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IMMERSIVE WINE AND FOOD PAIRING EDUCATION USING LARGE LANGUAGE MODELS AND COMPUTATIONAL INTELLIGENCE TO DESIGN ADAPTIVE LEARNING SYSTEMS

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Abstract

Experimental wine and food pairing experiences have become increasingly popular to improve gastronomy knowledge and appreciation in the changing field of culinary education. The integration of Computational Intelligence (CI) and Large Language Models (LLM) into adaptive learning systems created especially for teaching wine and food pairing is examined in this research. This study investigates how efficient LLM and CI tools are required to update and design an educational framework to create a personalized learning pathway by customizing instructional materials to each learner's preferences, past knowledge, and sensory experiences.

The study examines the potential of immersive technologies of (CI) tools such as Fuzzy logic Systems, Evolutionary Algorithms, and Swarm Intelligence, to simulate real-world pairing scenarios and enrich the learning experience. This research aims to evaluate the effectiveness of these adaptive learning systems in enhancing learners' outcomes compared to traditional methods vs modern methods. Results and findings suggest integrating LLM and CI tools with traditional educational techniques impacts student engagement and retention as well as upgrade suggestions on wine and food pairing. This study opens up the possibilities for further advancements in individualized learning by highlighting the revolutionary potential of CI in wine and culinary education and its potential technical challenges such as data bias-ism, privacy concerns, and quality information. Future implementations can focus on personalized feedback and pairings can be created based on algorithm tools, and cross-culture global pairing principles.

Keywords: *Wine and Food Pairing, Large Language Models, Computational Intelligence, Adaptive Learning Systems, Wine Education*

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1. Introduction

Education pattern of wine and food pairing is a palate sensory subject, that needs special adaptive learning systems (Kasneci et al., 2023). The same principles and teaching styles do not work efficiently for all individuals due to the complex classification of wines, different dietary and cultural preferences of learners, and different food preparation techniques as per region. Versatile wine quality with many styles and acceptance of unique combinations of wine pairings, brings complexity to understand wine principles. As per researches traditional education methods efficiency is not sufficient to provide a personalized, engaging experience to deliver knowledge to different regions wine enthusiasts (Taylor et al., 2008).

The complex classification, types, sub-types, and wine by styles confuse learners on how to segregate wines and build the pairing charts. Due to the usage of many languages and tough spellings of terminology and pronunciation issues, wine learners face challenges (Croijmans et al., 2019). The ability of a learner to pick what aromas and taste flavors are present in wines, is also a challenge based on skill and the number of taste buds they have (Anderson, 2018; Ellis & Caruana, 2018).

Despite the presence of digital information modes still there is a gap in availability of adaptive learning systems for existing wine pairing education. The study illustrates how by opting LLM's and CI tools creates engaging, learning environments and enhances the learning pathways (Xu et al., 2024; Fernandes, 2017) for advanced customized education frameworks. To make the learning systems more adaptive for wine enthusiasts as per individual approach and learning capability LLM and CI tools are supportive. It helps to appreciate and pair wines with cuisines in a more compatible manner (Hryciw et al., 2023).

The application of these technologies can make wine and food pairing education more accessible and engaging (Leiker et al., 2023). It revolutionizes the whole culinary education and makes it effective for a broader audience. Vast information and data algorithms makes wine and food pairing knowledge easy to deliver, and continuous feedback helps to design and evaluate the adaptive learning system on time as per wine enthusiasts more efficiently (Laak & Aru, 2024; Zhang et al., 2024).

This research explores whether LLM and CI tools usage can be integrated with traditional wine and food pairing education methods, and how it can be beneficial for learners with customized learning experiences and with what challenges occur up. Through detailed literature review, case studies, and reports, it explores how LLM and CI can elevate a better adaptive learning educational framework based on individual preference pedagogies. The study examines the current usage and challenges while using LLM and CI in wine education, and how it escalates the learning standards in a refined way.

RQ1 What is the role of traditional education methods in increasing the skills, confidence, and user experience of different wine learner segments?

RQ2 Which learning method is more effective for wine pairing with food - either with AI-based LLM and CI tools or traditional learning practices?

RQ3 What are the challenges faced by learners and their impact on LLM and CI tools for wine and food pairing in education?

2. Research Objectives:

1. To evaluate the effectiveness of traditional education methods as per skill, confidence, and user experience of different wine learner groups.

2. To compare the efficiency of LLM and CI tools vs traditional learning practices for adaptive learning systems in the field of wine and food pairing education.

3. To assess the impact of challenges in the usage of LLM and CI tools for wine and food pairing education among wine learners.

3. Literature Review

3.1.1 Wine Education Challenges

Wine is a complex subject because, there are so many styles of wines from different regions and terroirs. Researchers found major obstacles in referring to wine and food pairing principles as every wine enthusiast has a different palate, different dietary and cultural preferences, and different learning and living styles (Taylor et al., 2008).

The education system is modernizing every day therefore only digitization, and usage of images, and videos are insufficient to train about wine and food pairing by trainers, and sommeliers with logical reasoning in a harmonious manner. As per researchers learners' need more visual aids, and multimedia teaching pedagogies (Sannino et al., 2013). As per professionals learning, an adaptive learning system approach is required where LLM and CI can play a crucial role.

Extensive range of grape varietals, terminology in various languages, difficult pronunciations, and to understand the diverse aromas, flavors, textures, and body of so many wines makes wine and food pairing challenging to learn. Even the same grape varietal wines at different terroir differ on palate which makes this subject lengthy and even more complex (Anderson, 2018; Ellis & Caruana, 2018).

3.1.2 Traditional Methods Opted

Traditional education methods with the support of books, presentations, videos, and some tasting sessions offers theoretical and practical learning up to a limited scale. Researches have identified that sommeliers, and expert trainers' teaching pedagogies plays an impactful and critical role in imparting knowledge, exposure, and experience to the learner (Taylor et al.,

2008)Traditional methods are not individual-centric or based on the preferences of learners. The number of wine paring principles or learning techniques are limited which creates a barrier to easy learning in an effective way (Spence, 2020). Traditional education methods have their limitations in the context of offering unique pairings, cost-effective sessions by experts, and hands-on learning experience (Al-Gindy et al., 2020).

3.1.3 Role of LLM and CI Tools

Researchers found LLM and CI based models are vastly used in data analytics based on personalized recommendations in many subjects. Preferences by data algorithms act as powerful tools for generating tailored content, analyzing user preferences, and providing customized recommendations (Laak & Aru, 2024; Zhang et al., 2024). The research investigates how with the support of LLM and CI-based learning systems, learning pedagogies can be designed by wine educators effectively to deliver the knowledge. A study illustrates leveraging vast knowledge and Natural Language Processing capabilities of these models, can deliver highly contextualized and engaging content with support of educational platforms. That caters to the unique preferences and learning styles of each individual (Bacciu et al., 2023).

The application of CI facilitates in improving the suggestions based on user interactions, feedback, and real-time data analysis which makes the adaptive learning system more efficient (Hryciw et al., 2023). Text written by humans can be understood, analyzed, and interpreted by LLM, such as GPT-3 (Laak & Aru, 2024).

To understand and write human-like text, LLM has an unparalleled ability (Laak & Aru, 2024). These models have been designed with vast data, and information and enable individuals to understand languages, gather information, and to create logical and appropriate responses (Kasneci et al., 2023).

Integration of massive language models along with wine and food pairing education has the potential to completely transform the educational process. Tested by researchers these models can be used to create customized course materials, lead interactive question-and-answer sessions, and provide learners with immediate feedback and suggestions (Stampfl et al., 2024).

3.1.4 Integration of Adaptive Learning

Adaptive learning systems modify the learning material, and deliverance according to individual learners' needs by examining their preferences, learning styles, and interactions with the educational platform and updates at regular intervals to ensure continuous improvement. Presently traditional educational methods opted by a wide array of professionals but the integration of such tools (LLM and CI) with traditional techniques makes the wine pairing knowledge and skills deliverance adaptable (Bacciu et al., 2023; Hryciw et al., 2023; Picard et al., 2023; Zhang et al., 2024).

Machine learning algorithms and data analysis techniques offers adaptive learning systems to provide personalized experiences with the support of data based on hospitality professionals, or students' behavior, preferences, and feedback. Researchers illustrates collaborative filtering and content-based recommendation algorithms can be decoded by the system and suggest wine

and food pairings to all learners (Yu et al., 2017). NLP supports quick responses by understanding the queries and offers a smoother interaction (Zhang et al., 2024)

As wine and food pairing education continuously evolves, the combination of these technologies (LLM and CI) tools with traditional education framework will play a crucial role in enhancing the learning experience, to promote better understanding.

3.2 Conceptual Framework

3.2.1 Role of Sommeliers and Educators Expertise in wine education using LLM and CI tools

The presented model illustrates the connections, and how with the usage of (LLM and CI) adaptive learning systems and pathways can be created (Gan et al., 2023; Leiker et al., 2023). The expertise of sommeliers, chefs, educators, and trainers can be merged to bridge the gap to deliver adequate knowledge, on tasting skills, to build the confidence, and makes it user-friendly as a straight forward subject for individuals in an engaging manner (Xiao et al., 2024).

As per study hospitality schools wine trainers, and educators have vast knowledge and academic experience with a huge series of pedagogies, but how to deliver knowledge and drive the necessary skills in hospitality students, professionals, or wine enthusiasts is required on individual basis (Crawford et al., 2014). Responsibility to design the curriculum efficiently related to wine and food pairing is of wine educators and to train students or professionals of different cultures having different dietary preferences where they can use LLM and CI tools (Crawford et al., 2014; Marneros et al., 2020).

Wine sommeliers and culinary industry experts have better product knowledge and upgraded skills as they implement essential changes at regular intervals and later on, educators deliver it to wine enthusiasts. Sommeliers train the professionals of F&B service industry about wine and food pairing based on updated trends and bridge the gap to understand the science behind sensory perception, and pairing technique skills (Schifferstein et al., 2020). Guests from different regions have different cultural, dietary, and palate preferences as per individual (Galmarini, 2020). As they visit hotels and share what are their choices of wines with specific cuisines, it gives clues to sommeliers for future references apart from generic wine pairing principles (Harrington 2005).

3.2.2 Learning methods adaption by hospitality students and wine enthusiasts

Focusing on the hospitality industry programs they are versatile and not static, new creative modern techniques opted to train learners as per their approach to equip them with better knowledge and skills (Green & Sammons, 2014). It bridges the gap between classroom knowledge and real-world service operations in restaurants and hotels (Askren & James, 2020). Continuous evolution in the industry and different dietary, and cultural preferences of students and learners' capabilities, traditional education methods are not completely working as mentioned (Maier & Thomas, 2013) as they are teaching the same principles for wine and food pairing in every situation.

New experimental learning methods or advanced technology-based teaching methods are required (Askren & James, 2020) to educate them more practically and suggest the right options and continuous feedback is essential to improvise the adaptive learning paths (Paunova-Hubenova et al., 2020).

3.1.1 Integration of LLM tools in wine and food pairing education

LLM can analyze learners' choices to suggest optimal pairings that match the flavors, textures, and traits of a dish or wine with balance and plays a vital role in transforming wine and food pairing education. Phytochemical contents in a dish can be searched with support of Computational Gastronomy (Rita et al., 2024). It engages learners in discussions and real-time feedback by understanding their principles (Taylor et al., 2008).

These models generate customized learning materials as per the diverse scholarly needs of the learners. The complex possible pairing of wine and food aromas, flavors, and tastes makes it a subject of exploration and needs extensive training. Continuous evolution in food and wine-making techniques generates a training demand to bridge the gap between its application and food science research (Harrington, 2005;Schifferstein et al., 2020). In modern times recognized wine schools such as MBA programs in wine, WSET, and CMS courses are efficiently training but they are not cost effective, and on-the-job training in cellars or wineries is another option but not available to all (Brain, 2019). For depth knowledge and research by learners LLM proved as an efficient tool for synthesizing and disseminating complex pairings and summarize information in an adaptive manner (Boyko et al., 2023).

Inference & Query tools support personalized recommendations for learners about wine pairing. Experimental hands-on learning with examples is supportive to both beginners and experts from different regions based on controversies (Tu et al., 2024). Examples of Inference-based tools are Wine Searcher, Vivino, Hello Vino, The Sommelier Company, and Wine Folly. Query-based tools for wine pairing examples, refer to Ask Decanter, Google Assistant, Pairing with Wine Enthusiasts, or Plonk-Wine pairing application support to understand all queries.

3.2.3 Integration of (CI) tools in wine and food pairing education

Artificial Intelligence and Machine Learning are extensively used for analyzing various aspects of food pairing (Moulahoum & Ghorbanizamani, 2024). CI has the prospect to revolutionize the learning approach of wine and food pairing, and to educate gastronomic professionals about it. There are many teaching methods under CI to train learners about wine pairing as per adaptive learning methods (Chen et al., 2022). Some effective tools of CI are the Fuzzy Logic System, Evolutionary Algorithms, and Swarm Intelligence. These CI based tools provide personalized recommendations based on large sets of data using their sub-tools like predictive analytics, and reinforcement learning (Li & Zhang, 2017; Nguyen & Walker, 2019).

Fuzzy logic mathematical systems works with reasoning on an approximate basis. In this system, values are between 0 to 1 (Guijarro-Mata-García et al., 2015). It can suggest flexible wine and food pairings based on various combinations such as acidity, sweetness, tannins, flavors, and intensity. It may create adaptable pairings based on balance, complexity and length of wine or as per regions or style of wine. It needs some input and convey options accordingly,

which can be used as learning. The benefits of a Fuzzy Logic System for forming a learning system are, it is flexible with wine pairing principles, it suggests personalized learning and pairing as per palate, it enhances the other educational tools, and it is interactive and adaptive as continuously evolves based on feed-backs (Guijarro-Mata-García et al., 2015).

As per research Evolutionary Algorithms are a class of optimization techniques to find the optimal solution to a problem individually (Yu, 2018). Used to optimize complex problems with several variables and parameters such as population size, mutation rate, and selection method (Byrne et al., 2014). Using Evolutionary Algorithms wine educators can develop personalized recommendations based on the individual and cultural preferences of students, sommeliers, professionals, or learners.

Swarm intelligence is a self-organized system by nature to solve complex problems by cooperation and interactions without a single leader. It is useful where the space solution is large, complex, and not understandable. Applications under Swarm Intelligence are optimization problems, machine learning, and data clustering. Image processing and game theory can be used for wine and food pairing education. It helps in the optimization of flavor profiles, personalized pairings, and multi-dimensional optimization such as body, serving temperature, wine style, acidity, etc., and to uncover the complex interaction between the chemical and sensory components of wine and food (Johnson, 2009; Fang & Li, 2021). It can help to create learning tools to understand the wine and food pairing principles with ease (Bastian et al., 2010; Kustos et al., 2020).

3.2.4 Potential of LLM and CI tools

The essentials of wine and food pairing are flavor profile, wine characteristics, complementary and contrasting pairings, regional pairing, and personal preferences. LLM tools have the ability to enhance wine and food pairing knowledge (Nolfi, 2024). LLM supports to analyze difficult language and metaphors used in wine and food descriptions. CI sub tools such as machine learning further support LLM to design wine pairing education content (Franceschelli & Musolesi, 2023). Algorithms and big data on LLM support, to make out the most precise pairing based on cultural and dietary preferences.

The major objectives are to frame a better learning platform related to wine and food pairing. With the support of LLM and CI to work on key components of effective learning such as knowledge acquisition, skill development, confidence building, interactive learning, and user experience and engagement. CI techniques support personalized content-based learning and LLM supports detailed information and descriptions. These platforms focus on developing practical wine and food pairing skills. It also engages learners through quizzes, personal challenges, and discussions and creates a memorable experience for them (Gan et al., 2023).

Fig. 1 Proposed Research Model

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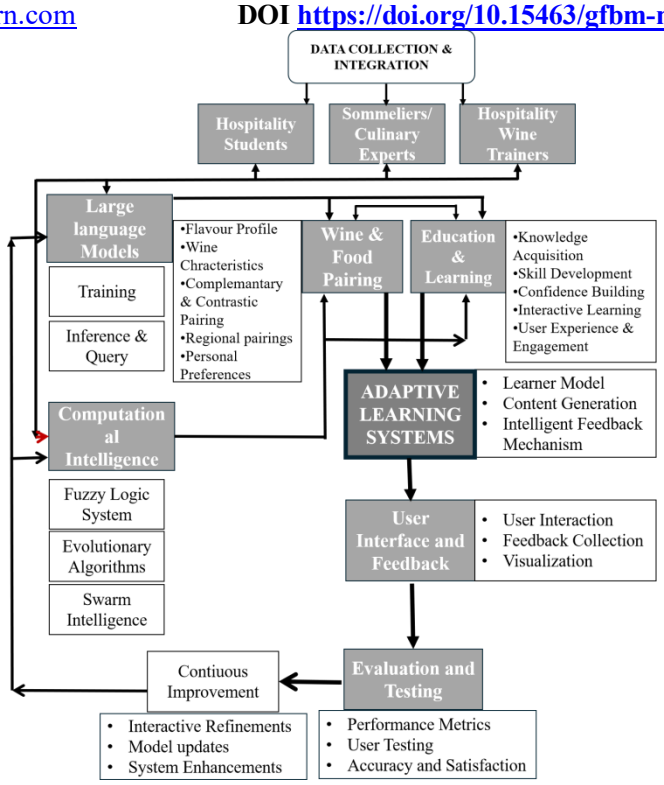

Model Author's Own

4. ***Research Methodology***

4.1 Hypotheses

H1: Traditional education methods significantly improve the skill, confidence, and user experience of different wine learner groups in comparison to self-studying.

H2: LLM and CI tools vs traditional learning practices significantly enhance adaptive learning systems in the field of wine and food pairing education.

H3: Biased data, privacy concerns, and quality information are significant challenges in the implementation and usage of LLM and CI tools for wine and food pairing education.

This study employs a mixed-method approach, with both quantitative and qualitative data being collected. Since it is a palate sensory subject, qualitative data coding is necessary to explore complex observations and emotions to compare the results (Cresswell & Plano Clark, 2011). A quantitative survey-based study employing criterion purposive sampling. As wine is a palate sensory subject and AI are such topics which are not familiar to everyone, so applied this sampling technique for more accuracy (Nyimbili & Nyimbili, 2024).

Sampling Data is gathered from 385 active respondents from the self-administered questionnaire. Data is collected from people connected or have knowledge about wine in detail including sommeliers, chefs, hospitality trainers, lecturers, hospitality students, and wine enthusiasts. As the population size is finite, a concurrent formula is opted. In hotels, the number of chefs, sommeliers, or qualified wine professionals are limited who studied about wine. Rest data is collected from Delhi NCR hotel management college students and trainers and as per that the total population for all is above 10000. Structured questionnaires are applied here to

analyze their learning experiences with traditional learning methods vs AI tools such as LLM and CI. Qualitative data supports to explore emotion, expressions, and mood as human perceptions to quantify is challenging. Qualitative data is coded and analyzed thematically (Naude & Badenhorst-Weiss, 2020). (Sahoo, 2022) utilized 30 responses in previous studies considering the constraints of the topic. Structured face to face 28 interviews & 2 telephonic interviews were conducted., totaling it to 30 wine experts sommeliers, and chefs interviewed from the industry to understand user perceptions, challenges, and the practical implications of LLM and CI integration in an educational context.

For Hypothesis, the T-Test was applied and the data was collected by subjecting participants to pre and a post-test in a controlled environment with adequate white light and temperature. Where 10 wines of different styles were to be tasted with 11 dishes including starters, main course, and dessert to judge tasting and pairing skills of sampling participants in both the pre and post-test. All of the participants were WSET and CMS-certified, or experienced wine service professionals with a minimum 5 years of experience. The age group of participants is between 25 years to 50 years. Before both wine tasting sessions in pre-test and post-test for consistent quality knowledge deliverance about wines a WSET level 3 certified instructor with adequate experience, trained and educated them about the wine pairing principles and wine basics.

Wines for tasting include 3 white wines, 1 rose wine, 3 red wines, 1 dessert wine, and 2 sparkling wines of different grapes and styles. A pre-test was conducted on 31st March 2024 which was based on self-study vs traditional wine pairing studying methods. After a time series gap of 50 days on self-studying basis by participants about wine pairing by using (LLM)- Chat GPT and (CI) tools, a post-T Test was conducted on 19th May 2024 on traditional education method learning vs LLM and CI-based learning method performance.

For tasting, 30ml first pour and 15ml additional pour were offered if required by the participants in identical tasting wine goblets to all. 6 wine goblets were placed in 1st service and then additional 4 wine goblets were placed. Each goblet has a number 1 onwards from left to right. Participants were instructed to taste the wines in a sequence from light-bodied to full-bodied. To start with sparkling wines, then white wine, after that blush wine, then red wines, and ended with tasting of dessert wines along with the dishes course-wise. Wines served as per standard temperatures as per grape and style of wine. As palate cleanser non sparkling water and unsalted crackers were also kept along with coffee beans. This process is opted in both pre and post-test.

All participants were provided with a tasting evaluation sheet in which they had to mention the 1st,2nd, 3rd, and 4th preferences of wine along with each dish or give remarks if they didn't like any particular wine without any discussion. In the end, subjective remarks were also taken by all for the whole learning and tasting experience.

Both pre and post-test ends with an evaluation, the objective is to judge the knowledge level difference after LLM and CI based learning method, questionnaire consisted of 10 multiple choice questions. Multiple choice questions-based questionnaires were opted for the data collection, due to the visibility of answers it is easy to recall and tick the correct option by novice participants (Brady, 2005; Considine et al., 2005).

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Population Size (N): is unknown
Confidence Level (Z): A 95% confidence level corresponds to a Z-score of 1.96
The margin of Error (E): The acceptable level of error in your results, e.g., 5% (0.05).
Proportion (p): The estimated proportion of the population that has the characteristic of interest. If unknown, use 0.5 (the maximum variability).
Sample Size for Finite Population:

$$n = \frac{Z^2 \cdot p \cdot (1 - p)}{E^2}$$

$$n = \frac{(1.96)^2 \times 0.5 \times (1-0.5)}{(0.05)^2}$$

The sample size is 370 but analyzed with 384 collected samples

4.2.1 Survey Data Analysis

Category	**Sub Category**	**No. of Respondents**	**% of Respondents**
Age	18-25	185	48.05
	25-35	68	17.66
	35-50	112	29.09
	50-70	20	5.19
Education and Qualification	Bachelors	216	56.10
	Masters	118	30.65
	P.hd.	20	5.19
	Diploma and others	31	8.05
Certifications in the field of wine and food	Food / Bakery and cuisines	97	25.19
	Wines/ spirits and Bar	86	22.34
	Wine and food pairing	49	12.73
	None of these	153	39.74
Certified educator in the field of wine or food	Certified educator of food and wine	55	14.29
	Certified educator in hospitality and tourism	71	18.44
	Faculty, lecturer, trainer, educator	72	18.70
	Other professions	187	48.57
Profession	Hospitality & Tourism, Aviation	318	82.60

	Science stream-based - Engineer/ Medical etc.	8	2.08
	Commerce stream-based - CA, CS, Economics/ Business management, etc,	45	11.69
	Arts stream-based Jewelry Designing, Fashion Designing, Craft, Textile	14	3.64
Role of expert wine sommeliers and chefs in wine and food pairing	Wine pairing can be done better by sommeliers & chefs as they can judge emotions	101	26.23
	Mood and expressions are understandable by humans, not software so need Sommeliers	45	11.69
	Wine pairing is a palate sensory subject so needs sommeliers not only (LLM) or (CI)	36	9.35
	To update (LLM) and (CI) need chefs and sommeliers	13	3.38
	All of these	190	49.35
How effective do you find these traditional methods in helping you to understand wine and food pairing & label reading	Not Effective	30	7.79
	Little Effective	22	5.71
	Moderately	99	25.71
	Effective	108	28.05
	Very Effective	126	32.73
Challenges in Traditional Wine & food Pairing Education Framework	There is no challenge in the present wine and education framework	47	12.21
	Content is presented in a very theoretical and not engaging manner	107	27.79
	Options of learning - video and image-based are difficult to collect or expensive	50	12.99
	Due to different dietary and cultural preferences, a single education framework can't work	181	47.01
Challenges in traditional wine and food pairing education framework	Old methods of learning do not create long-lasting learning	70	18.18

	The methods are not interesting and time-consuming	36	9.35
	Challenges appeared as books are based on limited content	60	15.58
	Only golden rule-based wine and food pairing mentioned	35	9.09
	All of above	155	40.26
	None of these	29	7.53
A major challenge in traditional wine and food pairing education	To create the skill of wine and food pairing tasting	110	28.57
	To bring confidence what is the approach and concept to apply for pairing	84	21.82
	To create the knowledge and understanding required for wine and food pairing	108	28.05
	To make the sessions interactive and engaging so focus should be more	83	21.56
Benefits of traditional wine and food pairing educational framework in comparison to (LLM) and (CI) equipped adaptive learning systems	It can work for all in almost an equal way	48	12.47
	It is easy to design and implement	61	15.84
	It is very cost-effective	45	11.69
	No fake, wrong, or biased data	28	7.27
	Maintains privacy as per learners' doubts	16	4.16
	All of above	172	44.68
	None of these	15	3.90
Have you used (LLM) such as (Chat GPT and BERT) for wine and food pairing education	Not at all	144	37.40
	Very little	58	15.06
	Sometimes	92	23.90
	Many times	47	12.21
	Used a lot	44	11.43

Have you used (CI) tools such as Fuzzy Logic systems, Swarms Intelligence, and Evolutionary Algorithms for wine and food pairing education and learning	Not at all	166	43.12
	Very little	47	12.21
	Sometimes	87	22.60
	Many times	58	15.06
	Used a lot	27	7.01
Large Language Models (CHAT GPT) and computational Intelligence offers a better Adaptive learning system than traditional methods for wine and food pairing	Yes	165	42.86
	No	96	24.94
	No clues and information	124	32.21
As per adaptive learning systems offered by (LLM) and (CI) what is the major benefit	The learning model created by these tools supports judging the capability of the learner first	82	21.30
	The content design is made in accordance and is interesting and engaging	162	42.08
	The timely feedback mechanism and evaluation of the learning pathway in accordance	89	23.12
	None of these	52	13.51
Are (LLM and CI) such tools for literacy there even in youngsters and the present generation completely	0-20%	47	12.21
	20-40%	71	18.44
	40-60%	96	24.94
	60-80%	116	30.13
	80-100%	36	9.35
	Negligible	19	4.94

What is the biggest challenge while using (LLM) and (CI)	Wine pairing is a sensory subject it can support only to boost knowledge not skill	128	33.25
	There is a lot of data bias-ism and wrong data on large language models	100	25.97
	It is difficult to understand such algorithms and content quality concern	134	34.81
	Learning privacy concerns are limited	23	5.97
What challenges can be easily resolved with (LLM) and (CI) related to wine and food pairing education	Learning platform based on Individual learning approach	54	14.03
	Personalized Recommendations	53	13.77
	Instant Feedback	67	17.40
	Explain everything as per language choice and work as per new unique pairings	89	23.12
	All of above	122	31.69
Potential Challenges and limitations of implementing (LLM) and (CI) support to wine educators are	They don't know how to use these tools efficiently	53	13.77
	It is an expensive option	54	14.03
	It is an option but can't give very efficient results	74	19.22
	(LLM) and (CI) are not useful for palate sensory subjects to give an understanding to learners	98	25.45
	All of these	106	27.53
Specific features you like to see in (LLM) and (CI) based learning systems used by educators regarding wine and food pairing education	Easy caption and tabulation	47	12.21
	Algorithms need to be expressed in detail so understood by anyone	81	21.04
	Graphics and images	62	16.10
	Flowchart presentation	32	8.31
	All of these	163	42.34

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4.2.2 Quantitative Data Analysis

As per the survey, 48.05% of learners were hospitality students (general samples) or young professionals and 51.95% were hospitality trainers and lecturers, certified sommeliers, chefs, and food critics. Out of all samples, 51.43% are educators, trainers, sommeliers, and lecturers, and the rest are from other professions and 33.07% have done certifications in the field of wine and food pairing. As per data, 47.27% of respondents stated sommeliers are required as they can judge mood, emotion, expressions, and celebrations, and a palate sensory subject can be judged by them in a better way not by machines or AI tools, and 52.73% stated all parameters can be judge by sommeliers only, not possible by LLM or CI. Only 13.5% of learners stated traditional methods are not very effective, as per rest samplers it is effective to a very effective way of delivering wine and food pairing knowledge but due to different cultural and dietary preferences of individuals, there is a need for different methods of delivering knowledge as per a statement by 47.01% professionals. 92.47% of learners and sommeliers also highlight some challenges of traditional methods like its time-consuming, expensive, not having long-lasting effects, etc. As per the survey, major challenges of the traditional education framework are, 28.57% stated there is a lack of skill development, 21.82% stated a lack of confidence to apply the approach of wine pairing, 302 samples out of 385 stated a lack of knowledge, skill, confidence, and understanding and 21.56% stated sessions are not very engaging and interactive. 96.10% population sample size stated some benefits also of traditional wine education framework like it can work for all, it is easy to design and implement, it is cost-effective, no data bias-ism and maintains privacy. 52.46% of wine sommeliers or hospitality students did not use LLM much and only 23.64% of users use it well for research, knowledge, or training at all. Same way 55.33% of users hardly used Fuzzy Logic Intelligence and only 22.07% of users used it well for wine and food pairing education. Through this survey, we make out that 42.86% of users think LLM and CI can make an adaptive learning system for wine education, 24.94% think there is not much use for it but 32.21% have no clues about CI at all. As per this data, 21.30% of learners think adaptive learning systems by LLM and CI support to judge the capability of the learner, 42.08% stated it's interesting and engaging, 23.12% stated it gives timely feedback helps in evaluating the learning pathway, and 13.51% have no clues. Only 39.48% of wine and food education interested people have the knowledge to use these tools. The major challenges in LLM mentioned by the sample population are, that 33.25% stated it is a palate sensory subject that can only support knowledge, 25.97% mentioned issues related to data bias-ism and 34.81% stated it is difficult to understand such algorithms by all, as per 5.97% in content quality and privacy is the challenge. Also, almost everyone mentioned some of the benefits of LLM and CI such as learning platforms based on individual learning approaches, personalized recommendations, instant feedback, and explaining everything as per the choice of language and work as per new pairings. However the potential challenges with these tools are, 13.77% don't know how to use them efficiently, and it's an expensive option as per 14.03% of learners and professionals. It does not give very accurate and efficient results as 19.22% of learners and 25.45% believe as it is a palate sensory subject a good understanding is not possible without hands-on experience and as per 27.53% samplers.

4.2.3 Graphical Analysis of Objectives based on quantitative data.

Fig 2 Fig 3

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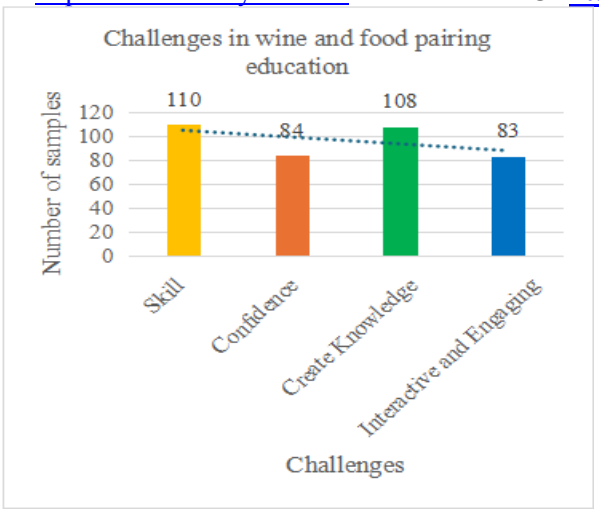

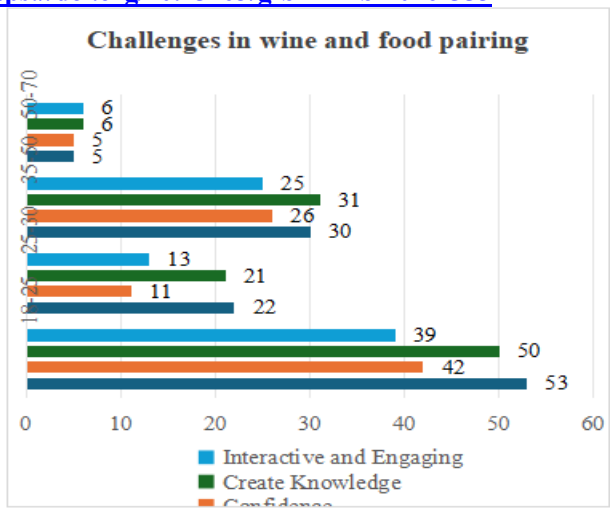

Fig 2 and 3 charts based on challenges in traditional wine and food pairing education challenges

Fig 4

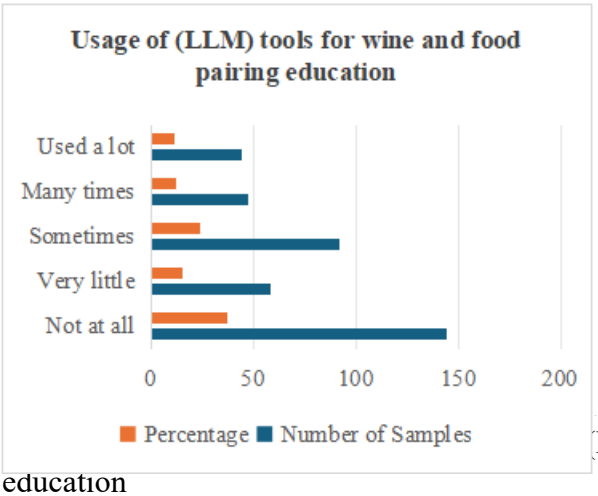

Fig 5

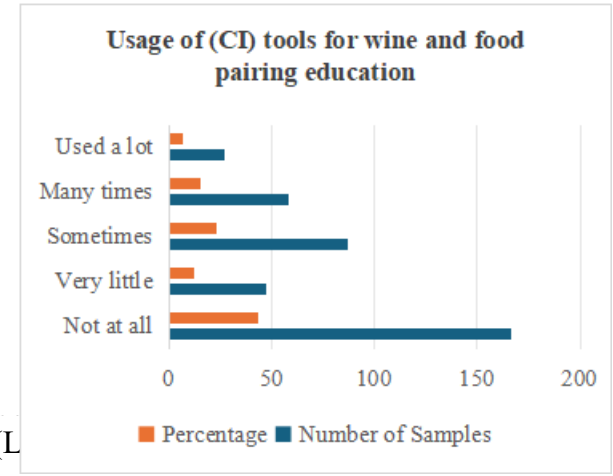

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Fig 6

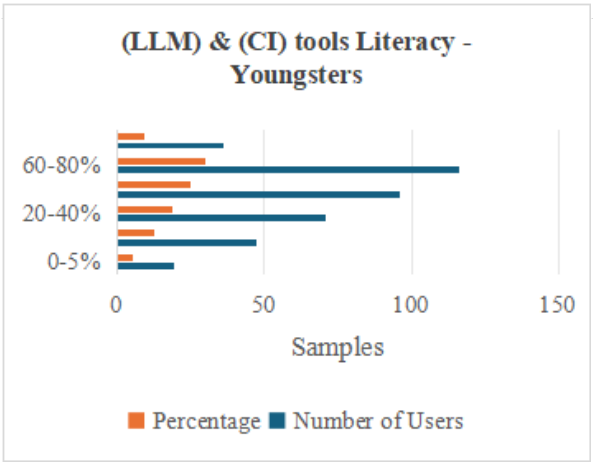

Fig 7

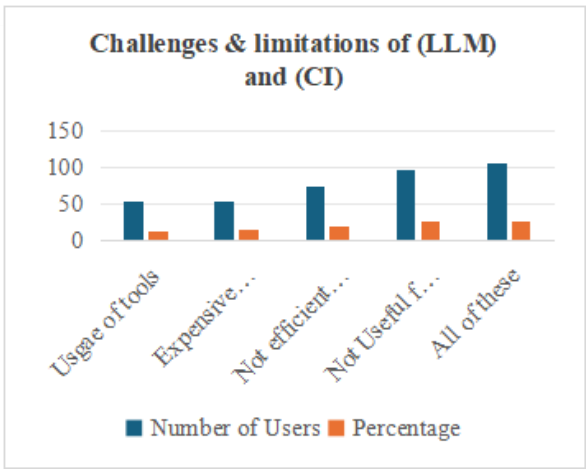

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Fig 6 and Fig 7 relate to Challenges and limitations of (LLM) and (CI).

4.2.4 T Test

The study is conducted to showcase if any differences took place in the preferences between pre-test and post-test.

Table 1

Experimental Group	Control Group
Age Group 21yr to 58 yrs	Age Group 21yr to 58 yrs
Male 7	Male 7
Female 3	Female 3

Mean Scores and Standard Deviations based on p-values of T-tests.

	Mean Scores	S.D.
Self Study impact on Skill	5.35	0.53
Self Study Impact on Confidence	7	0.707
Self Study Impact on User Experience	6	0.624
Traditional Education method impact on skill	6.725	0.478
Traditional Education Method Impact on Confidence	7.7	0.422
Traditional Education Method impact on user experience	6.9	0.459
(LLM) and (CI) tools impact on skill	7.24	0.377
(LLM) and (CI) tools impact on confidence	8.29	0.366
(LLM) and (CI) tools impact on user experience	8.18	0.358

Table 2

T-TEST P VALUE SCORES

Self Study Impact vs Traditional Education	**Traditional Education Vs (LLM) and (CI) Tools**
Based on Skill - (0.0000094 < 0.05)	Based on Skill - (0.000651 < 0.05)
Based on Confidence - (0.0013 < 0.05)	Based on Confidence - (0.0000186 < 0.05)
Based on User Experience - (0.0019 < 0.05)	Based on User Experience - (0.000000012 < 0.05)

As per Table 2 in all the comparisons and T-Test, value scores are much lesser than (< 0.05) which shows all are null hypotheses. There are statistically significant differences in skills, confidence, and user experience between the groups. Two sets of T-test scores applied - Self-study vs Traditional Education, and Traditional Education vs (LLM and CI) tools usage. Based

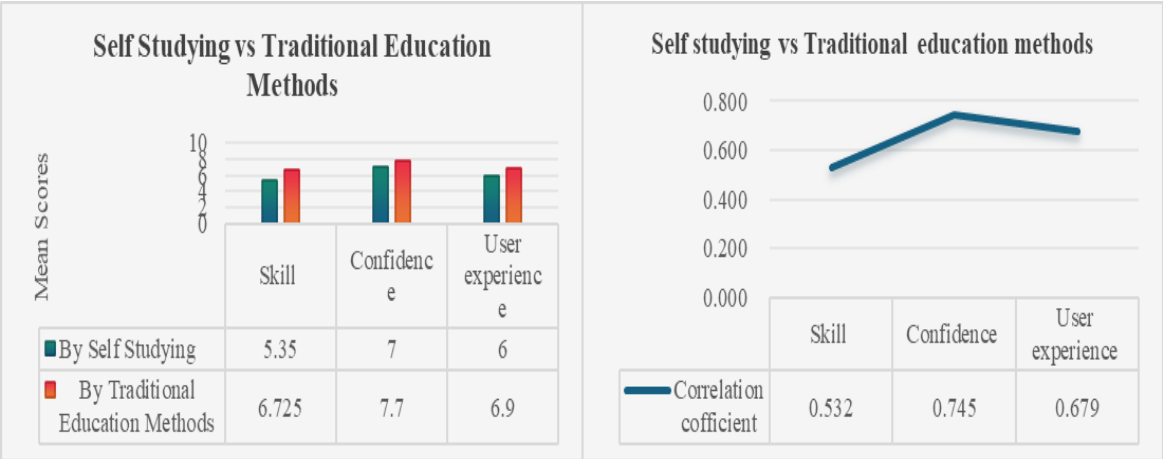
on user experience it shows a stronger level of statistical significance. Interpretation shows As per self-study traditional Education methods give better results and if start using AI tools integration such as (LLM and CI) it can be improved further.

4.3 Hypothesis Testing:

4.3.1 TestingH1:

Paired Sample T-Test: A Paired Sample T-Test is applied to compare the mean scores of skill, confidence, and user experience satisfaction. This test is suitable for observing the improvement in mean scores.

Metrics	Mean Scores By only self-studying	Mean Scores By Traditional Edu. Methods	Difference	Statistical Difference	Coefficient Correlation
Skill	5.35	6.725	+1.375	$p < 0.05$	0.532
Confidence	7	7.7	+0.7	$p < 0.05$	0.745
User Experience	6	6.9	+0.9	$p < 0.05$	0.679

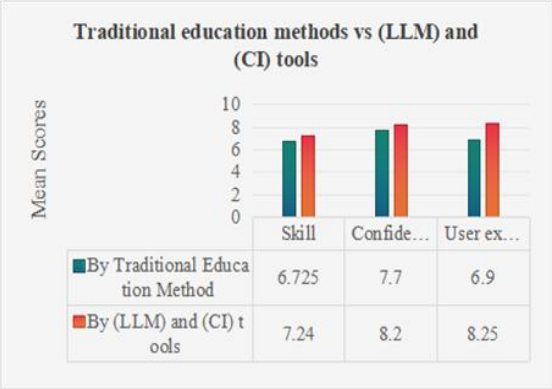


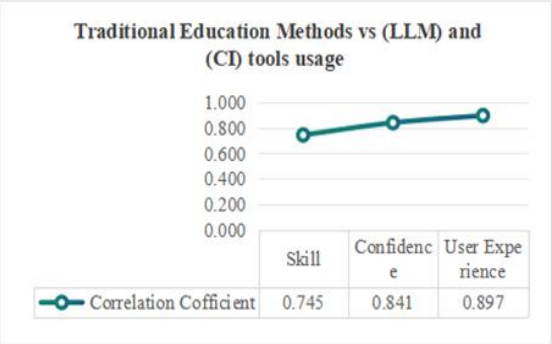
Interpretation: Learning Mean Scores of self-studying significantly improved with traditional educational methods in the case of skills from 5.35 to 6.725. For confidence 7 to 7.7, and user experience satisfaction increased from 6 to 6.9. There is a positive correlation between skills, confidence, and user experience to some extent.

4.3.2 Testing H2 :

Metrics	Mean Scores By Traditional Education Methods	Mean Scores By (LLM) and (CI) tools	Difference	Statistical Difference	Coefficient Correlation
Skill	6.725	7.24	+0.515	$p < 0.05$	0.745
Confidence	7.7	8.2	+0.5	$p < 0.05$	0.841

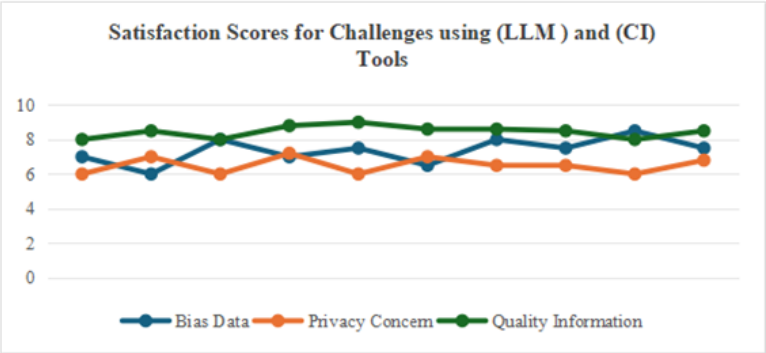
User Experience	6.9	8.25	+1.35	$p < 0.05$	0.897





Interpretation: Learning Mean scores of traditional education methods improved with further usage of LLM and CI tools. In skills, it increased from 6.725 to 7.24 in confidence, it increased from 7.7 to 8.2, and in case of user experience it increases from 6.9 to 8.25. As the coefficient correlation scores are above 0.7 for all so there is a positive correlation and the highest in user experience is 0.897.

4.3.3 Testing H3:



Interpretation: As the mean scores for biased data are 7.35, for privacy is 6.5, and for quality information is 8.45. It reflects privacy is the biggest challenge where learners are not very satisfied using (LLM) and afraid of data bias-ism and quality information to some extent.

5. Results:

The results intimate the integration of LLM and CI tools with traditional methods for wine and food pairing education enhances the learning ability of any age group which brings more accuracy to wine and food pairing recommendations. The satisfaction mean scores increased from self-studying to traditional educational methods and then further by integrating LLM and CI tools usage up to 10-15%. Out of the major 3 challenges Data bias-ism, privacy, and quality information privacy is the biggest challenge of our data search.

Training or inference and query tools such as Vivino, Hello Vino, Wine Folly, Google Assistant, and Ask Decanter help all learners to understand the pairing principles easily. Swarm

intelligence, Evolutionary Algorithms, and Fuzzy Logic system tools under CI with reasoning and optimization techniques act as a self-organized system. They support solving complex problems and create an adaptive learning system as per the need of the learner with their micro-level features such as population size, mutation rate, and selection method and a support for students, experts, and sommeliers while wine and food pairing.

5.1.1 Findings and Implications:

For a quality and stringent interpretation of findings, and analyzing the significance of adaptive education methods for simplifying a palate sensory subject about wine education with integration of AI tools LLM and CI. Thematic analysis is opted along with interpretation results of t-test scores. As per different cultural, dietary, and individual preferences, the efficiency of traditional educational methods is better than self-study but can be improved further with AI Tools LLM and CI (Kumar, 2024). The practical implications of LLM and CI tools are, they increase the efficiency of advising wine and food pairing principles. Studying with LLM and CI tools is more effective than self-study or traditional education methods. Allows individuals of different cultures and preferences to learn about wine and food pairing without travel. Unique pairings with the evolutionary algorithms and big data can be created but need to work on how incorrect information can be filtered out, if some data is searched or added by us how it can be kept confidential on a choice basis of the system user and if a group try to create fake data it can be filtered out to avoid data bias-ism. LLM and CI tools make the learning system more adaptive (Maghsudi et al., 2021) for everyone but a continuous update from experts and sommeliers is also required as new dishes and wines are crafted every day. Cultural and dietary preferences are also changing to some extent in most of the places due to modernization and globalization. As human emotion, mood, and expression are not incorporated in AI Tools, it's still a challenge how to get perfect results.

5.1.2 Thematic Analysis

Key Themes:

User-Centric Experience:	The usage of LLM and CI tools makes the wine pairing education system adaptive more personalized and accessible individually.
Wine Palate Sensitivity:	LLM and CI tools make the learning system adaptive and engaging, based on what cultural and regional differences or eating habits an individual has, and give wine pairing suggestions accordingly.
Smart pairing education by experts:	For accurate pairings in the future, AI Tools such as LLM and CI need to include experts' opinions as it is a sensory and palate-based subject that gets affected by emotions, expressions, and mood.
Bridging AI tools with wine Pairing:	Privacy, data bias-ism, and quality knowledge are the major challenges such as what we search for available to anyone, fake data leads to data bias-ism and quality content goes down so need to resolve this with advancements in LLM and CI tools.

5.2 Conclusion:

The integration of LLM and CI with the traditional education framework makes a unique adaptive learning system that is capable of delivering quality information and knowledge as

per the learner's strengths and ability to learn about wine and food pairing. LLM tools support analyzing the taste, flavor, and aroma of wine and to pair with the dish accordingly. LLM-based tools Inference and query support in personalized recommendations and experimental learning for learners. Flexible wine pairings can be resolved with the usage of a mathematics system called Fuzzy Logic System under CI. Complex problems such as judging the acidity, body, complexity levels of aromas, and balance in wine can be judged and resolved with the CI tool Swarm Intelligence. Through LLM we can understand wine in different languages including difficult vocabulary and metaphors that support label reading. Learning outcomes and understanding results are much better after LLM and CI usage as per test surveys. Learning these tools makes the learning process simpler and more engaging which is important to learn a complex subject wine from a student or beginner's point of view. There are some challenges like data bias-ism, privacy, and quality information that need to be worked up for the advancement and accurate usage of LLM and CI tools, so these tools become more reliable and acceptable at the global level by all learners, hospitality students, and sommeliers. Due to these challenges, it underscore the need for research, in the future it is required to develop LLM and CI tools adaptable for quality education purpose about wine for such palate sensory subject.

5.3 Limitations and Future Research:

As per research, there are some limitations such as only 10 samples opted in each T-test to generalize the statements for all. Research on the choice of wines or dishes may bring changes in the result opted for the experiment. Multiple choice questions-based questionnaires have been opted for the data collection that can affect the results. The option of only 1 instructor itself is a limitation as he has limited teaching pedagogies to clear the doubts of all and a single teaching pattern. Subjective knowledge discussion is lacking and how an individual develops knowledge on their own.

The future areas of research include how to make the availability and usage of LLM and CI tools and how these tools can work without data bias-ism, and privacy concerns and give quality filtered information referred from some research papers or books not from blogs or other general content. Future research can be conducted to detect the expressions, emotions, and moods of a person before wine suggestion by AI tools.

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