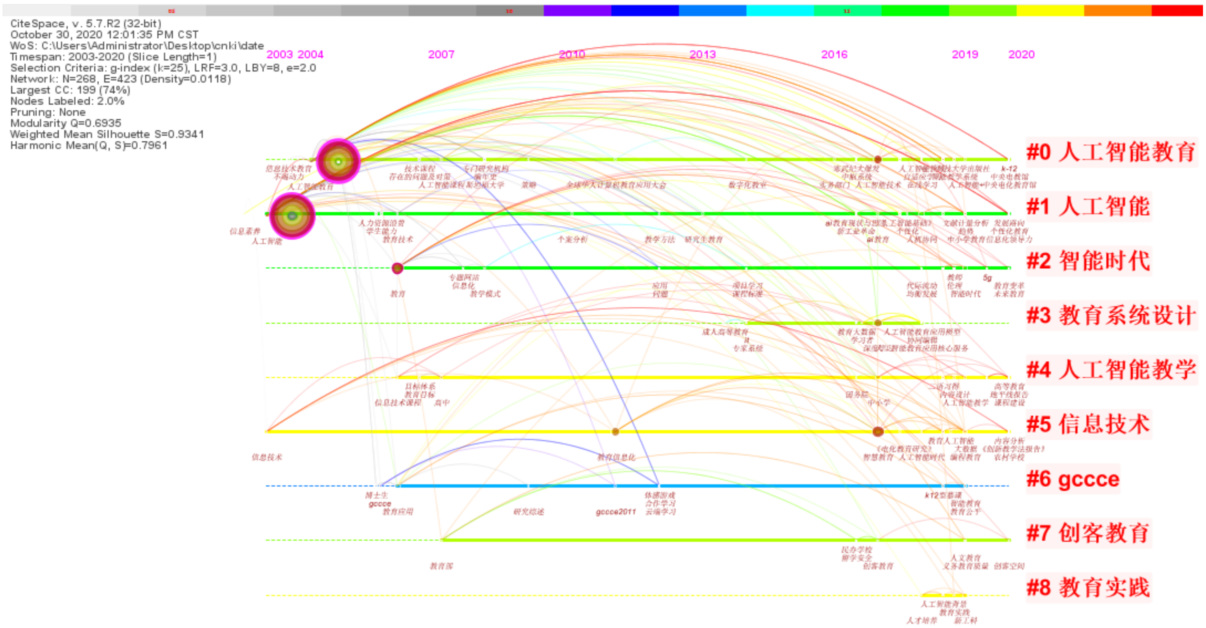

Figure 4. Timeline of research hotspots on the application of artificial intelligence in education.

centrality of "AI," "AI education," and "education" are in the top position. The corresponding node area is large, which indicates the accuracy of data retrieval and topic matching, and the series of keywords are consistent and comprehensive in the domestic concept.As shown in Figure 3, "smart education," "educational applications," "deep learning," "primary and secondary schools," and "education informatization" are the main research hotspots.

3.4 Keyword evolution analysis of research on the application of artificial intelligence in education

In addition to static analysis of the distribution of research hotspots of AI in education, it is also necessary to pay attention to the time zone changes of hotspots to discover the future development direction more effectively. We set the time segmentation as 2003–2020, select the node Keywords, set the node threshold as Top N = 20, and output the result as "Time Zone" to form the time zone distribution of AI in education research hotspots (Figure 4).).

The time-zone distribution chart of research on the application of artificial intelligence in education consists of a series of keywords in the corresponding time intervals, and the keywords corresponding to each time interval indicate the hot issues of research on the application of artificial intelligence in education in this time interval.From Figure 4, it can be seen that the research on the application of AI in education from 2003 to 2020 is rich, and the whole is developing in depth. 2003–2020, with the increasing improvement of intelligent technology, the development of 5G, Wap, cloud computing, smartphones, mobile Internet, and other technologies tend to mature, and user needs are more extensive, profound research on AI education, artificial intelligence, and the intelligent era was conducted in this stage; in 2003, scholars mainly profiled information literacy and AI terminals; in 2004, the main direction of research was information technology education, including AI education, etc.; in 2006, scholars profiled the technology curriculum and the problems that existed.

4. CONCLUTION

The emergence of artificial intelligence technology has pointed out the direction for the intellectual development of computer network technology. Applying this technology to computer network technology is conducive to enhancing the technical level of computers and better-providing quality services for social and economic development.

Through the visual analysis of this study, the author believes that research can be conducted in the following five areas.

Increase the research and development of educational AI products and improve the quality of technical services: The research and development of educational AI products and the improvement of technical service quality require efforts from many aspects.First, we should strengthen the cooperation between experts in the field of education, artificial intelligence experts, and enterprise personnel to understand the current realistic needs of education, find the fit between artificial intelligence and education, and promote the development and application of intelligent products in education.Second, the functional modules of educational AI products should be continuously expanded to effectively meet students' personalized learning needs and teachers' teaching requirements at different stages. Currently, the Chinese government actively advocates the introduction of AI-related courses in primary and secondary schools, so it can develop educational AI products that go with them, such as programming-based teaching tools and software, as a way to assist education and teaching and optimize students' learning effects.Third, to establish a complete education AI product safety supervision and evaluation system, standardize industry standards, and increase market supervision and monitoring efforts to ensure that enterprises provide safe, high-quality products and services for the development of education AI.

Broaden the application space of artificial intelligence in education, multi-disciplinary cross-collaboration to help the development of education innovation: dig deeper into the application value of artificial intelligence in education, expand the application space so that it can better provide services for education and teaching.Artificial intelligence technology can break the barriers to education and effectively integrate formal and informal learning. Therefore, it is recommended that the Chinese government establish an AI education service platform to gather global high-quality education resources and precisely push learning resources suitable for learners' development according to their needs. Establishing an AI education management platform in China to track and record learning process data and conduct deep mining and learning analysis to comprehensively understand learners' interests and real-life needs can help to realize personalized education and lifelong learning.

Build a harmonious symbiosis "human-machine combination" new ecology, enhance the sense of trust in artificial intelligence in education: the integration of artificial intelligence and education is an important trend in the intelligence era.Educational AI will replace the repetitive work of teachers and reduce their pressure and burden to a certain extent, allowing teachers to spend more time optimizing the instructional design to facilitate students' personalized learning. However, education involves cultivating students' moral qualities, values, and emotional attitudes that cannot be replaced by artificial intelligence and still needs to be done by teachers.Therefore, "human-machine integration" will become the mainstream trend of future education development. Specifically, mechanical and repetitive tasks will be completed by machines, such as replacing teachers to correct homework, organizing and collecting learning materials, arranging exams, etc. Teachers will focus more on emotional interaction with students, shaping students' personalities, cultivating moral qualities, and improving higher-order thinking skills.In addition, human-machine trust is a critical factor in developing educational AI. Establishing a long-term human-machine trust mechanism is a prerequisite for building a harmonious and symbiotic "human-machine combination" new ecology. Therefore, it is necessary to accelerate the improvement of the AI governance system, develop and embed ethical standards, create a more powerful, safe, and trustworthy educational AI application system, and promote the peaceful development of AI and education integration.

Strengthen the "government, enterprise, academia and research" multi-party cooperation, collaborate to promote the rapid development of artificial intelligence in education: the integration of artificial intelligence and education is a long-term and arduous task, only "government, enterprise, academia and research" multi-party cooperation to promote collaborative, will achieve significant results.First of all, the government should attach great importance to the development of educational AI, establish a sound system to guarantee the system, and continue to increase the financial support for educational AI to protect the innovation of intelligent technology.Secondly, enterprises should increase the design and development of educational AI products, expand product supply, improve service quality, and cooperate extensively with schools and research institutes to broaden the development channels of enterprises.Again, schools should actively explore the education and teaching mode supported by AI technology, offer AI-related courses, and focus on cultivating students' data science literacy and computational thinking skills to meet the development needs of the future intelligent era and continuously deliver talents for enterprises and research institutions. Finally, research institutes should focus on the frontier of AI development, widely conduct theoretical research on AI educational applications, and build a new generation of educational AI theoretical systems. Through continuous technical breakthroughs and product innovation, solve the technical problems faced in the development of educational AI and provide technical support for developing enterprise products.

Establishing educational AI demonstration sites and exploring the application model of educational AI: Based on the principle of "piloting first, leading by points and gradually promoting," we will select areas and schools with good informationization conditions to establish educational AI demonstration sites and explore the application model of educational AI, and gradually promote it to the whole country.Specifically, the demonstration site hired industry or university AI experts as consultants to provide regular guidance on the construction of the demonstration site and worked to build a team of information technology personnel, including AI teachers. In addition, artificial intelligence business training is provided to administrators and teachers in pilot district schools to strengthen education administrators' understanding of AI educational applications and to enhance teachers' ability to apply AI technologies. Finally, an effective incentive and guarantee system is developed to encourage teachers and administrators to innovate the application of AI technology, innovate the education and teaching model, and improve teaching standards.

In the era of big data, the integration of artificial intelligence and computer network technology is deepening. Based on the characteristics of artificial intelligence technology, the application of artificial intelligence in computer network technology in the era of big data can be explored and analyzed in depth. In addition, AI technology will also complement blockchain, the Internet of Things, and cloud computing technology. Therefore, the future of artificial intelligence education is promising, and there will be a sharp shortage of artificial intelligence talents. Even artificial intelligence has been able to be applied in early childhood education; these are opportunities and challenges for the development of artificial intelligence education.

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The effect of marketing intelligence adoption on enhancing profitability indicators of banks listed in the Egyptian stock exchange

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ABSTRACT. The purpose of this study is to examine the effect of marketing intelligence (MI) adoption on enhancing the profitability indicators of banks adopting MI and listed in the Egyptian stock exchange. A statistical analysis was carried based on data collected, using a questionnaire instrument to measure the efficiency of adopting MI among 12 banks adopting MI and listed in the Egyptian stock exchange. The study focuses on using 2 measures of profitability indicators; return on equity (ROE) and return on assets (ROA).The profitability indicators (ROE, ROA) of 12 central banks adopting MI and listed in the Egyptian stock exchange were measured during the period (2012–2021). Then, statistical analysis was conducted based on data collected using the simple linear regression model. The results of the study indicated a significant effect of MI adoption on enhancing the profitability indicators of 12 banks adopting MI and listed in the Egyptian stock exchange.

KEYWORDS. Marketing intelligence (MI), profitability indicators, return on equity (ROE), return on assets (ROA)

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1. INTRODUCTION

The Egyptian banking sector is one of the huge service sectors that contribute to Egypt's economic growth, creating around a third of the whole nation's annual GDP. However, this sector operates in a fast changing environment characterized with highly competitive market. Moreover, the competitive pressure intensively increased due to the penetration of foreign and private banks to the Egyptian market. (Haripriya, 2020, p. 71; Kamu and Njuguna, 2020, p. 21; Al-Weshah, 2017, p. 5; Jeyarani and Thangaraja, 2016, p. 756).

Intensifying competition forced banks operating in Egypt to offer more technologically – based services in order to better serve their customers including automated teller machines (ATMs), plastic cards, mobile banking, internet banking, and electronic fund system. (Haripriya, 2020, p. 71; Vishnoi and Bagga, 2020, p. 5, Ismaeel and Alzubi, 2020, p. 2, Al-Hashem, 2020, p. 688; Moghaddam et al., 2014, p. 84). Therefore, the banks operating in Egypt are required to adapt to that highly competitive market and respond to these rapid changes in the marketplace.

In the light of severe competition between banks operating in the Egyptian market, the adoption of MI within banks was absolutely necessary, in order to be able to respond to the market pressures and compete with larger banks in the marketplace. That's why; the vast majority of banks operating in Egypt have adopted MI. This study focuses on 12 central banks adopting MI and listed in the Egyptian stock exchange. MI adoption was the key to success for those 12 banks listed in the Egyptian stock exchange, in terms of managing their marketing activities, as well as analyzing large amount of marketing information gathered about their customers, competitors, and marketing environment. (Azeez, 2020, p. 535; Vishnoi et al., 2019, p. 1). MI helped those 12 banks to predict their customers' needs and interests, know their competitors, and analyze the internal and external marketing environment to determine their strengths, weaknesses, opportunities, and threats; referred to SWOT analysis. (Azeez, 2020, p. 538; Noviyanti et al, 2020, p. 1236).

Furthermore, financial analysis is an essential tool used by banks' management to gain a break through in the financial situation of those 12 banks listed in the Egyptian stock exchange and make decisions related to their business. (Perisa et al, 2017, p. 233). Financial analysis allows banks' management to analyze and interpret their financial data which provides them with a deep understanding on their banks' financial situation and helps them to evaluate their banks' performance. (San and Heng, 2013, p. 651). Financial analysis involves calculating financial ratios. That's why; it is often called ratio analysis. (Lipunga, 2014, p. 43). There are many financial ratios that can be used to assess the bank profitability performance. This study uses two main financial ratios as measures to profitability indicators of those 12 banks adopting MI and listed in the Egyptian stock exchange; which are return on equity (ROE) and return on assets (ROA).

2. THEORETICAL FRAMEWORK

2.1 Definition of marketing intelligence (MI)

There are many definitions of MI, among of them include: "Marketing intelligence is the process of collecting daily information about important developments in the marketing environment that help managers to set, adjust, and update marketing plans". (Haripriya, 2020, p. 73; Rao, 2020, p. 126; Ade et al., 2017, p. 55, Al-Weshah, 2017, p. 3; Igbaekemen, 2014, p. 24; Moghaddam et al., 2014, p. 83). Inha and Bohlin (2018); Jeyarani and Thangaraja (2016) added that "marketing intelligence is the continuous and systematic collection and analysis of everyday information about any changes occurring in the company's marketing environment including competitors, technology, consumers' needs, preferences; attitudes, or buying behavior for the purpose of helping managers to better understand what is happening in the market and the available market opportunities. This in turn will help managers to make effective and accurate decisions". Moreover, Kamau and Njuguna (2020); Kant (2020) defined MI as "a system which can be viewed as a continuing and interacting structure of people, equipment, and procedures that are responsible for gathering, sorting, analyzing, and distributing pertinent, timely, and accurate information that help decision makers to improve their marketing planning, implementation and control". Furthermore, Vishnoi et al. (2019) stated that "marketing intelligence refers to the information, primarily quantitative in nature, that organizations gather through direct interaction and dialogue with market participants including customers, competitors, suppliers, sales force, social media, blogs, internet, or any combination of these in order to produce actionable insights for decision makers".

In addition to Vishnoi and Bagga (2020); Noviyanti et al. (2020); Lekhanya (2014) who defined MI as "a proactive mechanism used to scan, monitor, analyze, and evaluate marketing information gathered from all accessible points (internal and external marketing environment, marketing research, and market developments) in order to counteract on competitors' actions and prevailing market conditions for improving the company's competitive advantage and overall performance through enhanced and intelligent decision making".

2.2 Main dimensions of MI adoption

The following figure illustrates 5 main dimensions or variables that constitute the adoption of MI.

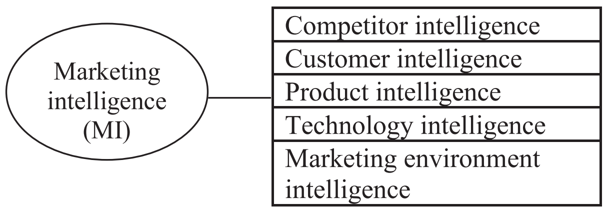

Figure 1. Main dimensions of MI.
Source: Vishnoi et al. (2019), p. 557.

2.2.1 Competitor intelligence: is the process of collecting and analyzing information about competitors, their trends, strategies, and future plans. This helps an organization to form a clear picture of the competitive environment where it works in, as well as helps it to build comprehensive competitive profiles. Competitor intelligence is based on the ethical gathering of different types of information including government records that are openly available. (Haripriya, 2020, p. 72; Maria et al., 2020, p. 4; Rao, 2020, p. 131; Vishnoi and Bagga, 2020, p. 1; Al-Hashem, 2020, p. 689; Noviyanti et al., 2020, p. 1236; Kumar, 2020, p. 88).

2.2.2. Customer intelligence: is the process of gathering and analyzing information about customers' buying behavior, intentions, preferences, motivations, concerns, beliefs, and perceptions. This helps an organization to create customers' profiles. As a result, an organization will be able to produce the products that satisfy customers' needs, as well as meet their expectations. (Maria et al., 2020, p. 4; Rao, 2020, p. 131; Carson et al., 2020, p. 797; Al-Hashem, 2020, p. 689; Noviyanti et al., 2020, p. 1236; Al-Weshah, 2017, p. 4; Al-Zoubi, 2016, p. 27; Lymperopoulos and chaniotakis, 2005, p. 485).

2.2.3 Product intelligence: is the process of collecting and analyzing information about an organization's products as well as about those of competitors. This provides an organization's management team with deep insights about product development and innovation activities. Product intelligence enables an organization to make individual product decisions including decisions about product attributes such as product quality, price, design, features, labeling, packaging, as well as after – sale services. (Shailza et al., 2020, p. 132;Kumar, 2020, p. 88; Kant, 2020, p. 117; Inha and Bohlin, 2018, p. 6; Ade et al., 2017, p. 56; Igbaekemen, 2014, p. 27; Ozturk et al., 2012, p. 231).

2.2.4 Technology intelligence: is the process of identifying and analyzing the technological opportunities and threats that may affect an organization's development. This helps an organization to understand what is going on in the surrounding world of technology, and adopt the technologies that help an organization to gain the most competitive advantage. The good technology intelligence provides an organization with a solid knowledge and support for planning and creating its own innovation path. (Shailza, 2020, p. 132; Kamau and Njugunga, 2020, p. 22; Ismaeel and Alzubi, 2020, p. 7; Inha and Bohlin, 2018, p. 6; Faryabi et al., 2013, p. 35, Ozturk et al., 2012, p. 331).

2.2.5 Marketing environment intelligence: MI goes beyond gathering information related to competitors and customers. It extends to gather information about the external marketing environment of an organization. The marketing environment intelligence aims at identifying the opportunities as well as the threats an organization faces in the external marketing environment. MI works to take advantage of the available opportunities and overcome the threats as well as try to turn them into investment opportunities. Due to global competition and the complexity of surrounding environment, it became difficult to predict the events surrounding the organization. MI reduces the environmental uncertainty through continuous monitoring of events that help to receive signals about any changes in the environment. This in turn leads to excellence and competitive advantage. (Ismaeel and Alzubi, 2020, p. 1 ; Kamau and Njuguna, 2020, p. 22; Vishnoi et al., 2019, p. 556; Inha and Bohlin, 2018, p. 6; Igbaekemen, 2014, p. 27; Faryabi, 2013, p. 35; Ozturk et al., 2012, p. 231).

2.3 Importance of MI adoption

The significant importance of adopting marketing intelligence within any organization stems from its crucial role in performing the following functions: MI gathers daily information on all developments in the marketing environment which help managers to design and modify marketing plans. (Haripriya, 2020, p. 73; Kumar, 2020, p. 86; Vishnoi and Bagga, 2020, p. 1; Rao, 2020, p. 129; Al-Weshah, 2017, p. 2; Moghaddam et al. 2014, p. 83; Ozturk, 2012, p. 229; Ubiparipovic and Durkovic, 2011, p. 25). MI is an important tool for gathering relevant information that help marketing managers to improve decision making under different conditions including certainty, uncertainty, and risk. (Al-Hashem, 2020, p. 690; Al-Weshah, 2017, p. 1006; Igbaekemen, 2014, p. 27; Ozturk, 2012, p. 229; Ubiparipovic and Durkovic, 2011, p. 25). MI is a future – oriented activity that helps managers in predicting and planning for the future reactions of competitors. This enables managers to overcome threats and avoid risks of competitors early, as well as exploit available opportunities in the marketplace. (Azeez, 2020, p. 535; Noviyanti, 2020, p. 1235; Inha, 2018, p. 14; Ade et al., 2017, p. 57; Ozturk et al., 2012, p. 228). MI helps to reduce the astonishments and the employees' inability against environmental changes, as well as minimizes the company's exposure to environmental risks and danger. (Al-Weshah, 2017; p. 2; Ade et al., 2013, p. 34). MI helps marketing managers to identify the organization's target market, and provides insights about both current and potential customers who are predisposed to buy the organization's products/services. This will guide organizations in directing their marketing activities to the right target market. Moreover, MI helps to analyze consumer buying behavior. Thus, an organization can produce the products that only satisfy and meet consumers' needs and wants. (Carson et al., 2020, p. 797; Maria et al., 2020, p. 4; Ade et al., 2017, p. 60; Lekhanya, 2014, p. 1005). MI helps marketing managers to create long-term relationships with customers, manage customer relationships, which results in increasing customers' satisfaction, loyalty, retention, and positive word of mouth. (Carson et al., 2020, p. 797; Vishnoi et al., 2019, p. 557; Faryabi et al., 2013, p. 36). Efficient adoption of MI is vital in shaping an organization's competitive advantage. MI helps an organization to compete with other organizations, by providing it with relevant information about its competitors. This helps an organization to expect it competitors' reactions and be able to plan for the next strategic moves. (Carson et al., 2020, p. 797; Maria et al., 2020, p. 4; Noviyanti et al., 2020, p. 1236; Haripriya, 2020, p. 72; Raw, 2020, p. 126; vishnoi and Bagga, 2020, p. 5; Inha and Bohlin, 2018, p. 1; Igbaekemen, 2014, p. 27). MI contributes to improving an organizations performance due to its effect on increased sales, maximized profitability, and enhanced market share. (Ismaeel and Alzubi, 2020, p. 2; Kamau and Njuguna, 2020, p. 23; Ozturk, 2012, p. 228; Nadeem and Jaffri, 2005, p. 2). MI plays an important role in encouraging innovation and creativity. The emergence of creative ideas from using MI helps an organization to produce new products and enter new markets. This results in improving an organization's competitive position. Thereby, it can survive and grow in competitive markets today. (Al-Hashem, 2020, p. 690; Carson et al., 2020, p. 797; Maria et al., 2020, p. 1, Noviyanti et al., 2020, p. 1240; Vishnoi and Bagga, 2020, p. 5; Al-Weshah, 2017, p. 2, Al-Zoubi, 2016, p. 26; Moghaddam et al., 2014, p. 87). MI helps an organization to analyze the marketing environment. This in turn enables marketing managers to identify the organization's strengths, weaknesses, opportunities, and threats (SWOT analysis). Also, MI helps in formulating the market penetration strategy, as well as market segmentation and market development strategies. (Maria et al., 2020, p. 1; Vishnoi and Bagga, 2020, p. 5; Ade et al., 2017, p. 52; Igbaekemen, 2014, p. 27; Ozturk et al., 2012, p. 228).

2.4 Bank profitability

The banking sector is the most important segment of a country's financial system. Banks act as financial intermediaries that provide different financial services. (San and Heng, 2013, p. 649). Moreover, Banks play a crucial role in the economic resource allocation of countries by chanelling funds from depositors to investors continuously. They offer all important services including providing deposits and loan facilities for personal and corporate customers, making credit and liquidity available under different market conditions, and providing access to the nations payment systems. (Lipunga, 2014, p. 41). San and Heng (2013) added that the health of the nation's economy is closely and positively related to the soundness of its banking system. A highly developed banking sector plays an important role in promoting the whole country's economic growth. Nuhiu et al. (2017) confirmed that the financial performance of banks has significant impact on a country's economic growth. Good financial performance of banks reward the shareholders for their investment and stimulates additional investment which will bring further economic growth. On the other hand, poor performance of banks may lead to their failure and the appearance of financial crisis which will have negative consequences on economic growth. (Massadeh et al., 2021, p. 67; Nuhiu et al., 2017, p. 161; Jolevski, 2015, p. 6). The soundness of the banks depends greatly on their financial performance which indicates into either the strength or the weakness of a particular bank. Financial performance is evaluated by the bank profitability. (Asqar, 2022, p. 141; Al-Taei and Al-Shakarchi, 2022, p. 69; Massadeh et al., 2021, p. 68; Perisa et al., p. 231; Nuhiu t al., 2017, p. 161; Hossain and Ahamed, 2015, p. 44; Lipunga, 2014, p. 41; Erina and Lace, 2013, p. 2; Akbas, 2012, p. 104).

Since healthy and sustainable profitability is one of the essential conditions for maintaining the stability of banking system, this study focuses on bank profitability indicators among the different performance measures of the banks which can be analyzed. (Akbas, 2012, p. 104). Bank profitability refers to the efficiency of a bank in generating earnings. (Lipunga, 2014, p. 41). Profitability is defined as the net income after tax or net earnings of a bank. Profitability of banks contributes to the economic development of the entire nation by providing additional employment and tax revenues to the government. Moreover, profitability contributes to the income of investors by having a higher dividend, and thereby improve the standard of living of the people (Asqar, 2022, p. 141; Al-Taei and Al-Shakarchi, 2022, p. 69; Perisa et al., 2017, p. 231; Nuhiu et al., 2017, p. 161; Hossain and Ahamed, 2015, p. 44; Lipunga, 2014, p. 41; Erina and Lace, 2013, p. 2; Akbas, 2012, p. 104). A number of previous studies argued that there are various ways to measure the bank profitability. They added that financial ratios are found to be the most generally used methods. Financial ratios help bank management to analyze and interpret the bank's financial data and accounting information, which in turn provides managers a deep understanding of a bank's financial situation and helps to evaluate a bank's performance. (Asqar, 2022, p. 142; Al-Taei and Al-Shakarchi, 2022, p. 72; Hossain and Ahamed, 2015, p. 43; San and Heng, 2013, p. 651). There are many financial ratios that can be used to assess the bank profitability performance. This study as well as previous studies focuses on using two measures of profitability indicators: return on equity (ROE) and return on assets (ROA). ROE and ROA are the most common used measures of bank profitability indicators. (Asqar, 2022, p. 141; Al Taei and Al-Shakarchi, 2022, p. 69; Hakudawal, 2021, p. 123; Al Harbi, 2019, p. 15; Perisa et al., 2017, p. 161; Hossain and Ahamed, 2015, p. 144; Lipunga, 2014, p. 41; Erina and Lace, 2013, p. 2; Akbas, 2012, p. 104).

3. METHODOLOGY AND DATA

3.1 Hypotheses development

This study examines the effect of MI adoption on enhancing the profitability indicators of banks adopting MI and listed in the Egyptian stock exchange. The following section presents the development of the main hypothesis based on the relationship between MI adoption and the profitability indicators of banks adopting MI and listed in the Egyptian stock exchange.

3.1.1 Profitability indicators: help the bank's management in the decision making process of the bank's operations, as well as maintaining the efficiency and future stability of the bank by providing the management with concrete and realistic information on a bank's financial aspects. (Al-Harbi, 2019, p. 14; Perisa et al., 2017, p. 231; Jolevski, 2017, p. 7). In particular, the value of the profitability indicators can serve as radar for any changes that may occur in the bank's investments and financing. (Hakuduwal, 2021, p. 123; Al-Harbi, 2019, p. 15; Perisa, et al., 2017, p. 231). Based on the above discussion, the following main hypothesis is proposed:

H1: There is no significant effect of MI adoption on enhancing the profitability indicators of banks adopting MI and listed in the stock exchange market.

(A) Return on equity (ROE): There are various ways to measure the bank profitability indicators. This study focuses on using two measures of profitability indicators; one of them includes return on equity (ROE). The following section presents the development of the first sub-hypothesis.

$$\text{ROE} = \frac{\text{Net income}}{\text{Average total equity}}$$

Return on equity is considered as an important measure of profitability indicators of banks. ROE is calculated as dividing net income (or net profits after tax) by average total equity. This indicator is most often shown in percentage. ROE measures bank accounting profits per dollar of book equity capital. ROE shows the efficiency of bank management in handling the shareholders' funds to generate profits. (Asqar, 2022, p. 142; Al-Taei and Al-Shakarchi, 2022, p. 73; Hakuduwal, 2021, p. 127; Hossain and Ahamed, 2015, p. 51). Higher ROE is preferable, as it implies that the management is efficient in managing the shareholders' funds and generating revenues to shareholders. Thus, the higher the value of ROE, the more profitable is the bank. This indicates into a more powerful bank that is capable of generating profits per unit of the invested capital. (Asqar, 2022, p. 142; Al Taei and Al-Shakarchi, 2022, p. 73; Hakuduwal, 2021, p. 127; Hossain and Ahamed, 2015, p. 51). Based on the above discussion, the first sub-hypothesis is proposed as follows:

H1A: There is no significant effect of MI adoption on enhancing the return on equity (ROE) of banks adopting MI and listed in the Egyptian stock exchange.

(B) Return on assets (ROA): A second alternative measure of profitability indicators of banks is return on assets (ROA). The following section presents the development of the second sub-hypothesis:

$$\text{ROA} = \frac{\text{Net income}}{\text{Average total assets}}$$

ROA is a comprehensive financial ratio that measures the profitability performance of banks. It is used as a main indicator of the bank profitability. ROA is calculated as the net income (or net profits after tax) divided by total assets. This indicator is most often shown in percentage. It indicates into the returns generated from the assets financed by the bank. (Perisa et al., 2017, p. 234; Nuhiu, 2017, p. 164; Lipunga, 2014, p. 44; San and Heng, 2013, p. 651; Akbas, 2012, p. 104). In this sense, ROA represents the efficiency of bank management in converting bank's assets into net income. Higher ROA is preferable because this means that the management is efficient in making profits by utilizing the assets, which indicates into high bank's financial performance. Thus the higher ROA, the more profitable is the bank, and vice versa. ROA is the best measure for bank profitability. This is because ROA is not distorted by high equity multipliers. ROA is also a proxy measure used to determine the bank's ability to generate income from the assets. (Asqar, 2022, p. 142; Al-Taei and Al-Shakarchi, 2022, p. 73; Hakuduwal, 2021, p. 127; Al Harbi, 2019, p. 15; Perisa et al., 2017, p. 231; Nuhiu et al., 2017, p. 161, Hossain and Ahamed 2015, p. 44; Lipunga, 2014, p. 41).

In short, ROA measures profitability from the perspective of the overall efficiency of how a bank utilizes its total assets to achieve high profits; whereas ROE measures profitability from the perspective of shareholders, i.e. the efficiency of how a bank utilizes shareholders' funds to generate profits. (Asqar, 2022, p. 142; Al-Taei and Al-Shakarchi, 2022, p. 73; Hakuduwal, 2021, p. 127; Al-Harbi, 2019, p. 15; Perisa et al., 2017, p. 231; Nuhiu et al., 2017, p. 161; Hossain and Ahamed, 2015, p. 44; Lipunga, 2014, p. 41).

Based on the above discussion, the second sub-hypothesis is proposed as follows:

H1B: There is no significant effect of MI adoption on enhancing the return on assets (ROA) of banks adopting MI and listed in the Egyptian stock exchange.

3.2 Measures

On one hand, a questionnaire tool was used to measure the research independent variable which includes the MI adoption in 12 central banks adopting MI and listed in the Egyptian stock exchange. The questionnaire was directed to people working within the information

Table 1. Operationalization of the independent variables of MI.

Variable	Operational measure	References
MI adoption	Dichotomous variable indicating 0 = No, 1 = Yes.	
• Customers	Mean of ten items on a five – point likert scale to evaluate the extent to which MI adoption helped the banks in predicting customers' behaviors & directions, analyzing customers' buying behavior, as well as determining customers' needs, interests and preferences.	Maria et al., (2020), Rao (2020), Carson et al., (2020), Al-Hashem (2020), Noviyanti et al. (2020), Al-Weshah (2017), Al-Zoubi (2016), Lymperopoulos and Chaniotakis (2005).
• Product or service	Mean of five items on a five-point likert scale to assess the extent to which MI adoption contributed to providing the banks with information about the current as well as the new banking services that can be provided to customers.	Shailza et al. (2020), Kumar (2020), Kant (2020), Azeez (2020), Inha dnd Bohlin (2018), Ade et al. (2017), Igbaekemen (2014), Ozturk et al. (2012).
• Analyzing the marketing environment	Mean of 11 items on a five-point likert scale to evaluate the extent to which MI adoption helped the banks in analyzing the marketing environment in order to identify its strengths, determine its weaknesses, exploit the available opportunities, and overcome competitors' threats.	Ismaeel and Al-Zubi (2020), Kamau and Njuguna (2020), Vishnoi et al. (2019), Inha and Bohlin (2018), Igbaekemen (2014), Faryabi (2013), Ozturk et al. (2012).
• Competitive risks	Mean of six items on a five-point likert scale to assess the extent to which MI adoption helped the banks in avoiding the risks of competitors, as well as analyzing any potential risks in the market.	Haripriya (2020), Maria et al. (2020), Rao (2020), Vishnol and Bagga (2020), Al-Hashem (2020), Kumar (2020).
• Information technology	Mean of five items on a five-point likert scale to evaluate the extent to which MI adoption helped the banks in adopting the most advanced information technologies in the marketplace, which in turn contributed to gaining a competitive advantage in technology.	Shailza (2020), Kamau and Njugungo (2020), Ismaeel and Al-Zubi (2020), Vishnoi et al. (2019), Inha and Bohlin (2018), Faryabi et al. (2013), Ozturk et al. (2012).

technology (IT) department in those 12 banks. The questionnaire consists of questions with closed – form responses using five – point likert scale. In this study, all variables of MI adoption were developed based on an extensive literature review. From the previous studies, it has been concluded that MI adoption consists of five key variables, namely: customers, product/service, analyzing the marketing environment, competitive risks, and information technology. Consequently, the independent variables included in the present study have been adopted from measurements used in previous MI studies. Operationalization of the study variables is summarized in table 1. The questionnaire was originally prepared in English and then translated into Arabic. On the other hand, the research dependent variable which includes the profitability indicators of those 12 central banks was also measured. This study focused on using two measures of profitability indicators: return on equity (ROE) and return on assets (ROA). The ROE and ROA were calculated for the period (2012 – 2021); in which ROE and ROA for a five-year period before the adoption of MI (2012–2016) were compared with their equivalent for a five-year period after the adoption of MI (2017–2021) in each of those 12 banks. Hence, the effect of MI adoption on the profitability indicators of those 12 banks can be observed. This study extracts the banks' data from their financial statements which include annual reports on the income statements and the balance sheets of those 12 banks for the period (2012 – 2021). The financial statements of those 12 banks were drawn from Egypt for Information Dissemination (EGID), found in Cairo, Egypt.

3.3 The sample and response rate

In order to maintain the privacy and confidentiality of banks, the 12 central banks listed in the Egyptian stock exchange are numbered from 1 to 12 instead of mentioning their names. The main concern of the present study is targeting the IT people working within the information technology (IT) department due to their great knowledge of MI adoption. There are nearly 40 people working within the IT department in each of those 12 banks. Based on the research population which consists of 480 people, the research sample size consists of 224 people which represent the minimum sample size. The simple random sampling technique was the most suitable one for this research. The questionnaire was distributed to 320 people working within the information technology (IT) department in the 12 central banks adopting MI and listed in the Egyptian stock exchange. 80 questionnaires were excluded and removed from the sample for being largely incomplete, and only 240 out of 320 were collected. The remaining 240 usable questionnaires reflected an acceptable response rate of 75%, which was considered highly reasonable with regard to MI adoption studies.

4. DATA ANALYSIS AND RESULTS

4.1 Validity and reliability

To measure the validity and reliability of the constructs of the questionnaire instrument, several procedures were followed. Firstly, an exhaustive literature review was carried out to identify the constructs and items that were used in the previous studies related to MI adoption. Secondly, a wide range of items were selected and refined to express the measures that are included in the present study. Thirdly, an initial version of the questionnaire was prepared in English, and then translated into Arabic. Finally, a pilot study was conducted through directing the questionnaire to 25 IT staff working in different banks operating in Egypt. Relaying on their comments and recommendations, some questions and items was deleted and modified to ensure that the questionnaire reflects the investigated concepts, as well as to improve the clarity and relevance of the questionnaire. For the purpose of assessing the reliability of the questionnaire, cronbach's α was computed to evaluate the internal consistency of the five variables of MI, which is the independent variable used in the present study. The results presented in Table 2 indicate that the alpha values reflect good significant reliability of questions, as it ranges between 0.526 and 0.657, with P-value < 0.001. Therefore, the study independent variables reflect a sufficient and satisfied degree of reliability.

Table 2. Cronbach's α Coefficients.

Variable	Cronbach's alpha	P-value
Customers	0.526	<0.001
Product/service	0.608	<0.001
Analyzing the marketing environment	0.612	<0.001
Competitive risks	0.645	<0.001
Information technology	0.657	<0.001

4.2 Descriptive statistics of the independent variables

The independent variable of the study is represented by MI adoption which consists of five independent variables namely; customers, product, analyzing the marketing environment, competitive risks, and information technology. As shown in Table 3, the mean values of all variables are ranged between 3.67 and 4.89, indicating that the respondents tend to agree or strongly agree to most of the statements that measure these variables. Table 3 reveals that the variable with the highest agreement and minimum variation (S.D. = 0.12) is the information technology. While the variable with the least agreement and maximum variation (S.D. = 0.35) is the competitive risks.

Besides, a comparison was conducted between the 12 central banks listed in the Egyptian stock exchange, in order to determine the differences among the 12 banks in terms of the efficiency of adopting MI within each bank. The comparison is based on the 5 main variables of MI; namely customers, product/service, analyzing the marketing environment, competitive risks, and information technology. The results of comparison are summarized in Table 4. As illustrated in Table 4; the results indicate that all the 12 central banks have adopted the MI. However, Bank 3, 8, 11, and 4 respectively come first, which indicates that those banks have adopted the MI in the most efficient way. While bank 12, 1, 5, 7, 9, 2 and 10 respectively come later, which indicates that those banks have adopted the MI less efficiently than the first group of banks. Finally, Bank 6 comes lastly, which indicates that it is has adopted the MI in the least efficient way. Table 4 also reveals the differences between the 5 main variables of MI adoption for each bank. In general, the information technology variable (97.85%) the most important variable in the MI adoption, followed by product/service (90.60%), followed by customers (87.70%), followed by analyzing the marketing

Table 3. Descriptive statistics of the independent variables.

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Customers	214	3.70	4.80	4.3766	0.24034
Product/service	214	4.20	5.00	4.5234	0.14410
Analyzing the marketing environment	214	3.73	4.73	4.2260	0.19415
Competitive risks	214	3.00	4.83	3.6721	0.35434
Information technology	214	4.60	5.00	4.8925	0.12349

Table 4. Comparison among 12 banks based on the 5 variables of MI.

	MI variables					
Bank number	**Customers**	**Product or service**	**Analyzing the marketing environment**	**Competitive risks**	**Information Technology**	**Total**
1	83.47%	88.84%	85.26%	79.65%	96.84%	**86.81%**
2	85.64%	90.18%	85.45%	75.15%	95.45%	**86.38%**
3	84.90%	90.60%	87.64%	78.67%	97.80%	**87.92%**
4	87.22%	89.56%	85.56%	75.37%	98.00%	**87.14%**
5	86.90%	91.80%	84.64%	72.50%	97.60%	**86.69%**
6	89.05%	91.24%	79.65%	70.79%	97.14%	**85.58%**
7	88.82%	90.82%	84.17%	68.63%	99.76%	**86.44%**
8	89.44%	90.22%	82.93%	79.44%	97.33%	**87.87%**
9	88.96%	90.56%	85.82%	67.47%	99.20%	**86.40%**
10	88.91%	90.18%	83.80%	68.33%	100.00%	**86.25%**
11	90.20%	90.60%	87.00%	71.33%	97.20%	**87.27%**
12	88.78%	92.67%	86.36%	69.26%	97.78%	**86.97%**
Total	**87.70%**	**90.60%**	**84.86%**	**72.89%**	**97.85%**	**86.78%**

environment (84.86%),and finally the competitive risks (72.89%). The results in Table 4 have concluded that: Based on the information technology variable; Bank 10 is the best bank that has the ability to use information technology (100.00%). However, the worst bank is bank 2 (95.45%). While, based on product/service variable; Bank 12 (92.67%) is the best bank that provides products/services. However the worst product/service is provided by bank 1 (88.84%). Moreover, based on customer variable; bank 11 (90.20%) is the most efficient bank in dealing with customers. However, the worst bank is bank 1 (83.47%). Furthermore, based on analyzing the marketing environment variable; bank 3 (87.64%) is the best bank. However, bank 6 (79.65%) is the worst bank. Finally, based on the competitive risks variable; bank 1 (79.65%) is the best bank in avoiding the competitive risks. However, bank 10 (68.33%) is the worst bank.

A comparison between the 12 central banks adopting MI and listed in the Egyptian stock exchange is illustrated in a bar chart, as shown in figure 2. The results in figure 2 reveal the differences among those 12 banks in terms of the efficiency of adopting MI.

4.3 Descriptive statistics of the dependent variable

The dependent variable of the study represents the profitability indicators of 12 central banks adopting MI and listed in the Egyptian stock exchange. This study focuses on using 2 measures of profitability indicators: return on equity (ROE) and return on assets (ROA). As shown in

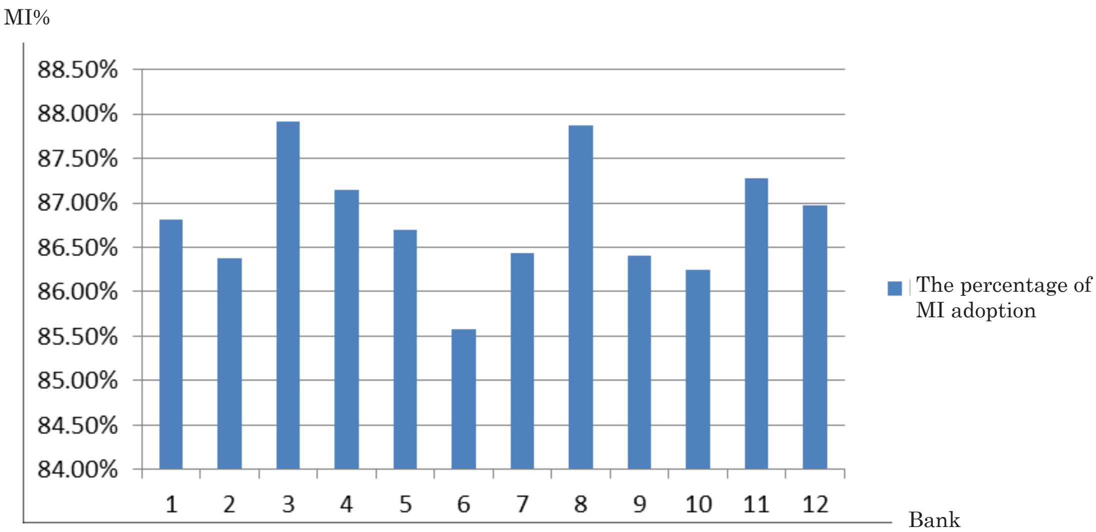

Figure 2. A comparison between 12 central banks in terms of the efficiency of adoptin MI.

Table 5. Descriptive statistics of the dependent variables and goodness of fit for normal distribution.

	Before		After	
	ROE	**ROA**	**ROE**	**ROA**
Mean	0.015983	0.1538	0.030067	0.2889
Median	0.0155	0.156	0.03	0.2835
Maximum	0.028	0.221	0.047	0.399
Minimum	0.007	0.049	0.016	0.185
Std. Dev	0.006108	0.034597	0.006257	0.058848
Coef. Var	38.2156	22.4948	20.81019	20.36968
Skewness	0.216123	-0.498	0.073132	0.001873
Kurtosis	1.770913	3.370287	3.032453	2.040236
Jarque-Bera	4.243727	2.822827	0.056116	2.302901
Probability	0.119808	0.243798	0.972332	0.316178

Source: The researcher relied on EViews8 Output.

Table 5, the results indicate that all dependent variables whether before or after the adoption of MI, reveal small data distraction due to their coefficient variation which is less than 100%, whereby the standard deviation of this variation is less than the mean. Table 5 also shows the mean values of the first profitability indicator (ROE) that was 0.015983 before MI adoption. While, after MI adoption, the mean values of ROE raised to 0.030067, with a percentage of increase equals to 88%. Similarly, the mean values of the second profitability indicator (ROA) was 0.1538 before MI adoption, and raised to 0.2889 after MI adoption, with a percentage of increase equals to 88% as well. Moreover, the mean values of ROE and ROA are very close to median values, which indicate that the distribution of these variables is symmetrical. In addition to Skewness values which confirm that the emerging results as well as all coefficient values are very close to zero. Also, the minimum and maximum values of ROE and ROA are positive values, which indicate that all ratios, whether before or after MI adoption, express profitability ratios. Furthermore, the results in Table 5 indicate that all Jarque-Bera statistical values are less than the tabulated chi-square (with its value = 5.99); which means that all dependent variables follow normal distribution. This result is in compliance with the sig values (p-value > 5%).

Furthermore, the normal (P–P) and (Q–Q) plots were conducted, and reveal that all data points are near or on the straight reference line, indicating that both ROE and ROA are normally distributed. Moreover, the effect of MI adoption on ROE and ROA of 12 central banks adopting MI and listed in the Egyptian stock exchange is illustrated in (figures 3, 4, 5 and 6). As shown below; figures 3 and 4 show the effect of MI on ROE, while figures 5 and 6 show the effect of MI on ROA. The ROE and ROA of 12 central banks for a five-year period before the adoption of MI (2012–2016) were compared with their equivalent for a five-year period after the adoption of MI (2017–2021). All figures reflect the high efficiency of adopting MI, and its effect was clearly observed on enhancing the ROE and ROA of the 12 banks after adopting the MI.

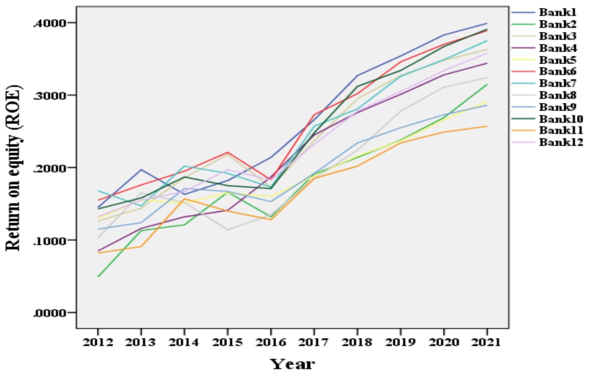

Figure 3.

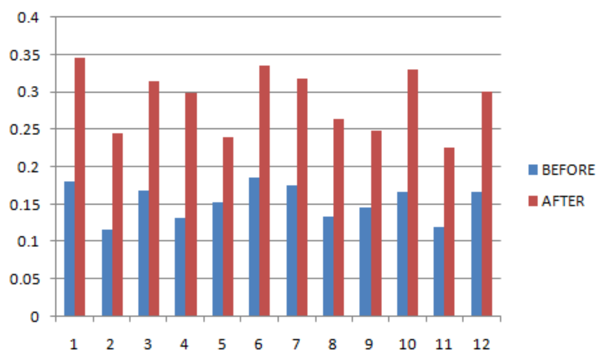

Figure 4.

The effect of MI adoption on ROE.

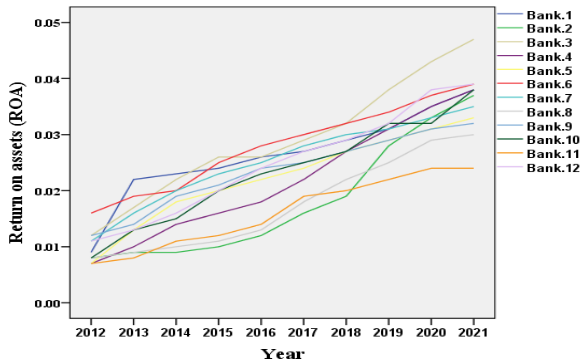

Figure 5.

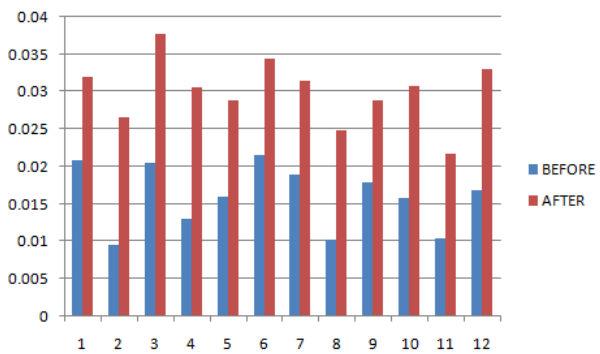

Figure 6.

The effect of MI adoption on ROA.

4.4 Correlation analysis

The correlation analysis of the variables of the study was conducted using Pearson correlation coefficient in order to examine the relation between MI and profitability indicators (ROE and ROA). The results of the correlation analysis are summarized in Table 6. The results in Table 6 show that; with 99% confidence level, there is a significant strong positive correlation between ROE and MI adoption, since the value of Pearson correlation coefficient is 0.816 with P-value < 0.001, and the strong positive correlation ranges between (0.7 and 1). Table 6 also reveals; with 99% confidence level, there is a strong positive correlation between ROA and MI adoption, since the value of Pearson correlation coefficient is 0.754 with P-value < 0.001.

Table 6. Pearson correlation coefficient between variables.

Variable	MI	
	Pearson correlation coefficient	P-value
ROE	0.816	< 0.001
ROA	0.754	< 0.001

4.5 Regression analysis

This study aims to examine the effect of MI adoption on enhancing the profitability indicators (ROE and ROA) of 12 central banks adopting MI and listed in the Egyptian stock exchange. Therefore, the simple linear regression model was used to test the two research sub-hypotheses. The independent variable (MI) will be expressed as dummy variable that takes the value 0 before the adoption, and takes the value 1 after the adoption. The following simple linear models were estimated as follows:

Reg.1: $ROEij = \beta 01 + \beta 11MIij + \varepsilon 1ij$ i = 1,2, …., 120. j = 1, 2, …, 10
Reg.2: $ROAij = \beta 02 + \beta 12MIij + \varepsilon 2ij$ i = 1,2, …., 120. j = 1, 2, …, 10

Where
ROEij: denotes the ith observed value of ROE within bank j.
ROAij: denotes the ith observed value of ROA within bank j.
MIij: denotes the ith observed value of MI within bank j.
$\beta 01$, $\beta 02$: refer to the intercept terms of Reg.1 and Reg.2 respectively.
$\varepsilon 1ij$: $\varepsilon 2ij$: denote the residual error terms of Reg.1 and Reg.2 respectively

4.5.1 The analysis of Reg. 1

The main aim of the present study is to examine the effect of MI adoption on enhancing the return on equity (ROE) of 12 central banks adopting MI and listed in the Egyptian stock exchange. The results of ANOVA are summarized in Table 7. As shown in Table 7, the results of ANOVA indicate that there is a significant effect of MI adoption on enhancing the ROE of 12 banks adopting MI and listed in the Egyptian stock exchange, since F-statistic is 234.998 with P-value < 0.001. Also, based on the value of adjusted R2 (0.663), this indicates

Table 7. ANOVA table of MI on ROE.

Model	Sum of Squares	df	Mean Square	F	p-value
Regression	0.548	1	0.548	234.998	< 0.001
Residual	0.275	118	0.002		
Total	**0.823**	**119**			

$R^2 = 0.666$
Adjusted $R^2 = 0.663$

Table 8. Regression coefficients.

	Coefficient	Std. Error	T	p-value	95% Confidence interval		Durbin Watson DW
					Lower limit	Upper limit	
Constant	0.154	0.006	24.680	< 0.001	0.141	0.166	1.817
MI	0.135	0.009	15.330	< 0.001	0.118	0.153	

Based on the above discussion, the first sub-hypothesis is rejected.

Table 9. ANOVA table of MI on ROA.

Model	Sum of Squares	df	Mean Square	F	p-value
Regression	0.006	1	0.006	155.657	<0.001
Residual	0.005	118	0.000		
Total	**0.010**	**119**			

$R^2 = 0.569$
Adjusted $R^2 = 0.565$

Table 10. Regression coefficients.

	Coefficient	Std.Error	T	p-value	95% Confidence interval		Durbin Watson DW
					Lower limit	Upper limit	
Constant	0.061	0.001	20.024	<0.001	0.014	0.018	1.901
MI	0.014	0.001	12.476	<0.001	0.012	0.016	

Based on the above discussion, the second sub-hypothesis is rejected.

that MI could infer 66.3% from the total variation of ROE.

In order to estimate the parameters of Reg. 1, the ordinary least square estimation method (OLS) was used, which is a parametric estimation method. Table 8 summarizes the regression coefficients. The results of Table 8 indicate that there is a positive relation between MI and ROE, and any change in the independent variable (MI) from 0 to 1 will lead to an increase of 0.135 in the predicted value of the ROE. Moreover, there is a significant effect of MI on ROE of 12 central banks adopting MI and listed in the Egyptian stock exchange, since (t-statistic = 15.33) with p-value < 0.001 and confidence interval (0.118, 0.153). Furthermore, the value of Durbin Watson (1.817) indicates that there is no serial autocorrelation problem, as the value is near to 2.

4.5.2 The analysis of Reg. 2

Similarly, the same analysis of the previous sub-section was conducted in order to examine the effect of MI adoption on enhancing the return on assets (ROA) of the 12 central banks adopting MI and listed in the Egyptian stock exchange. The results of ANOVA are summarized in Table 9. As illustrated in Table 9, the results of ANOVA indicate that there is a significant effect of MI adoption on enhancing the ROA of 12 central banks adopting MI and listed in the Egyptian stock exchange, since, F-statistic is 155.657 with P-value < 0.001. Also, based on the value of adjusted R2 (0.565), this indicates that MI could infer 56.6% from the total variation of ROA.

Table 10 summarizes the regression coefficients. The results in Table 10 indicate that there is a positive relation between MI and ROA, and any change in the independent variable (MI) from 0 to 1 will lead to an increase of 0.014 in the predicted value of the ROA. Moreover, there is a significant effect of MI on ROA of 12 central banks adopting MI and listed in the Egyptian stock exchange, since (t-statistic = 12.476) with p-value < 0.001 and confidence interval (0.012, 0.016). Furthermore, the value of Durbin Watson (1.901) indicates that there is no serial autocorrelation problem, as the value is near to 2.

According to all previous statistical analysis results, it can be concluded that the main hypothesis is rejected.

5. DISCUSSION

The present study contributes to the existing literature of MI adoption and its effect on enhancing the profitability indicators of 12 central banks adopting MI and listed in the Egyptian stock exchange; as the study explores a new domain (Egypt), and thereby filling a market gap. Since 2017, the adoption of MI has emerged as a modern marketing system in most of banks operating in Egypt. In this context, the present study aims to examine the effect of MI adoption on enhancing the profitability indicators of 12 central banks adopting MI and listed in the Egyptian stock exchange. The results of the study indicated a strong positive relationship between MI adoption and the profitability indicators of these 12 central banks. Moreover, the study provided empirical evidence that the MI adoption had a significant effect on enhancing the profitability indicators of those 12 banks. According to these results, the main hypothesis (H1) was rejected. This result may be explained by two facts: Firstly; MI adoption had a significant effect on enhancing the first profitability indicator (ROE) of those 12 central banks. As a result, the first sub-hypothesis H1A was rejected. This result was consistent with the findings of previous studies(e.g. Haripriya, 2020; Roa, 2020; Carson et al., 2020; Ismaeel and Al-Zubi, 2020, Kamau and Njuguna, 2020; Al-Hashem, 2020; Bohlin, 2018; Faryabi et al., 2013; Ozturk et al., 2012; Chaniotakis, 2005). Secondly; MI adoption had a significant effect on enhancing the second profitability indicator (ROA) of those 12 central banks. As a result, the second sub-hypothesis H1B was rejected. This result is consistent with the findings of these previous studies (Carson et al., 2020; Ismaeel and Al-Zubi, 2020, Noviyanti et al., 2020; Al-Weshah, 2017; Al-Zoubi, 2016; Igbaekemen, 2014; Faryabi et al., 2013). Despite the 12 central banks had adopted the MI, there were some differences between those banks in terms of the efficiency of adopting the MI. A detailed analysis of the five variables of MI adoption was conducted. The results revealed that the information technology variable was found to be the most variable to enhancing the profitability indicators of those 12 central banks. This result supports the findings of the previous studies (e.g.: Shailza, 2020; Kamau and Njugungo, 2020; Ismaeel and Al-Zubi, 2020; Vishnoi et al., 2019; Inha and Bohlin, 2018, Faryaabi et al., 2013, Ozturk et al., 2012. The following variable to enhancing the profitability indicators of those 12 central banks was product/service. This was asserted by a great body of literature review (e.g.: Shailza et al., 2020; Kumar, 2020; Kant, 2020, Azeez, 2020, Inha and Bohlin, 2018; Ade et al., 2017, Igbaekemen, 2014; Ozturk et al., 2012). A third following variable to enhancing the profitability indicators of those 12 central banks was the customers variable. This result is in line with several previous studies (e.g.: Maria et al., 2020; Raq, 2020; Carson et al., 2020; Al-Hashem, 2020; Noviyanti et al., 2020; Al-Weshah, 2017; Al-Zoubi,2016; Lymperopoulos and Chaniotakis, 2005. A fourth variable to enhancing the profitability indicators of the 12 central banks was analyzing the marketing environment. This supports the research results of other previous studies (e.g.: Ismaeel and Al-Zuibi, 2020; Kamau and Njugunge, 2020; Vishno; et al., 2019; Inha and Bohlin, 2018; Igbaekemen, 2014. Faryabi, 2013; Ozturk et al., 2012). The last fifth variable to enhancing the profitability indicators of the 12 central banks was the competitive risks. This results was consistent with previous studies such as (Haripriya, 2020, Maria et al., 2020; Vishnoi and Bagga, 2020; Al-Hashem, 2020; Kumar, 2020. From the previous discussion, it can be concluded that there are some banks that had adopted the MI more efficiently than others. As a result, the 12 central banks were ranked in terms of the efficiency of adopting MI. The results indicated that Bank 3, 8, 11, and 4 respectively come first, as those banks had adopted the MI in the most efficient way. While bank 12, 1, 5, 7, 9, 2 and 10 respectively come later due to adopting the MI less efficiently than the first group of banks. Finally, Bank 6 comes lastly, as it had adopted the MI in the least efficient way.

6. CONCLUSION

Currently, the Egyptian banking sector witnesses severe competitive pressure within the financial service market. Accordingly, the vast majority of banks are urged to adopt MI due its effect on improving operational efficiency and effectiveness, gaining competitive advantage, increasing sales revenues, maximizing profitability, as well as achieving growth and survival in the marketplace. This highlights the significance of the present study through examining the effect of MI adoption on enhancing the profitability indicators of 12 central banks adopting MI and listed in the Egyptian stock exchange. The results showed the significant effect of MI adoption on enhancing the profitability indicators (ROE, ROA) of those banks. This result is largely in accordance with the findings of previous studies related to MI adoption in different countries and contexts. This study contributes to both knowledge and practice fields of MI adoption. Regarding knowledge, little research work has been carried out regarding MI adoption in the service sector and particularly within the Egyptian context. Hence the present study contributes to filling this research gab concerning MI adoption within the banks listed in the Egyptian stock exchange. As for practice, marketing managers need to move theory into practice and gain better understanding of MI adoption process. In this context, the study provides guidelines for marketing managers to focus their attention on the five main variables that constitute and support the adoption of MI within any sector. These include: customers, product or service, analyzing the marketing environment, competitive risks, and information technology.

7. LIMITATIONS AND IMPLICATIONS FOR FUTURE RESEARCH

The research on which this study is based, like much social science research, is affected by several limitations. First, data were collected from self – reports, which may produce bias. Second, this study has been conducted in one country (Egypt). Moreover, the study focuses on one service sector (banking sector: only 12 central banks listed in the Egyptian stock exchange). Third, the present study aims to examine the effect of MI adoption on enhancing only 2 measures of the profitability indicators (ROE, ROA) of banks. Hence, the generalizability of findings needs more examination. In order to enhance the generalizability of the study findings, future researches need to be carried out on many other dimensions such as bank performance including sales revenues, market share, and competitive advantage.

The findings of the present study have several managerial implications for practice. For successful MI adoption, marketing managers need to understand the main requirements of adopting MI. The following managerial implications are suggested: First, top management commitment, support, and belief in the importance of adopting MI within banks. Second, using the latest up-to-date information technology which is considered to be the backbone of MI adoption. Third, MI adoption requires a strong financial position, as it is a long-term investment project which is very costly. Fourth, conducting effective training programs for all bank members especially IT staff, on a regular basis. Fifth, providing rewards and incentives in order to encourage and motivate the talent members for their devoted efforts. Sixth, building cross-functional team-works that are highly skilled, experienced, competent, and credible enough to be able to use MI efficiently.

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Does more intelligent trading strategy win? Interacting trading strategies: an agent-based approach

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ABSTRACT: An artificial financial market is built on the top of Genoa Artificial Stock Market. The market is populated with agents having different trading strategies and they are let to interact with each other. Agents differ in the trading method they use to trade, and they are grouped as noise, technical, statistical analysis, and machine learning traders. The model is validated by replication of stylized fact in financial asset returns. We were able to replicate leptokurtic shape of probability density function, volatility clustering and absence of autocorrelation in asset returns. The wealth dynamics for each agent group is analysed throughout trading period. Agents with a higher time complexity trading strategy outperform those with strategy comparing their final wealth.

KEYWORDS: Agent based model, Multi-Agent Financial Market, ARIMA, Machine Learning

1. INTRODUCTION

The World Bank statistics reveal that the market capitalisation of all listed companies on stock exchanges in the world reaches a total of 94 trillion US dollars in 2020.[1] There have broad range of studies aiming to explain dynamics of asset prices and model this complicated financial market structures. However, the capital market theory for asset pricing and the efficient market hypothesis (EMH) assumption were the most common approaches used. These approaches assume that prices are efficiently valued, and individuals are homogenous and rational. However, these assumptions have been challenged by both empirical data findings and complexity of the system. Therefore, alternative approaches have been introduced, Kahneman and Tversky (1979) proposed the prospect theory as a part of behavioural finance that describes how traders irrationally assess gain and losses asymmetrically. Cont (2001) also present a set of stylized facts of financial time series that cannot be explained by these traditional approaches. In this sense, agent-based models (ABMs) are introduced as a "paradigm shift" with more realistic assumptions as boundedly rational agents with heterogenous expectations. ABMs offer benefits over the traditional approaches such as emergent behaviour of system as result of interaction among system entities. Therefore,

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ABMs draw a wide attention and Jean-Claude Trichet, the former ECB president, writes that "We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents".[4]

An ABM is a simulation to model a system consisting of interacting agents. Agents can have static or adaptive rules to initiate their interactions with other agents and environment. It has great importance in terms of providing bottom-up understanding of systems. However, it is very complicated to analytically model the interactions among market entities and agents can also apply range of sophisticated learning capabilities especially when continuous adaptation exists.[5] In financial market perspective, traditional models fall short to explain the behaviour of market through extreme situations during financial crisis[6,7] since there is no such classical approach to capture behaviour of crashing markets. In this sense, ABMs can capture such extreme moves when built with necessary components and optimal parameter calibrations.

Simulating stock markets has been growing field, many models are proposed focusing on market mechanism, wealth dynamics and price dynamics.[9,10,11,12] The seminal paper of the Santa Fe Institute[13] was pioneering work in this field alongside with several other financial market models: Genoa Artificial Stock Market.[14,15,16] These models are differing in the way they set the market microstructure, agents trading strategies, network among agents and intelligence level in agents. A review of ABMs and its simulations in financial markets could be found in the literature.[9,17,18,19] The main studies in this field propose that developing ABM requires a proper design and four main design elements are needed: market mechanism, trading strategies, traded assets and trader types. The built model is subject to be validated by measures of modelled market.

The validation is the key part of ABMs since it ensures the appropriateness of the simulation for the modelled system. The success of a financial market model is measured by the ability of reproducing stylized facts observed in the real market.[3] Another approach for validation is to use modelled market parameters.[20,21,22] Llacay and Peffer (2018) use face validation differing from the mainstream. The stylized facts in financial markets are used for validation in literature and they are *absence of linear autocorrelation*[23]; *heavy tails*; *volatility clustering*[24,25]; *volume/volatility correlation*[3]; *aggregational Gaussianity*. There is no simulation model can reproduce all known facts due to increasing complexity of model, hence models are kept simple in compliance to Ockham's razor principle which asserts to use minimal entity for explanations.

The trading strategies agents employ play a significant role in building a financial market simulation model.[17] These strategies can range from zero-intelligent agents[26] to very intelligent agents compared to earlier studies.[27] In a recent study, Llacay and Peffer (2018) used agents with realistic trading strategies that takes historical price into account. The method used to take trade action mainly relies on future price forecast which can be any method, for example, evolutionary techniques such as genetic programming and artificial neural networks. Agents can also employ social learning method where agents observe other traders and change their strategy accordingly.[9,28] However, this may lead a herding behaviour in the market in line with Hott (2009) study which shows the herding behaviour as a reason for bubbles in financial markets.

Considering main components of agent-based models for financial markets, trading methods are main agent diversifying component in the model. In this sense, considering existing studies, there are a few studies that takes realistic agent trading strategies since the earlier studies mainly employ agents with zero-intelligent and agents using fundamental value and genetic algorithms. In this study, we aim to fill this gap by including agents using more realistic technical and fundamental trading strategies as well as machine learning approaches. The methods our agents use have been studied in the literature for price prediction. For example, Ariyo et al. (2014) used Autoregressive Integrated Moving Average (ARIMA) and Nelson et al. (2017) used Long Short-Term Memory (LSTM) as predicting method. On the other hand, Llacay and Peffer (2018) applied some realistic technical trading tools in their agent-based model. However, the most of prediction methods use historical data and do back testing to measure the success of the model. Hence, they ignore the used method interaction with market environment, and this assumes no price impact in the market. Considering this fact, we equipped our agents with realistic trading strategies and let them to interact with all market entities. With this, the agent's market effect is considered, and the model provides an insight into wealth dynamics of interacting agents. The model provides a realistic testbed for assessing financial market hyper-parameters such as price tick size.

We extend the GASM model by adding interacting intelligent agents and analyse market dynamics and wealth dynamics. We aim to make four main contributions to the agent-based financial market modelling literature by: (1) reproduction and validation of the GASM model results; (2) use of more realistic trading strategies which are commonly used by practitioners (3) we analyse wealth dynamics of agent types hence, the effect of intelligence level on wealth return; (4) showing the catalyser role of noise traders in the market.

The rest of the paper is structured as follow: Section 2 presents our simulation model. In Section 4, simulation results are given. Section 5 discuss our findings and Section 6 concludes the study.

2. PROPOSED MODEL

The artificial financial market has similar microstructure with GASM model, for a detailed description of the model structure.[40] The herding behaviour phenomena is modelled different from GASM model. Agents form a cluster with given probabilities and the final cluster is activated with a given probability that all agents belong to the cluster are either seller or buyer.

2.1 Trader Types

Traders are engaged to buy and sell financial assets in financial markets for themselves or on behalf of another parties. Traders vary in perceiving the market, they therefore employ different strategies for trading. At this point, the market theories come into account and help traders to see different beliefs about these complex systems. There are several studies give evidence to either for or against EMH. For example, Fama (1965) finds that historical prices cannot predict the future prices while Brock et al. (1992) and Kwon and Kish (2002) evidence that technical trading rules can beat buy-and-hold strategy for DJIA, FT30 and NYSE stock markets, respectively. In addition to this, statistical methods such as ARIMA[30] and LSTM[31] are used to predict future stock price for trading. In this sense, an environment with different types of agents reflects the heterogeneity of traders in real market. The literature in testing trading methods usually take a strategy as a baseline and do back testing to compare performances. Therefore, agent-based approach fills this gap partially although it is not possible to mimic the entire complex real market dynamics.

In the light given facts, the artificial stock market is populated with six types of agents who are named as the method they are equipped with: Noise, Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Bollinger Bands, ARIMA and LSTM. Agents will be named with the method they use in the rest of this paper. For all agents, the amount of assets (cash) to be traded is random fraction of assets(cash) and the limit price is a draw from a interval that is attached to historical volatility. Agents rely on their signal function when taking trading decision.

The noise traders have a great importance in keeping the market working since they act as a catalyser in the market and supply volume for intelligent traders.[8,35] *The RSI* is considered as a momentum indicator that gives signal of overbought or oversold. The method is developed by Wilder (1978) and the RSI value range from 0 to 100 and the RSI value is regarded as overbought if it is above 70 while it is oversold when it is below 30. *The MACD* is a technical trader tool developed by Gerald Appel in late 1970s. It is mainly based on exponential moving average (EMA) which is a type of moving average that takes the more recent data points the greater weight. *The Bollinger Bands* is a technical trader tool developed by John Bollinger in 1980s. It is volatility measure indicator that relies on the past price of asset and its volatility. The agents using $ARMA(p, q)$ as defined as in Tsay (2005), the multiple steps forecast with ARMA model is computed recursively. The ARIMA model use integrated data by differencing the raw data to meet the time series stationary. The ARIMA traders checks stationarity of stock price and do differencing till obtain a stationary series. The traders estimate ARIMA models with different lags to find optimal p and q values. They finally select the model with minimum Akaike information criterion (AIC). The forecast price values are predicted and that is fed into a decision-making process. *The LSTM* is recurrent neural network architecture developed by Hochreiter and Schmidhuber (1997). It is a machine learning method with deep networks and differs from feedforward neural networks with feedback connections since it can process sequences of data. The LSTM is widely used in predicting stock price movement and outperform baseline approaches.[31,39] The LSTM traders use simulation initialisation period stock price return to predict following 5-periods return so post orders accordingly.

3. MARKET INITIALISATION

At the beginning of simulation, the stock price p_0 is set to be \$100. The wealth is equally distributed among agents, each get 1000 stock (inventory) and \$100000 cash. The hyperparameters for market is set before simulation run as in Table 1.

There are total of 550 agent population of which 500 noise traders and 10 for each of RSI, MACD, Bollinger, ARIMA and LSTM traders. The tick size for asset price is one cent. Marchesi et al. (2003) extended the GASM model by populating the market with four different agents. Like this study, the most of agents are noise traders that enables the order matching mechanism working. The simulation time steps refer a trading day and simulation is consist of 5040 days which is approximately 20-year trading period since a year has average 252 trading days (Fig. 1).

Agents are in a partially observable environment since they only can access asset price. Agent types use technical trading indicators, statistical model for time series, and a machine learning, deep learning. All intelligent agents are reflective agents, rule-initiated, since they rely on signals for the forecast period. The stock market is closed form since there is no cash inflow.

The total wealth of agent i^{th} agent at time step t can be calculated as $w_i = c_i^t + a_i^t * p_t$, where c_i^t and a_i^t are the cash amount and assets of i^{th} agent at time step t and p_t asset price. The calculation of traders' final wealth is likewise. The wealth of a trader changes throughout simulation as a result of their interactions. The actions within market environment are based on the strategy trader employ to take buy or sell action. Building these strategies rely on the parameters that emulate realistic trading strategies, which is given in Table 2.

Table 1. Market initial parameters.

Market Parameters	Value	Description
N	550	Total number of agents
T	5240	Simulation time steps
PAC	0.001	Probability that agents create a cluster
PCA	0.002	Probability that cluster is activated
BP	0.5	Buy probability of noise traders
SMu	1.01	Mean of sell limit orders
SSK	4.5	Sell sigma K
BMu	1.01	Mean of buy limit orders
BSK	4.5	Buy sigma K
Agent Population	[500, 10, 10, 10, 10, 10]	Vector of agent population [Noise, RSI, MACD, Bollinger, ARIMA, LSTM]

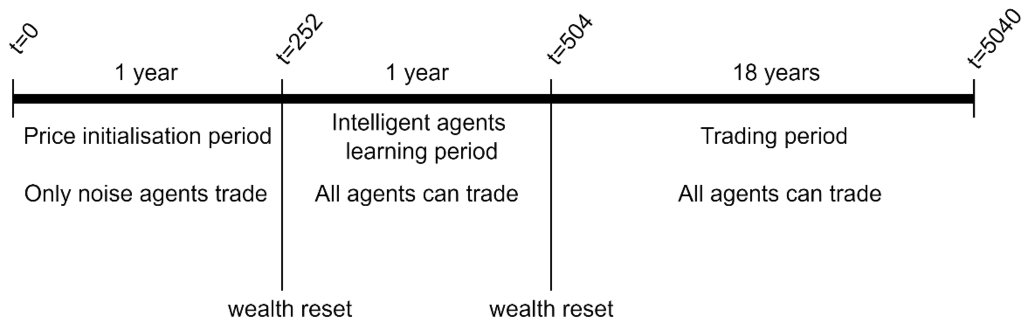

Figure 1. The artificial stock market periods.

Table 2. Agent initial parameters.

Agent Type	Parameters	Values	Description
Noise	$[p_i]$	[0,5]	Buy probability
RSI	$[n_{r1}, v_l, v_u]$	[14, 30, 70]	Periods of RSI, buy signal threshold, sell signal threshold
MACD	$[n_{m1}, n_{m2}, n_{m3}, \alpha]$	[12, 26, 9, 2/(n+1)	EMA(p), EMA(p), EMA(MACD) periods and smoothing constant
Bollinger	$[n_b, k_b]$	[20, 2]	Periods and constant k
ARIMA	$[p, d, q]$	[[1], [0,1], [1]]	p, d, q are lag order of AR, degree of differencing and MA window size, respectively. p, q take an integer value 1 and 2, depending on model selection AIC criteria. d is mainly 0 or 1.
LSTM	[HiddenLayer, Optimiser, Epochs, LearningRate]	[20, “adam”, 50, 1, 0.005]	HiddenLayer is the number of layers in between input and output layers. “Adam” is an optimiser for training deep neural networks. Epochs is the number of learning algorithm works through the training set. LearningRate is the step size of gradient descent on finding minimum of loss function.

2. SIMULATION MODEL AND RESULTS

In this section, the extended GASM model is simulated, and the result of the experiments are presented. We first let only noise traders to trade in the market for a given initialisation period hence, initial stock price is generated. The market then is populated with five more different traders who are called “intelligent” agents since those agents predict future price move. The market behaviour emerges under agent interactions.

The simulation is run with 500 noise traders and 10 intelligent traders for each method. Since the amount of asset to trade is a random friction of agent’s wealth, having 10 agents for each method will decrease the effect of randomness on average. Several simulations with same parameters were run and all give similar outputs. Therefore, results here are a representative simulation model for those series of simulation. The flow of simulation model is given in Fig. 2.

The model keeps the GASM main structure, however, some parameters are tuned after several experiments and intelligent agents are added to the market. The population share of traders in the market are determined with experiments. A market with more than 10% of intelligent agent population leads stock

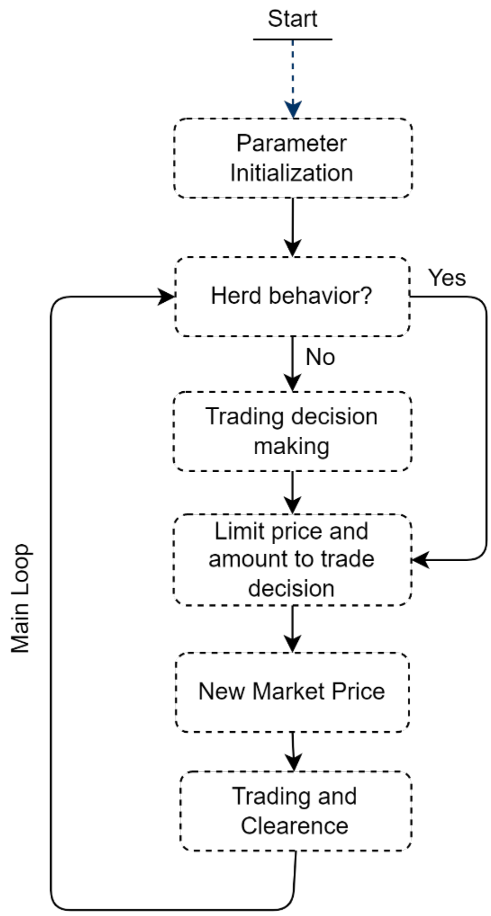

Figure 2. Stock Market Simulation Loop Structure.

Table 3. Agent decision estimation window and decision making.

Traders	Estimation Period (day(s))	Forecast Period (day(s))	Buy Rule (If …)	Sell Rule (If …)
Noise	-	-	$a > 0.5$, $where\ a \in U(0,1)$	$a < 0.5$, $where\ a \in U(0,1)$
RSI	14	1	$RSI < 30$	$RSI > 70$
MACD	9, 12, 26	1	$\Delta_t * \Delta_{t-1} < 0$ & $\Delta_t > 0$	$\Delta_t * \Delta_{t-1} < 0$ & $\Delta_t < 0$
Bollinger Bands	20	1	$p_t > SMA_{t,20}(pp) + 2 \cdot \sigma_p$	$p_t > SMA_{t,20}(pp) - 2 \cdot \sigma_p$
ARIMA	t	5	$\hat{p}_{t+1} > p_t$	$\hat{p}_{t+1} > p_t$
LSTM	t	5	$\hat{p}_{t+1} > p_t$	$\hat{p}_{t+1} > p_t$

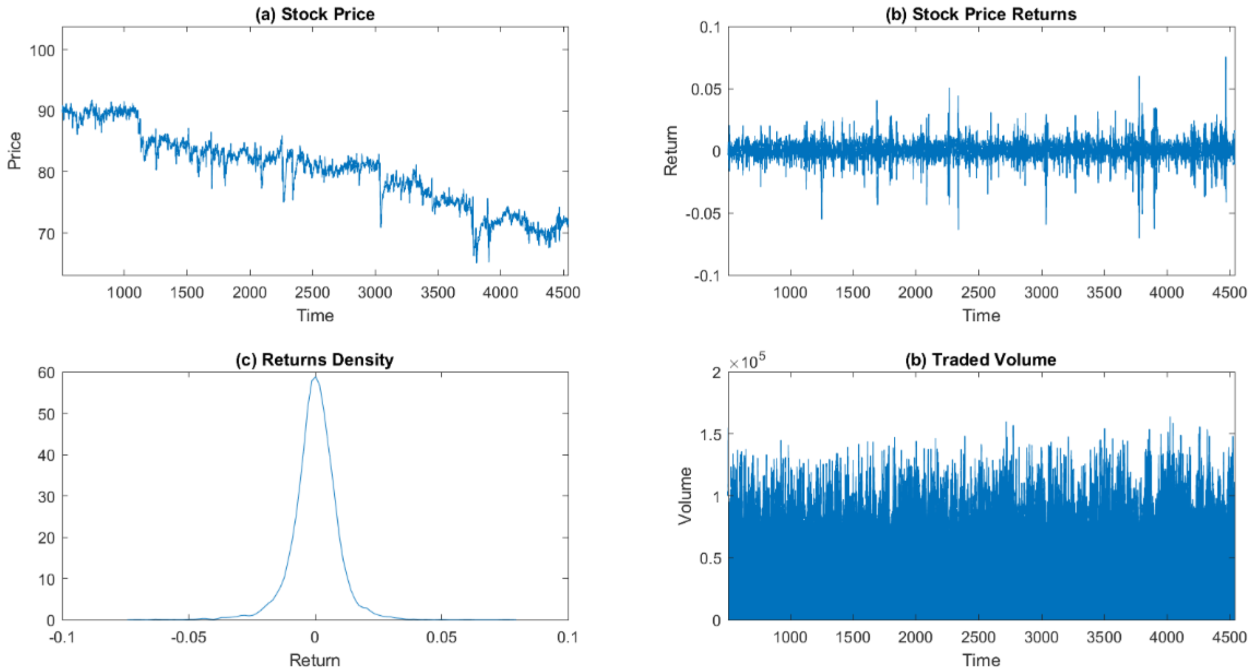

Figure 3. Market outputs over simulation time. Upper left panel: Asset price. Upper right panel: asset price log return. Lower left panel: asset price log return density distribution. Lower right panel : traded volume.

price jumps and halt in price formation process. The decision-making process is two part which are trading decision and the amount to trade. The amount to trade is random fraction of cash or assets. However, the trading decision depends on the method agents use, trading signal functions is summarised in Table 3. It shows the tuning options on parameters for agent trading methods hence, mostly used realistic trading parameters are used to condition realistic trading strategies.

2.1 Price, return and volume analysis

Financial market modelling with traditional approaches have assumption that stock returns are normally distributed. However, empirical findings show that returns have fatter tails than normal distribution.[3] In addition to this findings, daily stock returns have some characteristics that are well documented in Warner and Brown (1985). Therefore, the price and other emergent features of simulated market are supposed to exhibit these characteristics alongside stylized facts.

The price, return and volume outputs are presented in Fig. 3 and Table 4, the log returns of price is expressed as returns in the rest of this paper.

Table 4. Asset price and return related descriptive statistics.

Statistics	Price	Returns
Mean	81.98	0.000
Standard Deviation	6.58	0.0091
Minimum	65.12	-0.0702
Maximum	101.80	0.0754
Skewness	-0.33	-0.5172
Kurtosis	2.09	9.5849
Augmented Dickey-Fuller Unit Root Test	-0.6579	-87.2366***

Descriptives of price returns are in line with real world stock return features which has zero mean and have heavy-tailed distribution. The distribution is leptokurtic and left skewed with 11.65 kurtosis and -0.769 skewness measure. The price is not-stationary at level based on Augmented Dickey-Fuller test; it is first degree integrated series. The simulation parameters are tuned for different combinations of market and agent parameters. The most striking result is that increasing population of intelligent agents halts price formation so the market.

2.2 Validation

The validation of an agent-based financial market model is measured with the number of stylized facts the simulation model is capable to reproduce. The validity of our built model is tested by eligibility of outputs to real financial market features. As a seminal work, Cont (2001) documented a list of stylized facts for asset returns. Agent based models for financial markets have reproduce some these stylized facts but not all of them, so do ours. In addition to all market microstructure parameters, there are also six different types of agents interacting which increase the complexity of the stock market. The validation process is conducted for each fact given in Cont (2001).

Return autocorrelations

It is empirically showed that autocorrelation in asset returns is insignificant but intraday time scales could be exception.[3] There would be a price to be exploited otherwise, and this is an assumption of efficient market hypothesis. The estimated autocorrelation coefficient function (acf) values for simulation generated asset price returns indicates that there is a statistically significant negative autocorrelations for first two lags and fast decaying values afterwards. This is more like intraday small time scales feature of asset returns (Fig. 4a). The slow decay behaviour in absolute return autocorrelation function is another real market feature as stated in Cont (2001) (Fig. 5a). Volatility clustering is another real market feature that is measured by squared returns

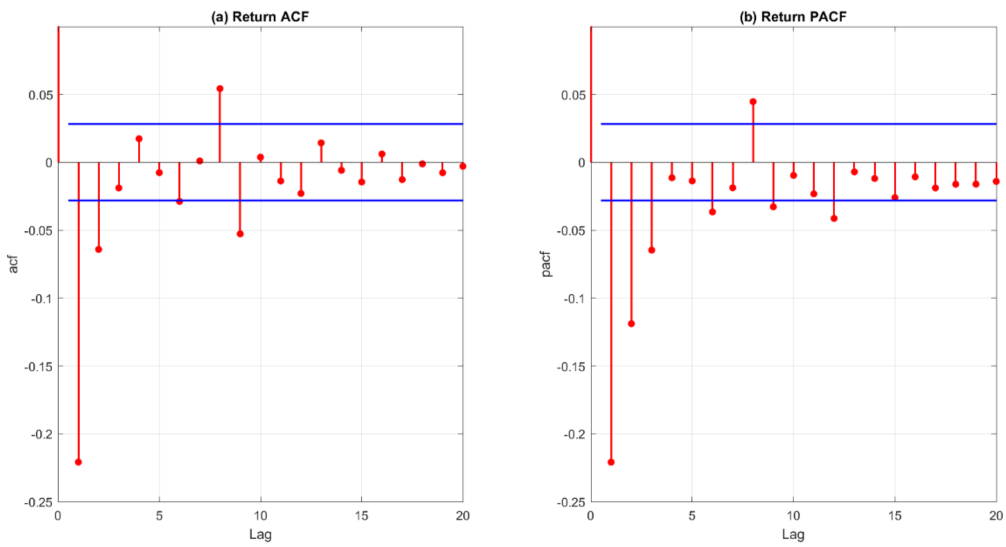

Figure 4. Return related autocorrelations. Left panel: return autocorrelation function. Right panel: Return partial autocorrelation function.

Note: Blue lines stands for 95% confidence interval.

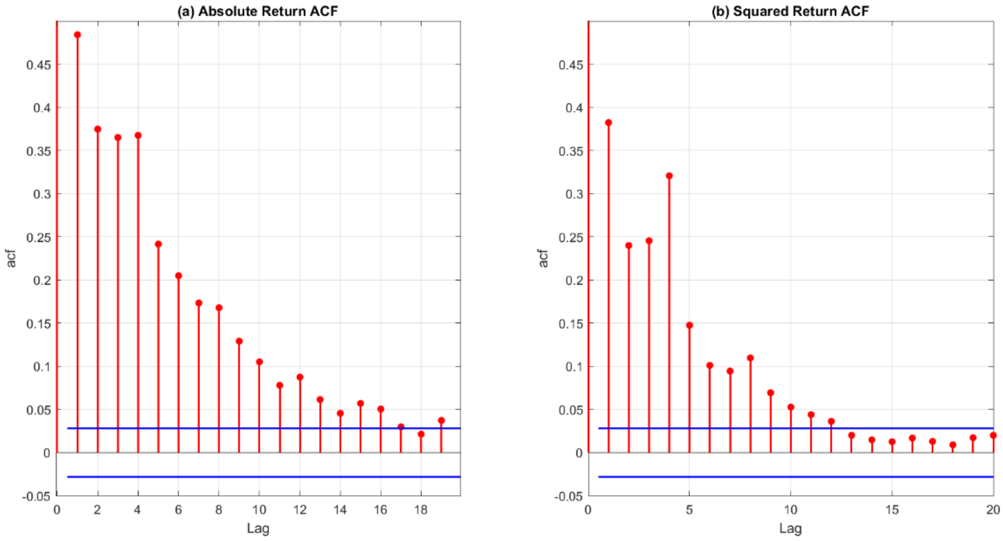

Figure 5. Volatility related autocorrelations. Left panel: absolute return autocorrelation function. Right panel: Squared return partial autocorrelation function.

Note: Blue lines stands for 95% confidence interval.

Table 5. List of stylized facts for asset returns that is used for simulation model validations.

Stylized fact	Testing	Does our model meet?
Absence of return autocorrelations	Autocorrelation plot	Partially
Heavy tails	Histogram Kurtosis	Yes
Slow decay of autocorrelation in absolute returns	Autocorrelation plot	Yes
Volatility clustering	Squared return autocorrelation plot	Yes
Aggregational Gaussianity	Skewness and Kurtosis	No
Volume/volatility correlation	Corelation	No
Leverage effect	Corelation	Partially

autocorrelation function (Fig. 5b) and tested with Ljung-Box Q-test. The test results show that there is an autocorrelation in squared return with test values [critical values] of 1960.22 [11.07], 2155.86 [18.31] and 2176.27 [24.99] for lag 5,10 and 15, respectively. This is a sign of long dependence of volatile market conditions so the conditional volatility behaviour.

Volume/return corelations

It is expected to asset return has negative correlation with volume, however the simulation output short fall to meet this feature since the calculated correlation is $r = 0{,}03$. Another stylized fact is leverage effect which is defined as negative correlation between return and change in volatility. The simulation output was able to reproduce a weak *leverage effect* with $r = -0{,}089$. The validity of our model with stylized facts is summarised on Table 5.

Testing all stylized facts given in Cont (2001) for asset price and volume outputs from simulation show that the model can replicate real market features and they are summarized in Table 5.

2.3 Wealth analysis

The literature in testing trading strategy methods relies on back testing mostly where the agent is assumed to have no market impact on price. However, trading agents have effect on market dynamics since they interact with market participants. This study aims to create a stock market testbed where agent interaction is considered, hence variety of sensitivity analysis can be applied. Satisfying some real market stylized facts, the agent-based model is capable of generate real market features. Therefore, the market is populated with different types of

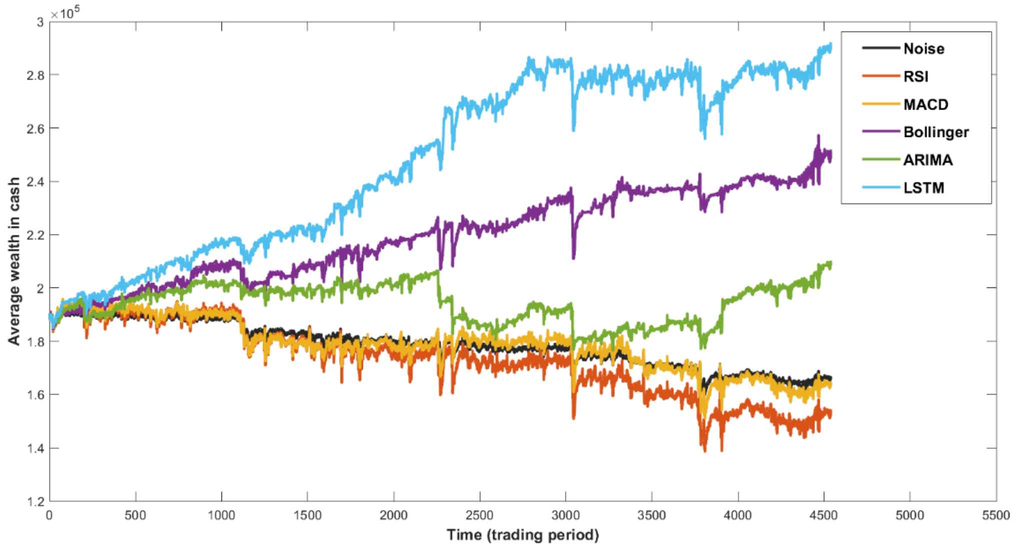

Figure 6. Average wealth of agent types in cash throughout trading period.

agents who compete to increase their wealth at the end of trading period.

One of the question this study aims to answer is if computationally intelligent agents can beat the overall market. In the light of this question, all agents behave as reflective agents with the signal they receive. The rules agent use to trade were summarised in Table 3. Based on these rules, agents entered market and start to trade. The average wealth of agent types over trading period is given in Fig. 6.

The agent named LSTM, which is a deep learning method, outperforms other agents by far. LSTM method is the most complicated and computationally costly method among others. Computation power can be considered as intelligence level in an interacting agent market. Therefore, it can be concluded that the more computational power the higher return. The number of days agents take long, and short positions is summarised in Table 5.

Table 5. Average number long and short positions over trading period.

Traders	Long positions	Short positions
Noise	2269	2266
RSI	120	131
MACD	368	369
Bollinger	125	126
ARIMA	127	4400
LSTM	2531	1811

Two agent group RSI and Bollinger are reluctant to take position since there is no up-down pattern in price long run. ARIMA and LSTM trade most of time since they take position based on their future price move prediction. The ANOVA is applied to mean wealth of agent types, agent wealth differs statistically at 1% significance level. The average wealth of agent type pairs was tested at 1%, except Noise-MACD agent pairs, the rest of 14 pairs has different wealth over the trading period. A boxplot for each agent group is created that also support this, see Fig. 7.

Although all agents belong to the same group use the same trading method, they differ in the amount to trade at each trading decision. Therefore, randomness in amount to trade decision give advantage to some traders. In this sense, each group has at least ten members and distribution checked at initial and final step to make sure same agent types are homogenous. To measure this, the Gini coefficient is calculated for all groups. The Gini coefficients is measure showing degree of inequality in wealth that ranges from 0 to 100. Zero coefficient means perfect equality while increase in it is a sign of inequality in wealth distribution. At the beginning of simulation all agents were endowed with same amount of wealth, hence the Gini coefficient was zero for each agent group. At the final timestep of simulation, the Gini coefficients are measured, and small inequalities occur during trading period since there is no coefficient greater than 10%, see Fig. 8.

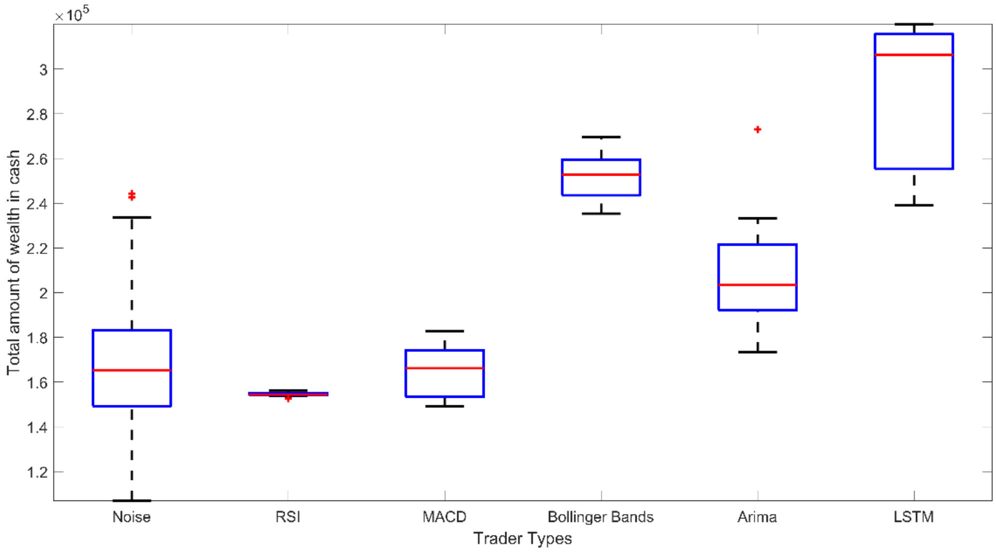

Figure 7. A boxplot for wealth comparison of different agent groups at final stage.

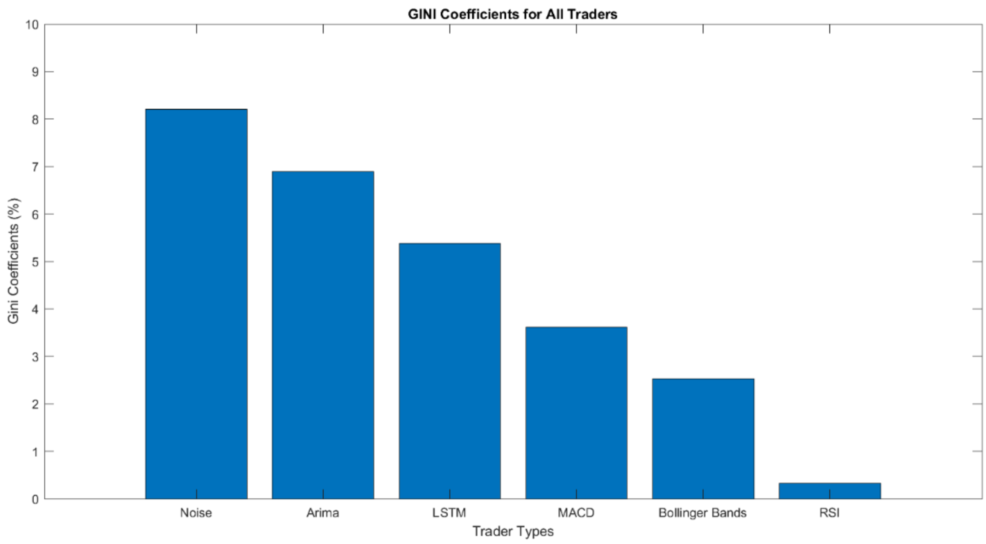

Figure 8. Gini coefficient of agent groups for total wealth at the final step of simulation.

Homogeneity in total wealth with same type agents were kept, and it remains stable at the end of simulation. Since the Gini coefficient is a measure of wealth inequality, the outliers in the wealth distributions lead higher coefficient that can be observed in Fig. 7 and Fig. 8.

3. DISCUSSION AND CONCLUSION

The study aims to gain a better understanding of trader interaction in stock markets and reproduce real market price features. An agent-based financial market simulation approach is employed to serve the purpose of this study since it takes agents' market impact into account. The model was able to reproduce real market "stylized facts", thus it is eligible to be used as testbed for experiments. Hence, we were able to equip agents with realistic trading strategies. The findings provide both an insight into rivalry of different intelligence level in agents and supporting evidence to dominance of computationally powerful agents. It is evident that agent using deep learning approach get the highest return among others with the highest time complexity method.

The artificial stock market was populated with agent groups using no trading strategy, RSI, MACD, Bollinger, ARIMA and LSTM methods. Catalyser effect of noise traders is tested as the increase in population of intelligent agents halts market and that is in line with Farmer et al., (2005). Zero intelligence in agents helps market to move and provide liquidity to the market. Our findings are also in line with back testing on real data, Siami-Namini et al. (2018) compares performance of ARIMA and LSTM methods where the LSTM trader outperforms. This is also can be taken as validity measure whereas Llacay and Peffer (2018) use also face validation and sensitivity analysis to validate their market model extended with realistic trading strategies.

Our results are consistent with the previous work of Raberto et al. (2001) and Marchesi et al. (2003) since it reproduces its results. Although it is challenging to represent complex dynamics of financial markets, a minimal model can still reproduce most of price dynamics.[43] The empirical findings of Cont (2001) fall into dispute with EMH assumptions. Therefore, a financial market with essential components is built and validity of empirical findings is tested. In addition to this, realistic trading strategies compete alongside agent interactions in our bottom-up market model. The emergent behaviour of the market is a result of agent interactions which is hardly traceable. Our agent-based financial market let agents to interact at micro level and analyse the behaviour of market dynamics under different parameter combinations. This can also be considered in a game theorical view since competence of different strategies resulted in price equilibria. Considering these aspects, agent based financial market approaches can help us to better understand market dynamics even in a competing strategies environment.

There are potential limitations of study that heterogeneity in agents is more diverse in real markets such as informed and uninformed traders; high-frequency traders, value traders. Although our model mimic real market price features, fundamental value of an asset is the key for major investors and could be added as one trader type. A more powerful computation can ease time complexity of simulation when agents with complex trading strategy is considered such as deep learning method. The findings are obtained from a set of initial market parameters, different combination of parameters can be applied when modelling a specific market. This field also draw huge interest in high-frequency trading and limit order book modelling[44], therefore there are variety of direction to apply machine learning tools for future research.

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