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EDITORIAL TEAM

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Welcome message from Editor-in-Chief

Dear authors, reviewers, and readers

It is with great pleasure that we present the first issue of Volume 6 of the Journal of Science and Agricultural Technology (JSAT), the official journal of the Faculty of Science and Agricultural Technology, Rajamangala University of Technology Lanna (RMUTL), Thailand.

JSAT is a multidisciplinary journal dedicated to publishing high-quality original research and review articles in the natural and applied sciences including biology, chemistry, computer science, physics, and materials science as well as in various branches of agricultural technology. These include plant science, animal science, aquatic science, food science, biotechnology, applied microbiology, agricultural machinery, and agricultural engineering. The journal also welcomes submissions addressing the economic, ecological, and environmental dimensions of agriculture, the sustainable use of natural resources and biodiversity in agro-ecosystems, and the technological and sociological aspects of sustainable food systems.

This issue features four research articles contributed by scholars from various institutions, reflecting the diversity and interdisciplinary nature of the journal. JSAT continues to be published on the Thai Journal Online (ThaiJO) platform and is indexed in Google Scholar, the Thai Citation Index (TCI), and the Digital Object Identifier (DOI) system under the National Research Council of Thailand.

We remain committed to maintaining rigorous peer review standards and to fostering academic collaboration both within Thailand and internationally. On behalf of the editorial team, I extend my sincere gratitude to our contributing authors, dedicated reviewers, and editorial staff for their invaluable support.

As Editor-in-Chief, I look forward to further enhancing the journal's visibility and academic impact, and I warmly invite researchers worldwide to submit their manuscripts and share their findings with the broader scientific community.

Best regards,

Asst. Prof. Dr. Tanongsak Sassa-deepaeng
Editor-in-Chief Journal of Science and Agricultural Technology
Faculty of Science and Agricultural Technology
Rajamangala University of Technology Lanna, Thailand.

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ABOUT THE JOURNAL

Journal of Science and Agricultural Technology (JSAT) publishes original research contributions covering science and agricultural technology such as:

• Natural and applied sciences: biology, chemistry, computer science, physics, material science and related fields. Papers in mathematics and statistics are also welcomed, but should be of an applied nature rather than purely theoretical.

• Agricultural technology: plant science, animal science, aquatic science, food science, biotechnology, applied microbiology, agricultural machinery, agricultural engineering and related fields.

Furthermore, the JSAT journal aims to span the whole range of researches from local to global application.

The JSAT is published two issues a year.
Issue 1: January - June
Issue 2: July - December

Submissions are welcomed from international and Thai institutions. All submissions must be original research not previously published or simultaneously submitted for publication or submitted to other journals. Manuscripts are peer reviewed using the double-blinded review system by at least 3 reviewers before acceptance. There is no publication or processing fee.

The journal financial support is provided by Rajamangala University of Technology Lanna, Thailand.

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INSTRUCTION FOR AUTHORS

1. Types of articles and formats

Manuscripts may be submitted to JSAT in the form of Review Articles or Research Articles and must be clearly and concisely written in English with appropriate pages.

2. Preparation of manuscripts

All manuscripts must be prepared and submitted as single Word file (.docx) (Word 2010 or higher). For English font, please use “Time New Roman” with text size of 12 point. Please prepare your manuscript in double-space on A4-sized page. Line number must be used continuous numbering in manuscript. The submitted manuscript should be organized as follow:

2.1) Title

The title of manuscript should be supplied with enough information to catch the attention of readers.

2.2) Author names and affiliations

Please clearly indicate the given name(s) and family name(s) of each author and check that all names are accurately spelled. Indicate the corresponding author by “*”. If authors have different addresses, numbered superscripts are required to refer to each address provided. The format of authors’ affiliations should be: 1. Department, University, City name, State name, Postal code and Country. Corresponding author must inform email.

2.3) Abstract and keywords

Abstract - A concise abstract with maximum of 200 - 250 words identifying the new and significant results of the study must be provided for all manuscripts.
Keywords: – At least 3 to 5 keywords must be given below abstract and use “comma (,)” to separate each.

2.4) Introduction

Author should prepare the introduction with suitable length and keep it as short as possible.

2.5) Materials and methods

This section contains details about materials, techniques, apparatuses, experimental design, and environment. Sufficient detail should be provided to permit the reader to repeat the experiments. For the manuscript reports the utilization of chemical, please provide the purity of all chemicals used in this part.

2.6) Results and discussion

In this part, the results and discussion can be combined or separated depends on author design. Please use tables, graphs, diagrams, and photographs to provide a clear understanding of the results. Quantitative measures of significance (P-values) should be presented. Authors may use either absolute P-values or a defined significance level as long as usage is consistent.
Discussion contains the interpretation of the results into existing literature. It should be clear and concise, address the related mechanisms and their significance.

2.7) Conclusions

Clear and significant conclusions should be provided and related to the results and objectives of your work.

2.8) Acknowledgments

In this section, financial and material support should also be mentioned. Authors should list all funding sources in this acknowledgments section. The names of funding organizations should be written in full. List those individuals who provided support during the research

2.9) References

2.9.1) In text citations, please use name-year system such as:

a. Before texts: Smith (2018)…., Tsuji and Hayate (2012)…., Smith et al.(2019)…., Smith (2018); Tsuji (2012)…., Smith et al.(2018a); Smith et al.(2008b)…..

b. After texts: …. (Smith, 2018), …. (Tsuji and Hayate, 2012), …. (Smith et al., 2019), …. (Smith, 2018; Tsuji, 2012), …. (Smith et al., 2018a; Smith et al., 2008b)

2.9.2) References list

Published literatures or unpublished works must be listed alphabetically by surname of author at the end of the manuscript. Each reference to a periodical publication must include, in order, the name(s) of the author(s), the year of publication, the full title of the article, the publication in which it appears, the volume and inclusive page numbers, and the digital object identifier (DOI), if available. Examples of references are listed as follow:

• ***Journal article***

Halmilton, M.B., Pincus, E.L., Fion, A.D., and Fleischer, R. C. 1999. Universal linker and ligation procedures for construction of genomic DNA libraries enriched for microsatellites. J. Dairy Sci. 27: 500-507. https://doi.org/xx.xxxxxxxxxx

Gupta, A.P., and Kumar, V. 2007. New emerging trends in synthetic biodegradable polymers-polylactide: A critique. Eur. Polym. J. 43: 4053-4074.

• ***Book***

Carr, R.L. 1976. Powder and granule properties and mechanics. Marcel Dekker Publisher, New York.

• ***Chapter in book***

Jackson, M.B. 1982. Ethylene as a growth promoting hormone under flooded conditions. In: Wareing, P.F. (ed) Plant growth substance. Academic Press, London. p.291-301.

• ***Proceeding, symposia etc.***

Pratt, A., Gilkes, R.J., Ward, S.C., and Jasper, D.A. 2000. Variations in the properties of regolith materials affect the performance of tree growth in rehabilitated bauxite mine-pits in the Darling Range, SW-Australia. In: Brion, A., and Bell, R.W. (eds) Proceeding of Remade Land 2000, the International Conference on Remediation and Management of Degraded Lands. Fremantle, 30 Nov-2 Dec 2000. Promaco Conventions, Canning Bridge. p.87-88.

• ***Dissertation***

Senthong, C. 1979. Growth analysis in several peanut cultivars and the effect of peanut root-knot nematode (Meloidogyne arenaria) on peanut yields. Ph.D. Dissertation. University of Florida, Gainesville, Florida.

3. Equation, figure, table and unit of measurement

Equation

All equations presented in the text can be prepared by Equation editor from Microsoft word or Math Type.

Figure

Data presented in figure must be written in English. Color or gray scale figure should be prepared as TIFF format (.tif) with at least 600 dpi. Photograph should be prepared as TIFF (.tif) or JPEG (.jpg) format with at least 600 dpi. Figure with caption should be placed next to the relevant text, rather than at the bottom of the file.

Table

Data presented in table must be written in English. Table with caption and footnote should be placed next to the relevant text, rather than at the bottom of the file.

Unit

Author should use the International System of Units (S.I.)

4. Structure of manuscript

- Title
- Author names and affiliations
- ABSTRACT
- Keywords
- INTRODUCTION
- MATERIALS AND METHODS
- RESULTS AND DISCUSSION (The results and discussion can be combined or separated depends on author design)
- CONCLUSIONS
- ACKNOWLEDGMENTS (if any)
- REFERENCES

5. After acceptance

Authors would be asked to send the “Copyright Transfer Agreement” to JSAT.

6. Publication or processing fee

There is no publication or processing fee.

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Study on a potentiality of plant aqueous extracts as natural dye fixatives in traditional dyeing processes using natural indigo from *Strobilanthes cusia* (Nees) Kuntze

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Received: May 21, 2025. Revised: June 6, 2025. Accepted: June 6, 2025.

ABSTRACT

This research investigated the use of five local plants in Northern Thailand which were *Camellia sinensis* (CS), *Moringa oleifera* (MO), *Oroxylum indicum* (OI), *Schefflera leucantha* (SL), and *Tinospora cordifolia* (TC) as stabilizing agents for indigo dyed fabric. The selected plants were extracted and examined for phytochemical compositions. It was found that CS-extract revealed the highest content of total phenolic compound, flavonoid and tannin of 2.40±0.46 GAE/mg DW, 3.31±0.29 QE/mg DW, and 0.23±0.01 ECGC/mg DW, respectively. MO total phenolic compound, flavonoid and tannin of 0.96±0.04 GAE/mg DW, 1.81±0.15 QE/mg DW, and 0.15±0.02 ECGC/mg DW, respectively. For antioxidant properties, CS and MO exhibited the most efficiency of 6564.4±55.6 mM Fe^{2+}/g DW and 6512.6±220.6 mM Fe^{2+}/g DW, respectively. Consequently, these might be responsible for the ability for color fixation. Particularly, MO with the excellent properties resulted in a good color fastness score at 3-4. In contrast, CS seemed to be less fixative ability than MO.

Keywords: *Strobilanthes cusia* (Nees) Kuntze, *Camellia sinensis*, *Moringa olifera*, indigo dyed fabrics, natural fixative agents

INTRODUCTION

Natural indigo dyeing is a longstanding cultural practice in Northern Thailand, particularly in the provinces of Chiang Mai, Phrae, Nan, and Lampang. Among the natural dye sources, *Strobilanthes cusia* (Nees) Kuntze (indigo plant) has been traditionally used for generations, aligning with both local cultural heritage and the contemporary demand for eco-friendly and sustainable textile products. The northern region of Thailand provides a favorable environment for the cultivation of *S. cusia*, owing to its relatively cooler temperatures and higher humidity compared to other regions. These climatic conditions not only support optimal plant growth but also contribute to the distinctive aesthetic quality of indigo-dyed fabrics produced in this area.

The traditional method of indigo extraction and vat dye preparation is a complex biochemical process influenced by multiple parameters, including the material-to-liquid ratio, fermentation time and temperature, lime ($Ca(OH)_2$) quality as resulted an optimum pH, and dissolved oxygen concentration. These factors critically affect the yield of the extracted pigment and the quality of the vat dye (Pattanaik *et al*., 2021; Li *et al*., 2019). Typically, the indigo leaves are naturally fermented in water for approximately 24 h The solution without debris is normally added with lime water and oxygenated using air pump for only 10 to 15 min at ambient temperature to extract the pigment. The insoluble form of the dye, Thai known as Hom-Peag, is precipitated and later collected. For indigo to be rendered soluble and suitable for textile application as a vat dye, it must first be reduced to its leuco form. This is traditionally achieved using *Tamarindus indica* (tamarind) as a natural reducing agent. However, the price and availability of tamarind are subjected to seasonal fluctuations, particularly during the rainy season, as a result of fungal infections and reduced fruiting associated with adverse weather conditions.

In response to these limitations, the present study explores alternative locally sourced reducing agents that may exhibit properties equivalent to tamarind in the *S. cusia* dyeing process. This study considers *Spondias mombin* as an alternative reducing agent for the vat dye process. *S. mombin* is a member of the Anacardiaceae family. Its extract has been shown to possess high levels of phenolic compounds and ascorbic acid, contributing to strong antioxidant properties (Akanda *et al*., 2021;

Oladunjoye *et al*., 2021). *S. mombin* is also widely available in local of Northern Thailand, offering a cost-effective alternative.

This study also investigated the use of plant-based dye fixative, which was essential for natural dyeing of cotton fabrics. Dye fixative enhances the affinity of the dye to fabric fibers, improving color fastness and durability. In the absence of an effective dye fixative, many natural dyes result in poor color retention. Moreover, the choice of dye fixative can influence the final hue of the dyed fabric, thus expanding the achievable color palette.

To identify eco-friendly alternatives to synthetic dye fixative, five plant species with characteristic bitter taste were selected for investigation as potential bio-mordants: *C. sinensis* (CS), *M. oleifera* (MO), *O. indicum* (OI), *S. leucantha* (SL), and *T. cordifolia* (TC).

C. sinensis (tea), a member of the Theaceae family, is rich in tannins, catechins, and flavonoids—particularly thearubigins and theaflavins—which act as dye fixative and contribute to its reddish-brown and yellowish-brown pigmentation (Sarker *et al*., 2024; Xu *et al*., 2025). These compounds enhance dye fixation and make tea an effective and environmentally friendly option for natural fabric dyeing.

M. oleifera, a species in the Moringaceae family, also contains high levels of polyphenols and tannins. These compounds are known to promote bonding between dye molecules and cotton fibers, thereby increasing color fastness (Benli, 2024). In addition to its dye-affinity potential, moringa is a rich source of antioxidants such as ascorbic acid, flavonoids, and carotenoids (Stohs & Hartman, 2015).

O. indicum (Bignoniaceae) has a long history of medicinal and culinary use in Southeast Asia. Its bark has traditionally been used as a dye, and its young pods contain flavonoids such as baicalin, oroxylin A, and 5-hydroxymethylfurfural, which may function as bio-dye fixative in cotton dyeing processes (Rojsanga *et al*., 2023).

S. leucantha (Araliaceae) is a less-studied species with over 200 identified triterpenoid saponins. Although it has not been previously reported as a dye fixative, its bitter taste and phytochemical composition warrant investigation into its potential bio-dye fixative activity (Wang *et al*., 2021).

T. cordifolia (Menispermaceae) is a herbaceous vine known for its rich phytochemical profile, includs phenolics, alkaloids, glycosides, and clerodane-type diterpenes (Sharma *et al*., 2019). Although there are no previous reports regarding its use as a dye fixative, the chemical composition of this plant suggests its potential applicability in dyeing processes.

This study aims to investigate the phytochemical properties of five selected plant species—*C. sinensis*, *M. oleifera*, *O. indicum*, *S. leucantha*, and *T. cordifolia*—and evaluate their efficacy as natural mordants in cotton fabric dyeing using *S. cusia*. Additionally, the potential of alternative reducing agents such as *S. mombin* is assessed to support sustainable practices in traditional indigo dyeing.

MATERIALS AND METHODS

Extraction of Indigo dye from Strobilanthes cusia (Nees) Kuntze

Fresh *S. cusia* leaves were collected early in the morning. One kilogram of the leaves was submerged in 10 L of distilled water and fermented naturally for 24 h at ambient temperature. All the debris was then removed. The amount of 120 g $Ca(OH)_2$: Maelao Chiang rai lime kiln, commercial grade, was gently added. After that the solution was stirred vigorously for 20-30 min or until the blue dye was precipitated to form an insoluble substance. The dye paste was then filtrated using cheesecloth and collected for the next studies.

Preparation of reducing agent solution

In this study, *S. mombin* (SM-) was used as a reducing agent compared to *T. indica* which was used in a traditional method. SM-extract was prepared at a concentration of 50, 100, 150, 200 and 250 g/L. Meanwhile, *T. indica* (TI-) extract was prepared at a different concentration of 15, 20, 25, 30 and 35 g/L. The two plants flesh were squeezed in hot water and removed waste.

Preparation of fixative agent

The different parts of herbal plants such as leaves of *S. leucantha*, *M. oleifera*, *C. sinensis*, stem of *T. cordifolia* and bark of *O. indicum* were freshly selected, chopped and air oven dried at 60°C for a few days. All dried plant parts samples were extracted in boiling water at a concentration of 10 g/L.

Characterization of reducing agent

The UV-Vis spectral analysis of the mordants was performed using a UV-Vis spectrophotometer: Libras70, Biochrom, across a wavelength range of 200 to 800 nm.

RESULTS AND DISCUSSION

Reducing property investigation

Reducing agent extracts of Spondias mombin and Tamarindus indica (TI-) appeared in a smoky pale yellow, and muddy brown color, respectively as shown in Figure 1.

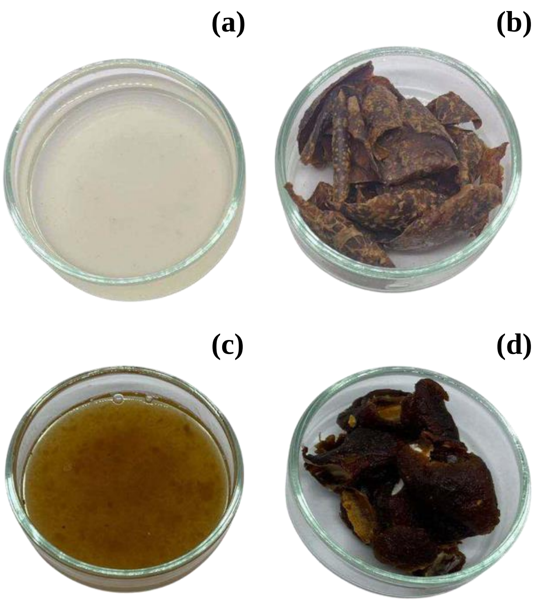


Figure 1. The appearance of (a) *S. mombin* extract, (b) *S. Mombin* dried flesh, (c) *T. indica* extract and (d) *T. indica* dried flesh.

The SM-extracts consists of plant pigments such as carotenoids, particularly β-cryptoxanthin which provides a pale-yellow color, Tiburski *et al.* (2011). The TI-extract was however presented the color of light brown which caused by enzymatic browning and Maillard reaction as indicated by Obulesu & Bhattacharya (2011).

To investigate the reducing properties, the extracts were used in various concentrations for fabric dyeing process and the results are shown in Figure 2.

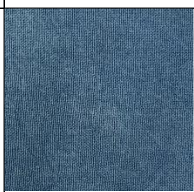
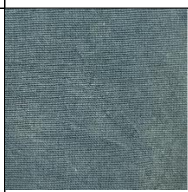
Reducers	Reducing agent concentration				
S. mombin extract	50 g/L	100 g/L	150 g/L	200 g/L	250 g/L
					
T. indica extract	15 g/L	20 g/L	25 g/L	30 g/L	35 g/L
					

Figure 2. Color obtained from fabrics dyed with *S. cusia* using *S. mombin* and *T. indica* extracts in various concentrations as the reducers.

According to Figure 2, using SM-extract and TI-extracts at various concentrations of 50-200 g/L and 15-35 g/L, respectively showed the optimal concentration of reducing agents. Applying SM-extract to vat dye at the concentration of 150 g/L provided a blue color with brighter than other concentrations. However, adding 25 g/L TI-extracts presented the brightest blue color among other concentrations. A comparison between the two reducing agents revealed that the use of TI-extracts resulted in a more pronounced blue hue compared to SM-extracts. This observation suggests that SM-extracts may be less effective as a reducing agent in the fabric dyeing process. Consequently, TI-extracts were deemed more suitable and were selected for subsequent experiments.

Fixative agent phytochemical composition and its ability

Fixative agent extracts of *T. cordifolia* and *S. leucantha* introduced pale yellow color. On the other hand, *O. indicum*, *M. oleifera*, and *C. sinensis* produced a color range from yellow to yellow-brown. The results showed in Figure 3.

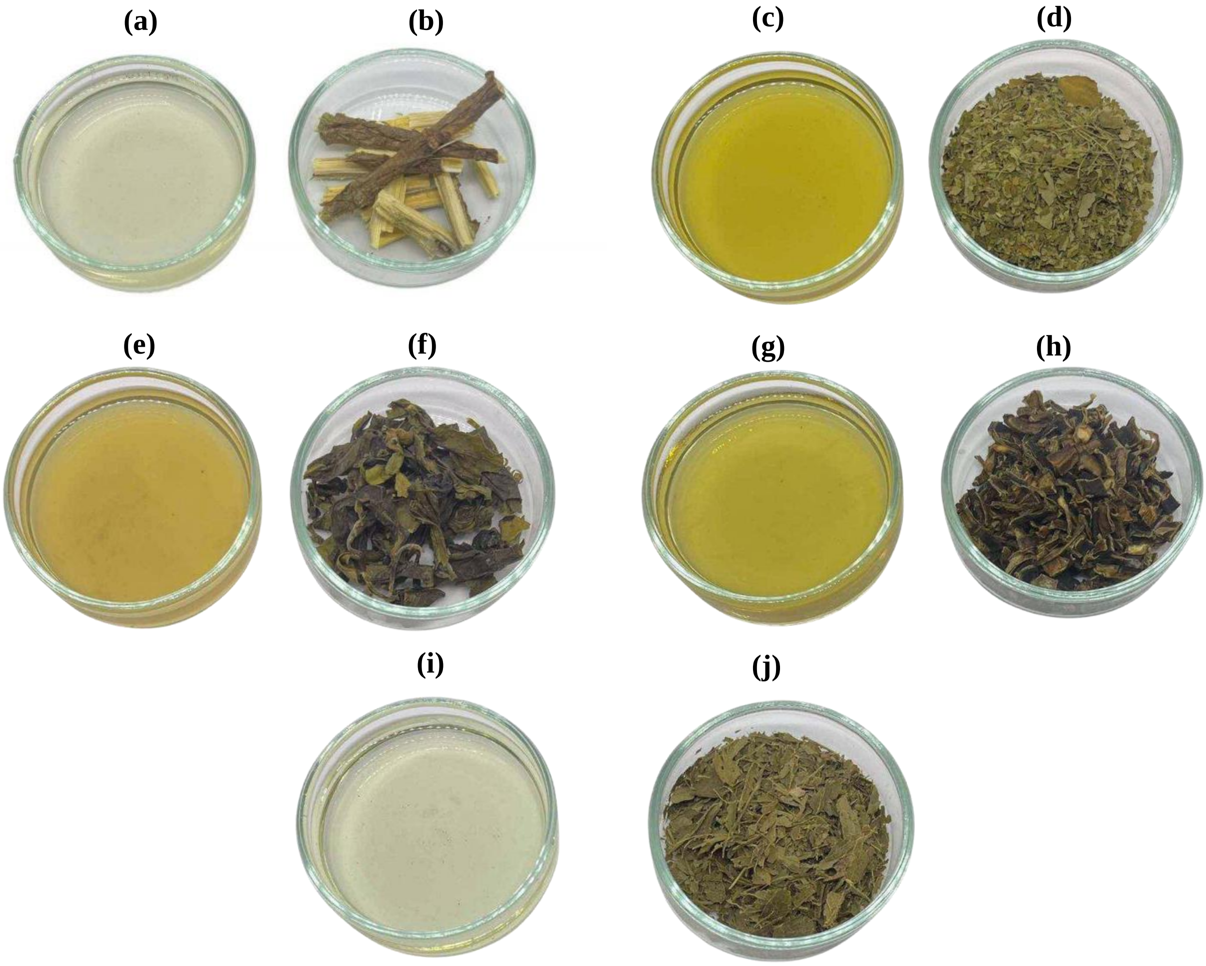


Figure 3. The appearance of (a) *T. cordifolia* extract, (b) *T. cordifolia* dried stem, (c) *M. oleifera* extract, (d) *M. oleifera* dried leaves, (e) *C. sinensis* extract, (f) *C. sinensis* dried leaves, (g) *O. indicum* extract, (h) *O. indicum* dried bark, (i) *S. leucantha* extract and (j) *S. leucantha* dried leaves.

The TC- and OI- extracts contain plant pigments mainly flavonoids, as reported in Tiwari *et al*. (2010) and Panomai *et al*. (2024), respectively. On the other hand, Quercetin was found in SL-extracts by El-Hagrassi *et al*. (2022). The CS- and MO- extract provided chlorophyll and carotenoid followed Aboulwafa *et al*. (2019) and Toscano *et al*. (2021).

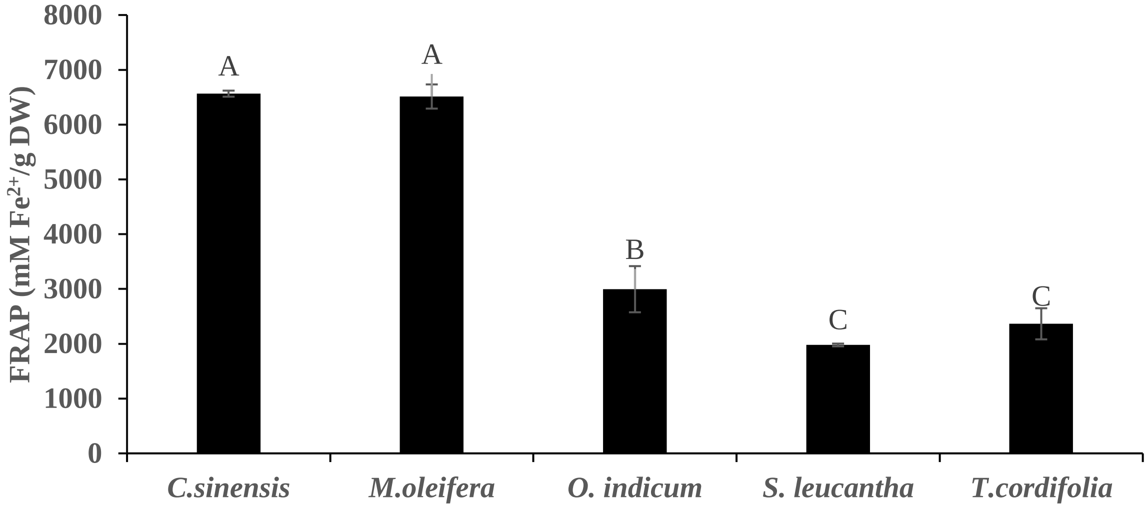


Figure 4. FRAP value of aqueous extracts expressed as mM Fe^{2+}/g of DW. Columns labeled with different letters were significantly different, $p < 0.05$ (n = 3).

Antioxidants serve a pivotal function in the natural dyeing of cotton textiles, especially in conjunction with bio-mordants. The presence of these compounds enhances color strength and improved color fastness, while also imparting bio-functional properties such as anti-bacterial and antioxidant activities to the dyed fabrics. Figure 4 illustrates the antioxidant activity of various extracts as assessed through the FRAP assay. The data indicate that the aqueous extracts of *C. sinensis* and *M. oleifera* exhibited the highest antioxidant properties (6564.4±55.6 mM Fe^{2+}/g DW and 6512.6±220.6 mM Fe^{2+}/g DW), which might be attributed to their significant polyphenol content, particularly in their phenolic and flavonoid fractions (Sassa-deepaeng *et al*., 2019; Baldisserotto *et al*., 2023). These extracts were followed by *O. indicum*, which demonstrated moderate antioxidant activity. In contrast, the extracts of *T. cordifolia* and *S. leucantha* displayed the lowest antioxidant activity (6512.6±55.6 mM Fe^{2+}/g DW). Numerous studies have demonstrated a positive correlation between antioxidant activity and the levels of phenolic compounds, flavonoids, and tannins presented in plant extracts (Muniyandi *et al*., 2019; Cosme *et al*., 2025). To further substantiate these findings, the phenolic, flavonoid, and tannin contents were also analyzed, with the results for phenolic content presented in Figure 5.

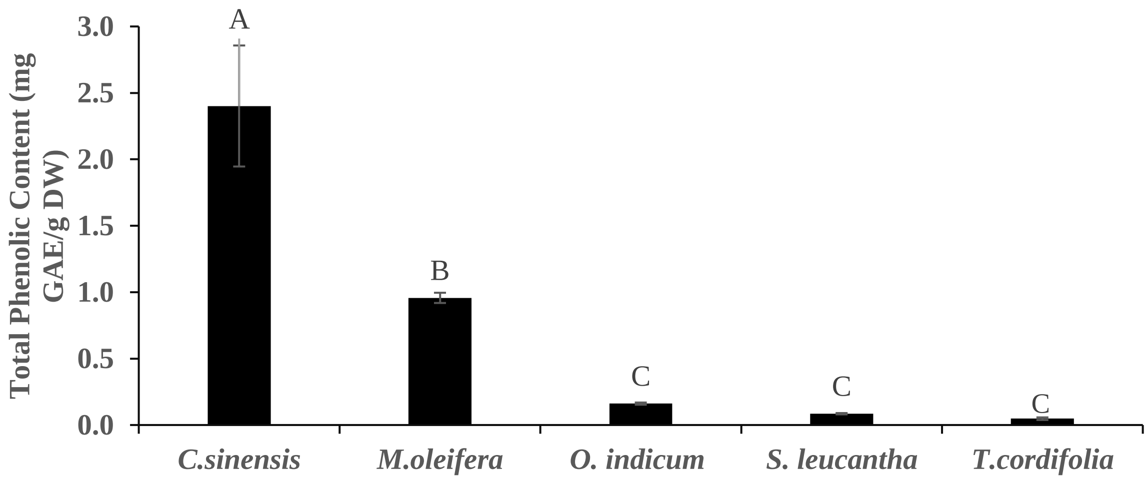


Figure 5. Total phenolic content of aqueous extracts expressed as mg GAE/g of DW. Columns labeled with different letters were significantly different, $p < 0.05$ (n = 3).

Phenolic compounds possess strong antioxidant properties, meaning they can donate electrons. In the dyeing process, particularly with vat dyes (like indigo) or natural dyes requiring reduction, phenolic compounds can act as natural reducing agents, converting dye precursors to their soluble (leuco) forms that can penetrate the fabric fibers. Thus, the total phenolic content (TPC) of the aqueous extracts is presented in Figure 4. Among the extracts, the highest TPC value was observed in the leaf extracts of *C. sinensis* (2.40±0.46 mg GAE/g dry weight), which is consistent with the findings reported by Sassa-deepaeng *et al*. (2019) and Murokore *et al*. (2023). This was followed by *M. oleifera* (0.96±0.04 mg GAE/g dry weight), which exhibited a moderate TPC. In contrast, the extracts of *O. indicum*, *S. leucantha*, and *T. cordifolia* demonstrated the lowest TPC values. Furthermore, the subclass of phenolic compounds, specifically flavonoids, was also examined, and the results are presented in Figure 6.

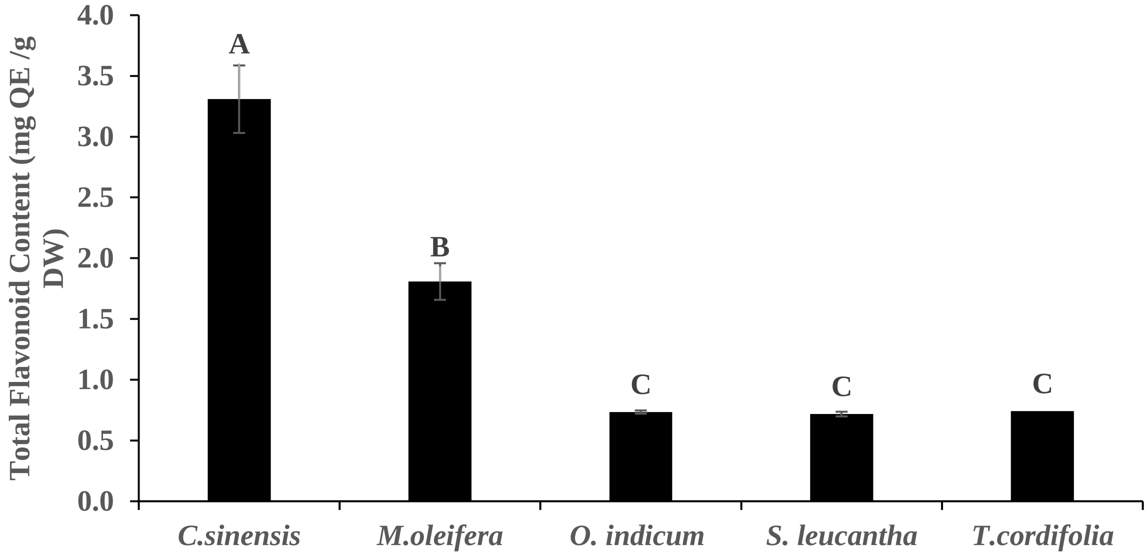


Figure 6. Total flavonoid content of aqueous extracts expressed as mg QE/g of DW. Columns labeled with different letters were significantly different, $p < 0.05$ (n = 3).

The total flavonoid content (TFC) in plant extracts is a crucial factor influencing the fabric dyeing process. Flavonoids, a diverse group of polyphenolic compounds, contribute to the dyeing process through various mechanisms, including their antioxidant and reducing properties, mordanting and fixation abilities, color development and hue alteration, and their role in enhancing dye stability. Moreover, flavonoids offer significant environmental and health benefits by reducing the use of harmful chemicals, thus making the process safer for workers and lessening environmental pollution.

The TFC of the aqueous plant extracts is presented in Figure 5. Among the extracts, the leaf extract of *C. sinensis* exhibited the highest TFC value of 3.31 ± 0.29 mg QE/g dry weight, which is consistent with previous studies by Sassa-deepaeng et al. (2019) and Murokore et al. (2023). This was followed by *M. oleifera*, which showed a moderate TFC value of 1.81 ± 0.15 mg QE/g dry weight. These results align with findings from the FRAP assay and total phenolic content analysis, further supporting the role of flavonoids as important contributors to the dyeing process. In contrast, the extracts of *O. indicum*, *S. leucantha*, and *T. cordifolia* exhibited the lowest TFC values.

In addition to flavonoid content, the tannin content of the extracts was also assessed, with the results presented in Figure 7.

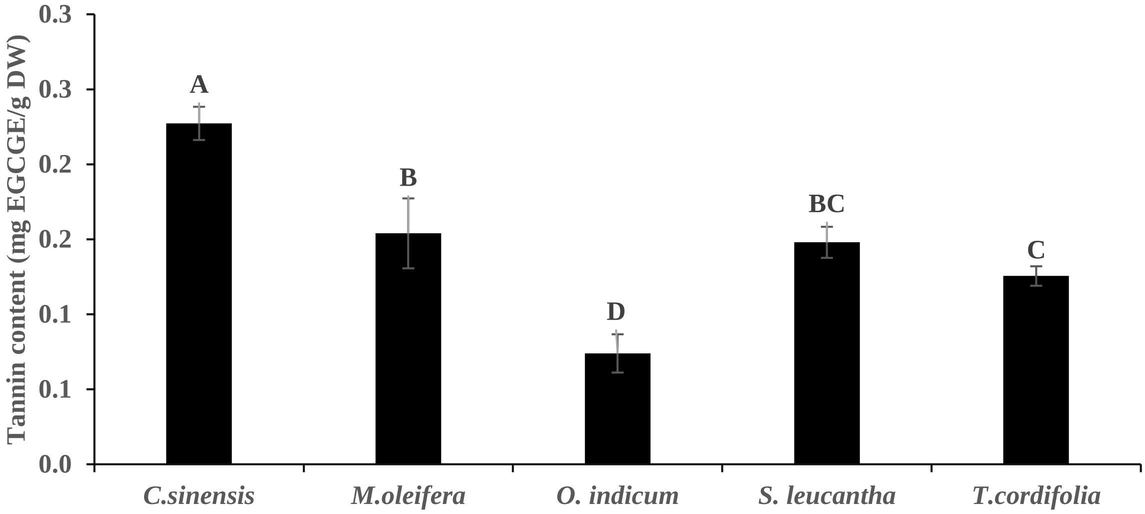


Figure 6. Tannin content of aqueous extracts expressed as mg EGCGE/g of DW. Columns labeled with different letters were significantly different, $p < 0.05$ ($n = 3$).

Tannin represents a key natural mordant in the dyeing of cellulose-based fibers such as cotton. Functioning as a binding agent, it facilitates the interaction between dye molecules and fiber substrates, thereby enhancing dye uptake, fixation, and overall colorfastness. Additionally, tannins contribute to pH stabilization during the dyeing process and can intensify the color of certain natural dyes. The tannin content (TC) of the aqueous plant extracts is presented in Figure 7. Among the samples analyzed, the leaf extract of *C. sinensis* exhibited the highest TC value (0.23 ± 0.01 mg EGCGE/g dry weight), consistent with the findings of Lambrecht *et al*. (2023). This was followed by *M. oleifera* and *S. leucantha*, both of which demonstrated moderate TC values of 0.15 ± 0.02 mg EGCGE/g dry weight and 0.15 ± 0.01 mg EGCGE/g dry weight, respectively. These variations in tannin concentration may contribute to differences in the shade and depth of coloration observed in dyed cotton fabrics. In contrast, the extracts derived from *O. indicum* and *T. cordifolia* displayed the lowest TC values among the samples tested.

The observed ferric ion reduction in the FRAP assay supports the antioxidant activity of the extracts, which is indicative of the electron-donating capacity of polyphenolic compounds (Khiya *et al*., 2021). Among the tested plant extracts, *C. sinensis* exhibited the highest antioxidant activity, followed by *M. oleifera*, *S. leucantha*, *O. indicum*, and *T. cordifolia*, respectively. Notably, *M. oleifera* demonstrated a high potential as a natural mordant, comparable to the traditionally used *C. sinensis*.

In addition to its antioxidant capacity, *M. oleifera* extract contained the highest levels of phenolics, flavonoids, and tannins among the tested plants, which are key contributors to its reducing properties. These phytochemical constituents are recognized for their ability to enhance dye fixation on natural fibers by forming stable complexes with both dye molecules and fabric substrates. Therefore, *M. oleifera* emerges as a promising alternative bio-mordant for traditional cotton fabric dyeing using *S. cusia*.

To further characterize the chemical composition of the extracts, UV–Vis spectrophotometric analysis was conducted, and the resulting spectra are presented in Figure 8.

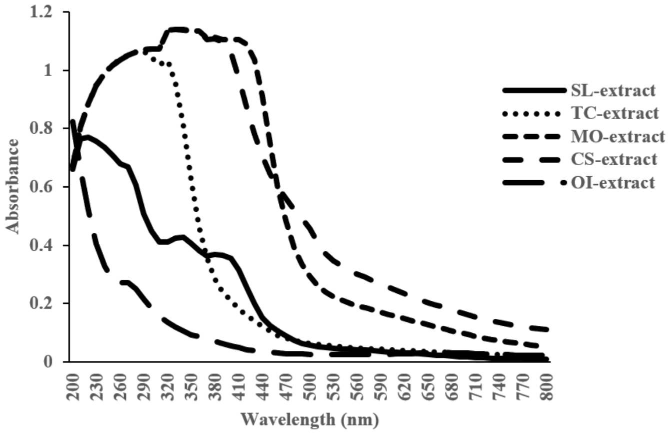


Table 6. UV-VIS spectra of 10 g/L crude extracts in distilled water.

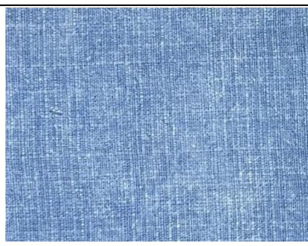
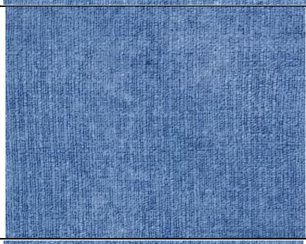
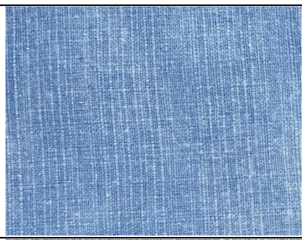
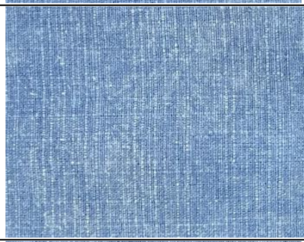
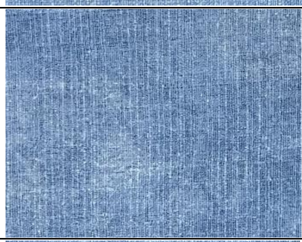
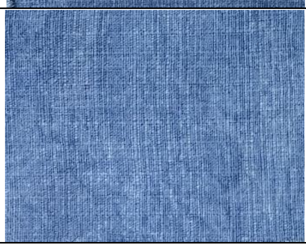
Fixative agents	Color before washing	Color after 5 times of washing	Wash fastness value
S. leucantha extract			3-4
T. cordifolia extract			3-4
M. oleifera extract			3-4
C. sinensis extract			3
O. indicum extract			3

Figure 9. The appearance of dyed fabrics after 5th times of dyeing using different fixative agent and wash fastness value.

Figure 8 was illustrated the characteristic spectra of the aqueous extract of fixative agents at wavelength of 200-800 nm. The profile suggested the broad peak at 350-440 nm for MO- and CS-extract. Kusmita, *et al*. (2015) introduced the peak of pigments in CS-extract such as pheophytin at 408 nm, pheophorbide at 409 nm, and violaxanthin at 417 and 438 nm. MO-extract provided the peak at 412 nm of the yellow color pigment supported by Aouf *et al*. (2024) which could be β-carotene, Dănilă & Lucache (2016). The TC-extract displayed a peak at 260 nm of phycocyanin pigment, Puri & Patil (2022). The SL-extract peak was at 220, 260, 340 and 410 could represent phycoerythrin and phycocyanin pigments, Dănilă & Lucache (2016). The OI-extract provided a similar UV-Vis profile pattern with SL-extract and could contain both phycoerythrin and phycocyanin pigments.

To investigate the fixative property, five fixative agents was applied to the final step. The 10% (w/v) bio-fixative agents were used. Later, the dyed fabric samples were tested for color fastness to washing. All fabric samples were washed 5 times and assessed the change in color with the grey scale. Color obtained before and after 5 times of washing were presented in Figure 9. As the results in Figure 9, it is revealed that fixing the fabrics color with 10% (w/v) of fixative agents mostly showed rating scale from 3. Color changes of indigo dyed fabrics with CS and OI was visible and staining was also noticeable. The fabrics color fixed with the rest of fixative agents, SL, TC, and MO, provided a wash fastness value number of 3-4 which defined a slight color change with a minimal staining.

CONCLUSION

Among the plant extracts tested, *M. oleifera* demonstrated the highest potential as a natural mordant, comparable to the traditionally used *C. sinensis*. This is attributed to its superior levels of phenolics, flavonoids, and tannins, which are critical for the mordanting process. The results indicate that *M. oleifera* extract can effectively fix dye to fabric, achieving a color fixation comparable to *C. sinensis*, which has been traditionally used for this purpose. Additionally, fabric treatments with 10% (w/v) fixative agents yielded satisfactory results, with a rating scale of 3 observed for *O. indicum* extract. Notably, visible staining was also apparent for the positive control using *C. sinensis*, further supporting the potential of *M. oleifera* as an effective mordant.

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Saliva amylase inhibitory property of certain herbs and spices in Lampang, Thailand

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ABSTRACT

Salivary α-amylase inhibitors (SaAIs) derived from spices and herbs have shown promise for the effective management of type 2 diabetes. This study aimed to identify potential SaAIs from aqueous extracts of 15 commonly used plants. Among these, *Albizia lebbeck* (L.) Benth. exhibited the highest inhibitory activity, followed by *Mimosa pudica* L., *Ipomoea aquatica* Forssk., and *Gymnema inodorum* (Lour.) Decne. Phytochemical analysis indicated that *A. lebbeck* demonstrated the strongest amylase inhibition, which was attributed to its high content of phenolics, flavonoids, tannins, and saponins. *M. pudica* also showed a significant saponin concentration. *I. aquatica* displayed notable amylase inhibitory activity linked to its phenolic, flavonoid, and protein content, although it also contained a high amount of reducing sugars. *G. inodorum* exhibited inhibition through a combination of phenolics, flavonoids, saponins, and proteins. The findings provide compelling evidence that dietary intake of *A. lebbeck*, *I. aquatica*, and *G. inodorum* may positively influence glycemic control. These results suggest that all four plants are promising candidates for further *in vivo* studies and potential drug development in mammalian models and humans.

Keywords: Plant extract, amylase inhibitor, tannin content, phenolic content

INTRODUCTION

Type 2 diabetes mellitus (T2DM) represents a significant and escalating public health concern in Thailand, characterized by increasing prevalence, a substantial proportion of undiagnosed cases, and challenges in achieving optimal disease management. Over the past decade, the prevalence of T2DM among Thai adults has risen markedly, from 7.5% in 2009 to 11.6% in 2021. Notably, among individuals aged over 65 years, the prevalence increased from 10.1% in 2014 to 19.6% in 2020. By 2019, approximately 4.8 million Thai adults were living with T2DM, with projections estimating this number will reach 5.3 million by 2039 (Sodeno *et al*., 2022; Pitchalard *et al*., 2022).

Effective glycemic control is essential for individuals with T2DM to prevent complications and maintain metabolic health. Salivary amylase, also known as α-amylase or ptyalin, plays a pivotal role in the initial digestion of dietary starches by hydrolyzing the α-1,4-glycosidic bonds, converting starch into smaller sugars such as maltose. This enzymatic activity can influence the glycemic index of foods, thereby affecting postprandial blood glucose levels. Emerging research indicates that higher salivary amylase activity may contribute to more rapid and pronounced increases in blood glucose following the consumption of starch-rich foods.

Given the critical role of salivary α-amylase in carbohydrate metabolism, inhibitors of this enzyme have attracted attention for their potential therapeutic applications in managing T2DM. Salivary α-amylase inhibitors (SaAIs), particularly those derived from natural sources such as spices and herbs, have demonstrated promising antidiabetic properties. The present study aims to investigate and identify potent SaAIs from aqueous extracts of 15 commonly used medicinal plants, as detailed in Table 1.

Table 1. Fifteen commonly used medicinal plants selected for the salivary α-amylase inhibitory activity study.

Scientific name	Thai name	Family	Part	Used as	Reference
Acmella oleracea (L.)	Puk Pet	Asteraceae	leave	anti-inflammatory, antioxidative, antifungal, analgesic, and bacteriostatic effects	Kowalczyk *et al.* (2024)
Albizia lebbeck (L.) Benth.	Puk Tud	Leguminosae	leave	Antioxidative, anti-inflammatory, and neuroprotective effects	Phoraksa *et al.* (2023)
Azadirachta indica A. Juss	Sa Dao	Meliaceae	bark	Antioxidative, and antimicrobial activity	Baby *et al.* (2022)
Basella alba L.	Puk Pung	Basellaceae	leave	Anti-Melanogenic, Antioxidative, anti-inflammatory effects	Linsaenkart *et al.* (2024)
Casuarina junghuhniana Miq.	Son pradipat	Casuarinaceae	bark	not well-documented	-
Coccinia grandis (L.) Voigt	Tum Lueng	Cucurbitaceae	leave	α-glucosidase inhibitory	Bunyakitcharoen *et al*. (2024)
Dolichandrone serrulata (Wall. ex DC.) Seem.	Kae Na	Bignoniaceae	bark	Anti-pyretic, anti-inflammatory and anti-mutagenic effects	Chaimontri *et al.* (2021)
Gymnema inodorum (Lour.) Decne	Chiang Da	Asclepiadaceae	leave	hypoglycemic effect	Norkum *et al.* (2023)
Ipomoea aquatica Forssk.	Puk Bung	Convolvulaceae	leave	Antioxidative effect	Joshi *et al.* (2021)
Mimosa pudica L.	Mai Ya Rap	Fabaceae	leave	Antioxidant, Antimicrobial and Antacid effects	Gandhi *et al*. (2023)
Piper sarmentosum Roxb.	Cha Plue	Piperaceae	leave	Anthelmintic, antifungal, antibacterial and cytotoxic effects	Ware *et al*. (2023)
Samanea Saman (jacq.) Merr.	Chamchuri	Fabaceae	leave	Antidiabetic effect	Babin-Reejo *et al.* (2014)
Tamarindus indica L.	Ma Kham	Fabaceae	bark	Antibacterial and Hypoglycemic effect	Fagbemi,*et al.* (2022), Mohd Adnan *et al*. (2025)
Tectona grandis L. f.	Sak	Verbenaceae	bark	Antioxidant, antipyretic, analgesic, hypoglycemic, wound healing, cytotoxic effects	Asdaq *et al*. (2022)
Zanthoxylum limonella (Dennst.)	Ma Khwaen	Rutaceae	seed	blood glucose reduction	Pattanawongsa *et al.* (2021)

This study was specifically conducted to investigate the anti-amylase inhibitory activity and to assess the total phenolic, flavonoid, tannin, saponin, terpenoid, alkaloid, and protein contents, along with the reducing sugar content, of the aqueous extracts.

MATERIALS AND METHODS

Plant materials

The spices and vegetables were collected from a local market close to Lampang Kanlayanee School in Thailand. An herbalist from Rajamangala University of Technology Lanna (RMUTL) verified the bark of the putative plants that were also harvested at this school, which is located at 18.28535942258579, 99.49865971349381, during October and November of 2024.

Sample preparation

A 100 g portion of the fresh sample was first rinsed with tap water, followed by distilled water upon arrival. It was then dried in a hot air oven at 55 °C until a constant weight was achieved. The dried material was ground using an electric blender. Fine powder was obtained by passing it through a 20-mesh sieves, and the resulting powder was stored at -20 °C for subsequent analysis. To prepare the aqueous extract of each plant, 100 mg of dried plant powder was boiled with 5 mL of distilled water at 85 °C for 30 minutes, following the method described by Sassa-deepaeng *et al*. (2023). After cooling to room temperature, the mixture was filtered using a 0.22-micron nylon syringe filter (Merck KGaA, Darmstadt, Germany). The filtrate was then used for further experiments.

Anti-amylase Inhibitory Activity Assay

The carbon material was prepared without heating (Whitener, 2016). GBC GSBC FBC and FSBC were prepared by slowly adding 50 mL of concentrated sulfuric acid to each of the large beakers, which contained 50 g of glucose powder, saturated glucose solution (50 g of glucose), 50 g of fructose powder and saturated fructose solution (50 g of fructose), respectively. The individual carbon samples were separated, washed with deionized water, and dried in a hot-air oven at 95 °C for 24 h. Similarly, SJBC was prepared by adding concentrated sulfuric acid to sugarcane juice (12% of reducing sugar) in a 2 L beaker. The carbon from this process was separated by filter paper. It was washed and dried at 95 °C for 24 h in a hot air oven. All of the carbon samples were stored in a desiccator.

Anti-amylase Inhibitory Activity Assay

The inhibitory activity of salivary α-amylase was evaluated following the procedure described by Xiao *et al*. (2006). Written informed consent was obtained from Miss Apisara Moolphueng who participated as researcher in this experiment. Forty microliters of salivary α-amylase solution, diluted 40 times in 0.1 M phosphate buffer (pH 7), was mixed with 50 µL of the sample at various concentrations in microplate wells (Bibby Sterilin Ltd., Stone, UK) and incubated at 37 °C for 30 minutes. Then, 40 µL of 0.2% soluble starch was added to initiate the enzyme reaction, which continued at 37 °C for an additional 20 minutes. Afterward, 100 µL of iodine reagent (5 mM iodine (Univar, Ajax Finechem, Australia) and 5 mM Potassium iodide (RCI Labscan, Dublin, Republic of Ireland)) was added, and the absorbance was measured at 630 nm using microplate reader (BIOBASE-EL10, Biobase Biodustry (Shandong) Co., Ltd., China). The enzyme inhibitory activity was calculated using the formula:

$$\alpha\text{-amylase inhibitory activity (\%)} = (C / E) \times 100$$

where E represents the optical density of the reaction containing both the sample (inhibitor) and the enzyme, and C denotes the optical density of the reaction containing the enzyme with the same volume of distilled water instead of the sample.

Total phenolic content

The total phenolic content (TPC) was determined using the Folin-Ciocalteu (FC) colorimetric method as described by Sassa-deepaeng *et al*. (2023). A 20 µL aliquot of the extract at varying concentrations was mixed with 100 µL of FC reagent (Merck, Darmstadt, Germany) and 1,980 µL of deionized water, followed by incubation at ambient temperature for 5 minutes. Then, 300 µL of 7% sodium carbonate solution (QRëC, Auckland, New Zealand) were added, and the mixture was incubated for another 60 minutes in the dark at ambient temperature. Absorbance was measured at 765 nm using a Metash UV-5200 spectrophotometer with UV-Professional analysis software. The total phenolic content (TPC) analysis was performed in triplicate. A calibration curve was prepared using gallic acid standards (Bio Basic Inc., Ontario, Canada). at various concentrations. Results were expressed as milligrams of gallic acid equivalent (GAE) per gram of dry sample weight.

Total flavonoid content

The total flavonoid content (TFC) was assessed following the method of Sassa-deepaeng *et al*. (2023). A mixture of 20 µL of extract and 380 µL of deionized water was prepared, followed by the addition of 100 µL of 5% sodium nitrite (Univar, Ajax Finechem, Australia) solution. After 5 minutes of incubation, the 100 µL of 10% aluminum chloride (Univar, Ajax Finechem, Australia) solution was added, and the mixture was left to stand for 6 minutes at room temperature. Finally, the 400 µL of 1M sodium hydroxide (Labscan, Bangkok, Thailand) solution was added. After a 15-minute incubation at ambient temperature in the dark, absorbance was recorded at 415 nm. The TFC was calculated using a calibration curve prepared with quercetin (Sigma–Aldrich, Germany) at different concentrations and expressed as milligrams of quercetin equivalent (QE) per gram of dry weight.

Total tannin content

The total tannin content (TTC) was also determine as described by Sassa-deepaeng *et al*. (2023), the 250 µL of extract was vigorously mixed with 450 µL of 1% vanillin (Merck KGaA, Darmstadt, Germany) reagent. After a 5-minute incubation, 300 µL of concentrated hydrochloric acid (Labscan, Bangkok, Thailand) was added, and the mixture was incubated for an additional 30 minutes at ambient temperature. The solution developed a red color. Absorbance was then measured at 500 nm. The TTC was calculated using a calibration curve prepared with epigallocatechin gallate (Myskinrecipes, Bangkok, Thailand) at different concentrations and expressed as milligrams of epigallocatechin gallate equivalent (EGCGE) per gram of dry sample weight.

Saponin content

The saponin content was determined following the method of Singh *et al*. (2019). A solution of 0.5% para-anisaldehyde (Myskinrecipes, Bangkok, Thailand) in ethyl acetate (Labscan, Bangkok, Thailand) and a solution of 50% sulfuric acid (Labscan, Bangkok, Thailand) in ethyl acetate (Labscan, Bangkok, Thailand) were the two reagents mixed in equal amounts. The standard and the tentative plant sample's aqueous extracts were dissolved in two milliliters of ethyl acetate followed by the addition of 1 mL each of reagent A and B. The solution was mixed and then incubated for 10 minutes at 60°C in a dry bath incubator (Major Science Co., Ltd., Taoyuan, Taiwan). After cooling at room temperature, the absorbance was measured at 430 nm. The saponin content was calculated using a calibration curve prepared with saponin from quillaja bark (Sigma Aldrich, Saint Louis, MO, USA) at different concentrations and expressed as milligrams of saponin equivalent (SE) per gram of dry sample weight.

Terpenoid content

The terpenoid content was determined following the method of Das *et al*. (2022). One milliliter of aqueous extract was taken in test tube and vortexed thoroughly with 3 mL chloroform (Labscan, Bangkok, Thailand) and 0.4 mL Concentrated Sulfuric acid (Labscan, Bangkok, Thailand) in controlled cooling box in the dark for 4 hours. The solution developed a reddish-brown color appeared at the bottom of the tubes. After decant supernatant, the 4 mL methanol (Labscan, Bangkok, Thailand) was added and absorbance was measured at 538 nm. the terpenoid content was calculated using a calibration curve prepared with myrcene (Myskinrecipes, Bangkok, Thailand) solution and expressed as milligrams of myrcene equivalent (ME) per gram of dry sample weight.

Alkaloid content

The alkaloid content was determined following the method of Shamsa *et al*. (2008). After 69.8 mg of bromocresol green (Myskinrecipes, Bangkok, Thailand) was completely dissolved in 3 mL of 2N sodium hydroxide (Labscan, Bangkok, Thailand) and 5 mL of distilled water, the mixture was diluted to 1000 mL with distilled water to create a bromocresol green solution. In order to prepare the phosphate buffer (pH 4.7), 0.2 M citric acid (42.02 g citric acid (Univar, Ajax Finechem, Australia) in 1 L of distilled water) was used to bring the pH of 2 M sodium phosphate solution (71.6 g di-Sodium hydrogen phosphate dihydrate (Kemaus, Cherrybrook, Australia) in 1 L of distilled water) down to 4.7. The 1 mL bromocresol green, 1 mL Phosphate buffer, and 0.1 mL aqueous extract were mixed and place in ambient temperature for 10 minutes. After adding 1.5 mL chloroform (Labscan, Bangkok, Thailand), the mixture was more incubated at the ambient temperature for 10 minutes prior to the solution developed a yellow color. The absorbance was measured at 470 nm. The alkaloid content was calculated using a calibration curve prepared with pure atropine sulphate (A.N.B. Laboratories Co., Ltd., Thailand) and expressed as milligrams of atropine equivalent (AE) per gram of dry sample weight.

Protein content

Protein assay was performed according to the Lowry's method described by Mæhre *et al*. (2018). The 0.1 mL aqueous extract was mixed with 0.9 mL of solution A (composed of 2 g/L potassium sodium tartrate (Univar, Ajax Finechem, Australia) and 100 g/L sodium carbonate (Univar, Ajax Finechem, Australia) in 0.5 M sodium hydroxide (Labscan, Bangkok, Thailand)), followed by incubation at 50 °C for 10 minutes. After cooling the samples to room temperature, 1 mL of solution B (containing 0.2 g/L potassium sodium tartrate tetrahydrate (Univar, Ajax Finechem, Australia) and 0.1 g/L copper sulfate pentahydrate (QRëC, Auckland, New Zealand) in 0.1 M sodium hydroxide) was added and place in ambient temperature to react for another 10 minutes. Subsequently, 3 mL of solution C (Folin–Ciocalteu phenol (Merck KGaA, Darmstadt, Germany) reagent diluted 1:16 v/v with water) was mixed in, and the samples were incubated again at 50 °C for 10 minutes. Absorbance was then measured at 650 nm. A protein content was calculated using a calibration curve prepared using bovine serum albumin fraction V (Sigma-Aldrich, St Louis, MO, USA) at concentrations of 0, 0.0625, 0.125, 0.25, 0.5, and 1 g/L and results were expressed in micrograms per gram of dry sample weight.

Reducing sugar content

The reducing sugar content was measured using the dinitrosalicylic acid (DNS method) described by Tharawatchruk *et al*. (2023). The DNS (Fluka Chemie GmbH, Buchs, Switzerland) reagent was prepared by combining a solution of DNS (2.5 g in 100 mL of 1 M sodium hydroxide) with a hot sodium potassium tartrate solution (75 g in 125 mL of distilled water). The mixture was then diluted to a total volume of 500 mL with distilled water. For the assay, the 0.9 mL of DNS reagent was added to 0.1 mL of an aqueous tentative plant extract in 1.5-mL microcentrifuge tube. The tubes were heated in boiling water for 5 minutes. The solution developed a red-brown color. Absorbance was measured at 540 nm. Reducing sugar content was calculated using a calibration curve prepared with 2 mM glucose (Univar, Ajax Finechem, Australia) solution and expressed as milligrams per gram of dry sample weight.

Statistical analysis

The data were processed using the Analysis ToolPak add-in of Microsoft Excel 2016 (Microsoft Corporation, CA, USA). One-way analysis of variance (ANOVA) and the least significant difference (LSD) test were employed to identify statistically significant differences, with a threshold of $p < 0.05$ considered significant.

RESULTS AND DISCUSSION

The saliva alpha-amylase inhibitory activity of 15-tentative plants was investigated. It was found that *A. lebbeck* exhibited the highest inhibitory activity at concentration of 20 mg/mL (81.59±5.84%), followed by *M. pudica* (32.26±2.17%), *I. aquatica* (26.27±0.94%), and *G. inodorum* (22.63±6.03%), respectively. The α-amylase inhibitory activity of samples was indicated in Figure 1.

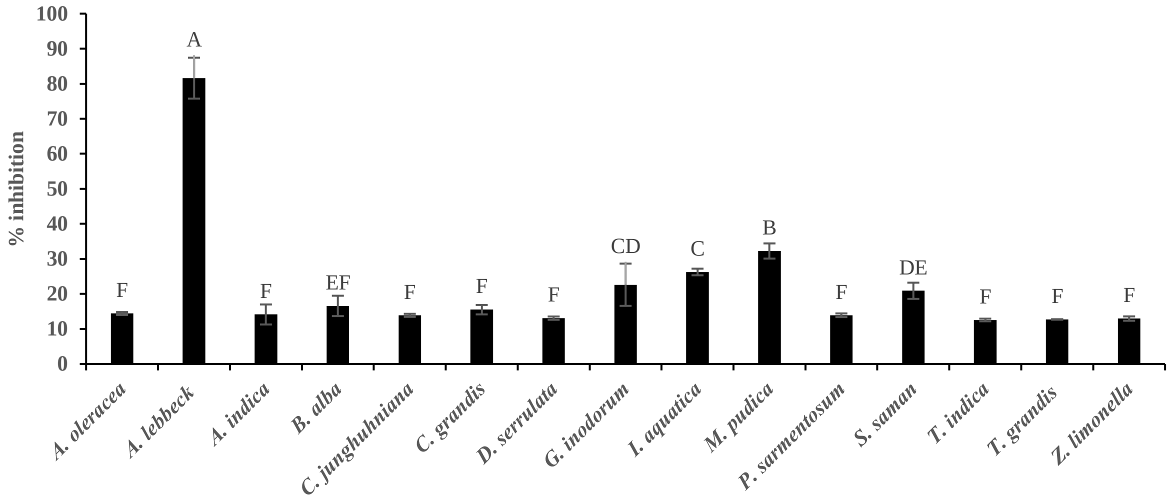

Figure 1. The α-amylase inhibitory activity of 15-tentative plants. Different letters indicate significant differences ($p < 0.05$).

Effect of pH on the adsorption of methylene blue

A. lebbeck exhibited the highest enzyme inhibitory activity, as previously reported by Jaiswal and Kumar (2017), followed by *M. pudica* (Shrestha *et al*., 2022), *I. aquatica* (Saikia *et al*., 2023), and *G. inodorum* (Phanjaroen *et al*., 2024). To investigate the correlation with specific phytochemicals, quantitative phytochemical tests were subsequently conducted, as reported below.

The secondary metabolites including total phenolic compounds, total flavonoids, tannins, saponins, terpenoids, alkaloids, reducing sugars, and proteins were extracted using water from the leaves, seeds, and stem bark of selected plant species. Comparative analyses revealed that the concentrations of total phenolic content were significantly higher in all samples exhibiting positive amylase inhibitory activity. Notably, *I. aquatica* leaves contained the highest phenolic content (2.75 ± 0.16 mg GE/g DW, followed by *G. inodorum* (1.95 ± 0.06 mg GE/g DW), *A. lebbeck* (1.12 ± 0.06 mg GE/g DW), and *M. pudica* (1.01 ± 0.24 mg GE/g DW), as illustrated in Figure 2.

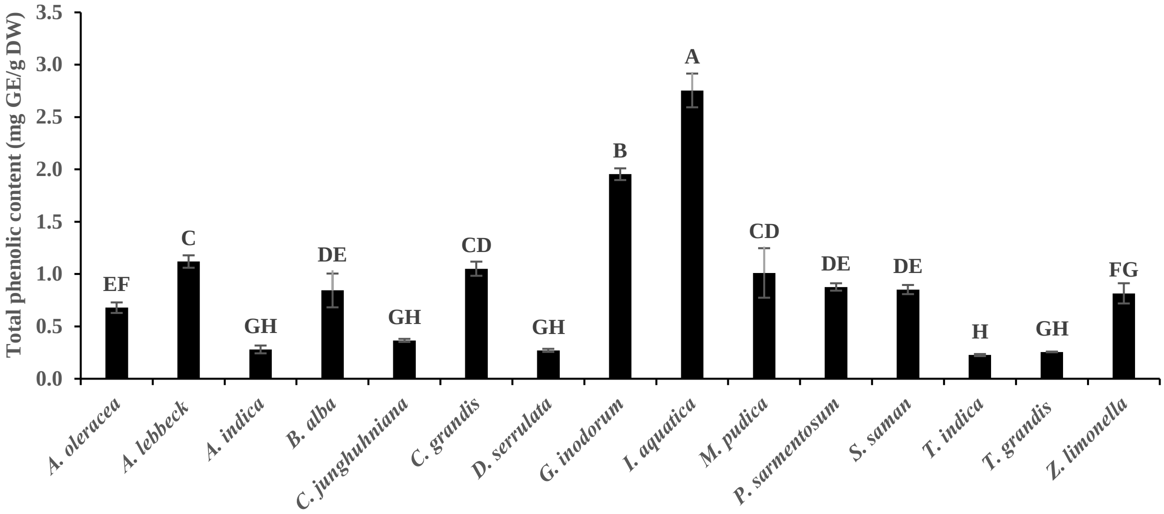

Figure 2. Total phenolic content of 15 plant extracts. Bars represent the standard deviation from triplicate determinations. Different letters indicate significant differences ($p < 0.05$).

These findings are consistent with those of Saikia *et al*. (2023), who reported that polyphenolic compounds, including polyphenol glycosides and phenolics in *I. aquatica*, are closely associated with amylase inhibitory activity. Similarly, Haideri *et al*. (2024) demonstrated that the phenolic composition of *G. inodorum* represents a major active constituent responsible for amylase inhibition. Kajaria *et al*. (2013) also documented that the polyphenolic compounds present in *A. lebbeck* play a potentially important role in managing diabetes through the inhibition of α-amylase. Interestingly, although *M. pudica* is not traditionally recognized as a food source in Thailand, data from Bohara *et al*. (2022) indicated that its aqueous extract, rich in phenolic compounds, also exhibits strong amylase inhibitory activity.

To examine the potential involvement of flavonoids in amylase inhibitory activity, the total flavonoid content (TFC) was quantified using the aluminum chloride ($AlCl_3$) colorimetric method. The results indicated that the concentrations of total flavonoid content were significantly higher in the three samples that demonstrated positive amylase inhibitory activity. Notably, *I.aquatica* leaves exhibited the highest flavonoid content (2.93 ± 0.29 mg QE/g DW), followed by *A. lebbeck* (1.99 ± 0.29 mg QE/g DW) and *G. inodorum* (2.03 ± 0.08 mg QE/g DW). In contrast, *M. pudica* did not show a comparable increase in flavonoid content, as illustrated in Figure 3.

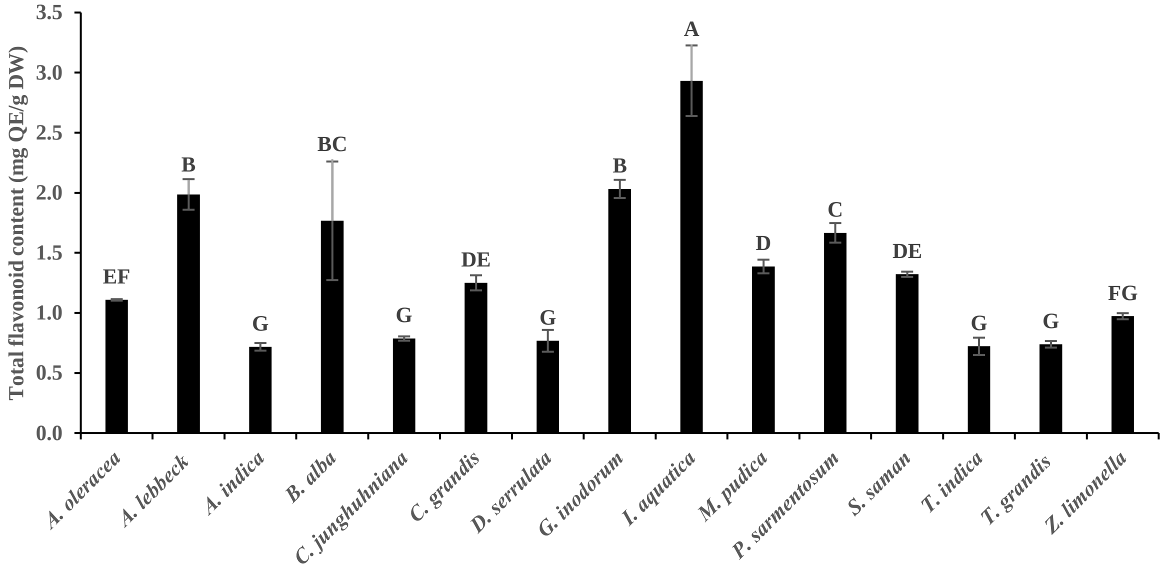

Figure 3. Total flavonoid content of 15 plant extracts. Bars represent the standard deviation from triplicate determinations. Different letters indicate significant differences ($p < 0.05$).

It was observed that *I. aquatica* exhibited the strongest amylase inhibitory activity, which was attributed to its high flavonoid content, including the presence of flavins and flavin-like compounds, as reported by Saikia *et al*. (2023). The extract of *A. lebbeck* was found to contain flavonols such as kaempferol and quercetin 3-*O*-α-rhamnopyranosyl (1→6)-β-glucopyranosyl(1→6)-β-galactopyranosides. Furthermore, amylase inhibition has also been documented in protein isolates derived from the seeds (Ekun *et al*., 2024) and bark (Jaiswal & Kumar, 2017) of this species. *G. inodorum* demonstrated strong α-amylase inhibitory activity, which has been attributed to the presence of myricetin (Haideri *et al*., 2024).

To evaluate the effect of tannins on amylase inhibitory activity, the total tannin content was quantified. The analysis revealed that *A. lebbeck* extract contained a significantly high concentration of tannins (0.46±0.01 mg EGCGE/g DW), which was positively correlated with its amylase inhibitory activity as showed in Figure 4.

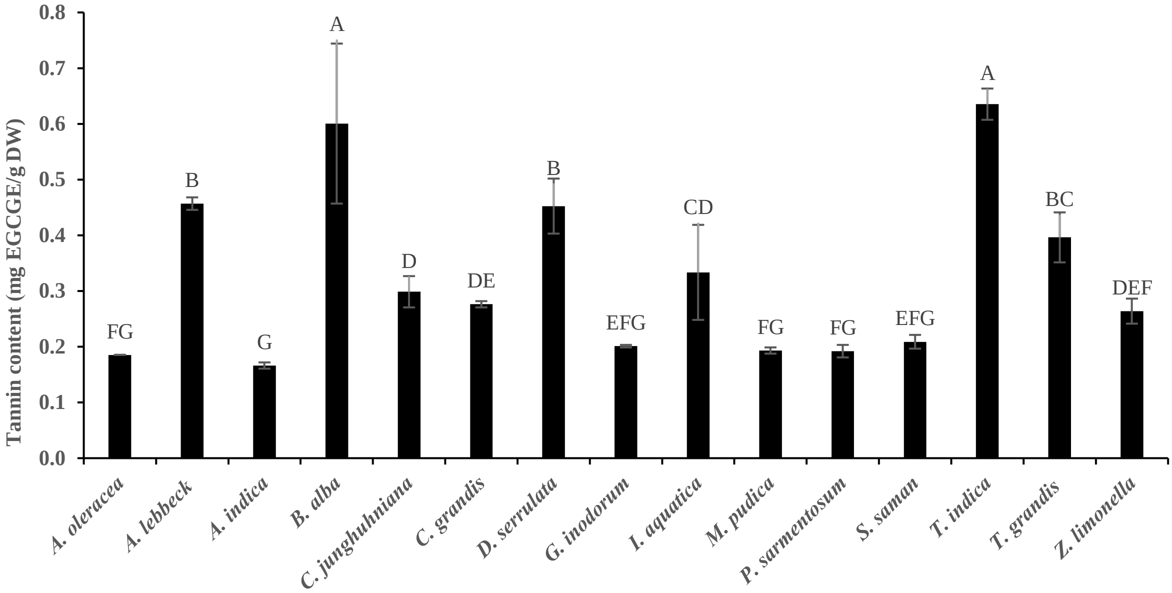

Figure 4. Tannin content of 15 plant extracts. Bars represent the standard deviation from triplicate determinations. Different letters indicate significant differences ($p < 0.05$).

This phenomenon can be explained by Zhang *et al*. (2023), who reported that tannins act as co-inhibitors of salivary α-amylase. Additionally, tannins have been shown to exert an inhibitory effect on α-glucosidase, an enzyme that plays a crucial role in the regulation of type 2 diabetes.

The saponin content was also analyzed, and the results indicated that *A. lebbeck* extract contained a significantly high concentration of saponins (79.62 ± 1.90 mg SE/g DW), which was positively correlated with its amylase inhibitory activity. This was followed by *M. pudica* (58.16 ± 1.51 mg SE/g DW) and *G. inodorum* (56.64 ± 1.53 mg SE/g DW), as presented in Figure 5.

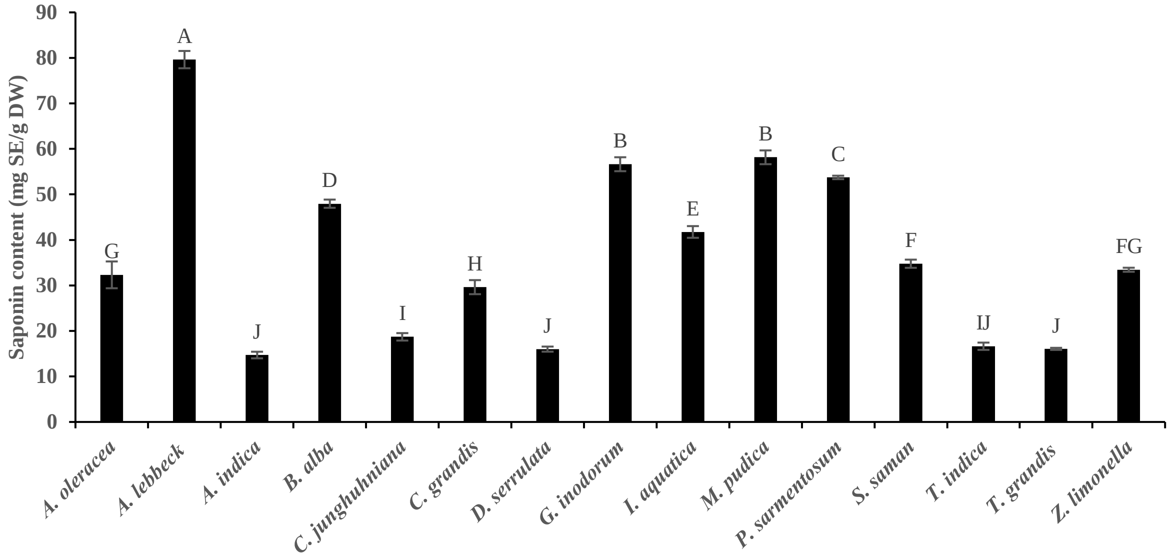

Figure 5. Saponin content of 15 plant extracts. Bars represent the standard deviation from triplicate determinations. Different letters indicate significant differences ($p < 0.05$).

The high saponin content in *A. lebbeck* was first documented by Desai & Joshi (2019). Saponins have also been reported in *M. pudica* (Rizwan *et al.*, 2022) and *G. inodorum* (Jeytawan *et al.*, 2022), although not specifically as amylase inhibitors. Nonetheless, saponins have been shown to moderately inhibit α-amylase activity (Ngoc *et al.*, 2023; Hanh *et al.*, 2016). In contrast, alkaloids and terpenoids were not detected in any of the samples, likely due to their presence in concentrations below the detection limit of the colorimetric method used. Thus, it can be inferred that these compounds do not contribute to the observed amylase inhibitory activity.

Protein was also detected in all samples. Based on protein estimation using Lowry's method, the inhibitory plant extract of *I. aquatica* extract exhibited the highest protein concentration (31.32 ± 0.31 μg/g DW), followed by *G. inodorum* (23.86 ± 0.83 μg/g DW), as presented in Figure 6.

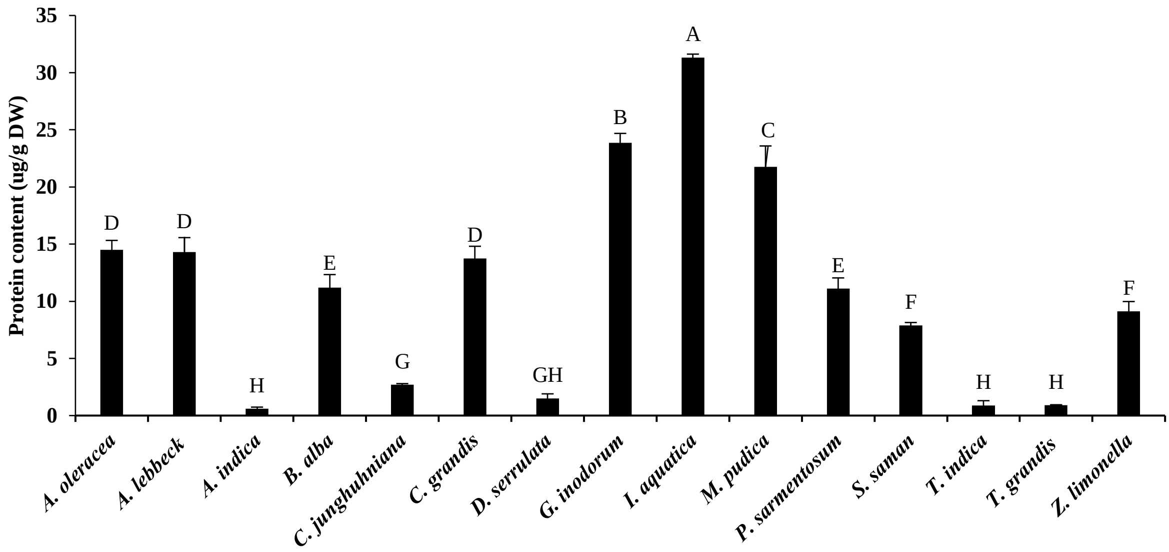

Figure 6. Protein content of 15 plant extracts. Bars represent the standard deviation from triplicate determinations. Different letters indicate significant differences ($p < 0.05$).

The high protein content in *I. aquatica* extract has been documented by Ali & Kaviraj (2018), and similarly in *G. inodorum* by Norkum *et al.* (2023). This may be related to their observed amylase inhibitory activity. Although no studies have specifically reported that proteins in these species act as α-amylase inhibitors, seed protein extracts from *A. lebbeck* have demonstrated inhibitory effects against both α-amylase and α-glucosidase (Ekun *et al*., 2024). Therefore, it can be hypothesized that proteins in these extracts may contribute as co-inhibitors of amylase. Further analysis is required to clarify the inhibitory role of proteins in these extracts.

The reducing sugar content was also analyzed to assess whether its presence could contribute to elevated blood sugar levels if the extracts are considered for regular dietary use. Notably, *I. aquatica* extract exhibited the highest reducing sugar content (1690.57 ± 43.17 mg/g DW), as shown in Figure 7.

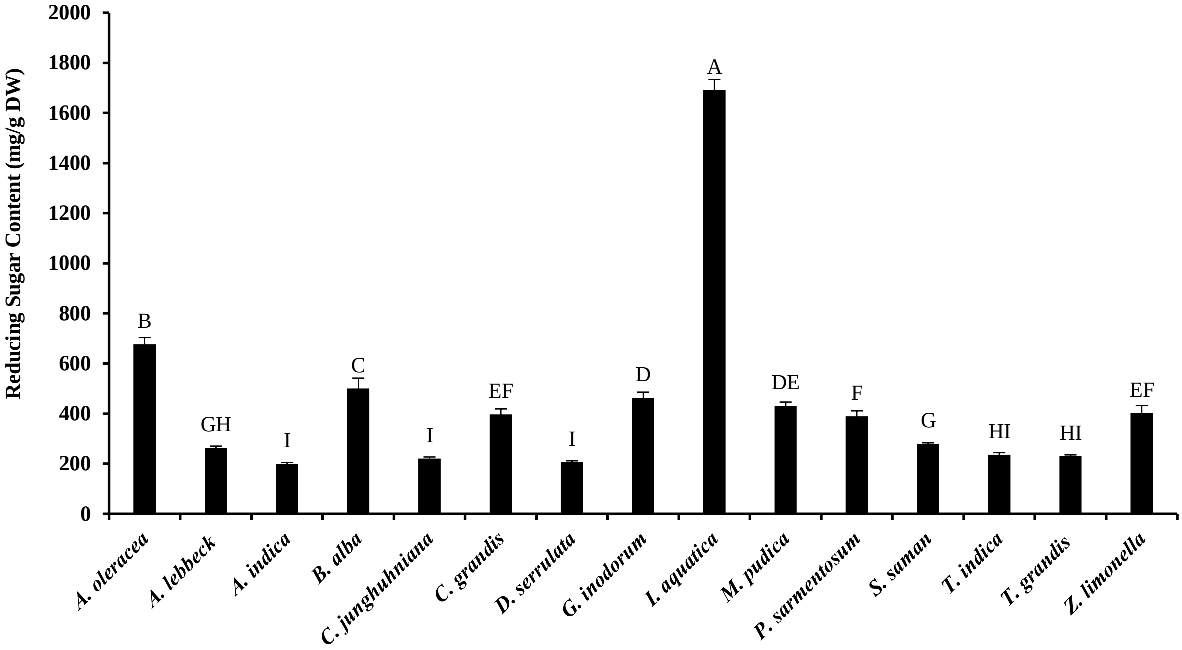

Figure 7. Reducing sugar content of 15 plant extracts. Bars represent the standard deviation from triplicate determinations. Different letters indicate significant differences ($p < 0.05$).

The presence of reducing sugars in *I. aquatica* leaves has been reported by Bokolo & Adikwu (2018). However, in contrast, consumption of the edible portions of *I. aquatica* over a one-week period was shown to effectively reduce fasting blood sugar levels (Malalavidhane *et al*., 2003). Therefore, it can be hypothesized that *I. aquatica* leaves may possess additional mechanisms for lowering blood sugar, which have yet to be fully elucidated.

CONCLUSIONS

This study demonstrated that *A. lebbeck* exhibited the highest salivary amylase inhibitory activity, followed by *M. pudica*, *I. aquatica*, and *G. inodorum*, respectively. The inhibitory effect of *A. lebbeck* was attributed to the presence of phenolics, flavonoids, tannins, and saponins, while the activity observed in *M. pudica* was primarily linked to its saponin content. *I. aquatica* also displayed amylase inhibitory activity, associated with its phenolic, flavonoid, and protein content, whereas *G. inodorum* demonstrated inhibition through a combination of phenolics, flavonoids, saponins, and proteins. Notably, a high reducing sugar content was identified in *I. aquatica*, highlighting the need for further investigation into its potential implications for blood sugar regulation.

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Optimization condition to produce sweet-noodles in milk using reverse spherification technique

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ABSTRACT

The principle of reverse spherification relies on the formation of calcium alginate, in which sodium alginate undergoes gelation in the presence of calcium ions. In this study, sweet-noodles in milk balls were produced by incorporating calcium lactate into the core solution and submerging it in a sodium alginate bath to form spherical gel structures. Optimization of the production conditions was conducted using Response Surface Methodology (RSM) with a Central Composite Design (CCD), focusing on two independent variables: sodium alginate concentration (X_1: 1.0–1.5%) and soaking time (X_2: 3–5 minutes). Each formulation was evaluated for its physical properties, including weight, size, color (L*, a*, b*), and membrane thickness. The results indicated that increasing both alginate concentration and soaking time enhanced gelation, resulting in increased bead size and film thickness. The optimal condition for producing sweet-noodles in milk balls was found to be 1.50% alginate concentration and 3 minutes of soaking time. Under this condition, the actual bead size was 15.93 mm. The predictive model was further validated, yielding a predicted bead size of 15.43 ± 0.49 mm, confirming the reliability of the optimization model.

Keywords: sweet-noodles in milk, reverse spherification, gelation

INTRODUCTION

Sweet-noodles in milk (Sarim) are a traditional Thai dessert made from mung bean flour served with aromatic sweetened coconut milk. It is especially popular during hot weather due to its refreshing nature (Tinnawong and Kamolbhibhat, 2015). As part of preserving and revitalizing traditional Thai desserts, there is a growing need to present them in novel forms to attract modern consumers. This aligns with global food trends emphasizing innovation and experiential consumption, as observed in the 2018 food innovation movement. Therefore, this study applied the spherification technique a modern culinary approach to develop a new form of Sarim, aiming to enhance its visual appeal and textural uniqueness while maintaining its original flavor identity.

In recent years, molecular gastronomy has introduced innovative techniques to transform the texture and appearance of traditional foods. Among these techniques, reverse spherification has gained considerable attention in modernist cuisine for its ability to create novel sensory experiences (Barrett, 2012). This technique involves incorporating calcium lactate into a liquid food matrix, which is then submerged in a sodium alginate bath, resulting in the formation of spherical structures (Vega & Castells, 2012). Depending on the formulation and processing conditions, the resulting beads can vary from having a thin, delicate membrane encapsulating a liquid core to being fully gelled throughout (Lee & Roger, 2012).

The fundamental mechanism of reverse spherification is based on the gelation of sodium alginate (SA) in the presence of calcium ions, leading to the formation of calcium alginate a stable hydrogel network (Navarro et al., 2012). Sodium alginate is a widely available, safe, and edible polysaccharide derived from brown seaweed. It is composed of β-D-mannuronic acid (M) and α-L-guluronic acid (G) units arranged in linear, non-branched chains (Saqib et al., 2022). Its ionic gelation property, especially in the presence of divalent or trivalent cations such as Ca^{2+}, promotes the cross-linking of polymer chains to form a gel membrane that effectively encapsulates a liquid core (Xu et al., 2024).

Calcium ions (Ca2+) is the most commonly used cross-linking ion in food or cosmetic systems. Typically, dropping a liquid containing Ca^{2+} into a polysaccharide solution (sodium alginate) to form hydrogel beads is known as “reverse spherification”. Studies have shown that the reverse spherification technique is suitable for preparing hydrogel beads with a large liquid core and a well-maintained spherical shape (Bubin et al., 2019) Therefore, the objective of this study is to investigate the optimal conditions specifically the concentrations of sodium alginate and the soaking time using Response Surface Methodology (RSM), to develop “sweet-noodles in milk” (Sarim) in spherical form via reverse spherification.

MATERIALS AND METHODS

Material for prepared sweet-noodles included pasteurized milk (Meji brand) and mung bean flour (PINE brand), with product from Sitthinan Co., Ltd. The chemical reagents used for the production of sweet-noodles in milk balls were food-grade. Sodium alginate was obtained from Kimica Corporation Ltd., Japan, and calcium lactate was purchased from Nutrition Co., Ltd., Thailand.

Production of green bean flour Sarim noodles in fresh milk

Mix 104.5 grams of green bean flour with 557 grams of water. Stir until fully dissolved. Heat the mixture over low heat, adding food coloring drops as needed: dark green and pink noodles. Cook over low heat, stirring constantly for 15 minutes. Once the mixture becomes translucent, transfer it into a piping tool and press into room-temperature water (using about ¾ of the pot's volume). After forming the noodles, scoop them out and allow the excess water to drain. Set the noodles aside for further experimental use.

Preparation of sweet-noodles in milk balls

Sweet-noodles in milk balls was prepared by adding sweet-noodle into sphere mold. After that, use the syringe to suck milk (adding calcium lactate) up and then pour it into sphere mold, with having sweet-noodle. Move the sphere mold into the freezer (-8 ^{o}C) until 24 hours. After a time, remove sweet-noodle in milk from sphere mold. As the sweet-noodle in milk drop-wise into the sodium alginate bath, a gelled membrane instantly formed around the sweet-noodle milky sphere. Then sweet-noodle milk ball was soaked in sterile distilled water and stored at 4 ^{o}C in the refrigerator.

Determination of physical properties of sweet-noodle milk ball

The weight of the sweet-noodle milk balls was measured using a two - digit precision digital balance. The diameter (size) was determined using a Vernier caliper. Color values, including lightness (L*), redness (a*), and yellowness (b*), were analyzed using a Hunter Lab MiniScan EZ (LAV series) colorimeter. The thickness of the gel layer was measured using a micrometer. To determine the optimal conditions for sodium alginate concentration and immersion time, the physical analysis results were used to examine the relationships between the variables of interest through Response Surface Methodology (RSM).

Study of optimized condition of sweet-noodle milk ball

A statistical experiment design based on the response surface methodology to central composite design (CCD) was planned. The two independent variables were concentrations of alginate (X_1) and soaking time (X_2). The sodium alginate concentrations were varied from 1 to 1.5% and soaking was varied from 3 to 5 minutes. The sweet-noodle milk balls were prepared as described above and their physical properties were examined.

Statistical analysis

A statistical experimental optimized condition to produce sweet-noodle milk balls was measured by using response surface methodology to central composite design to study the effect of sodium alginate and soaking time on the gelation of sweet-noodle milk balls.

Mix mung bean flour with water

Stir until dissolved, add food coloring dissolved

Heat and stir continuously for 8 - 10 minutes until translucent

Add air to make strands using a piping tool

Sarim noodles

Put sarim noodles into the mold

Warm pasteurized milk

Add sugar and stir until

Smoke with candles 2 times

Smoked milk

Mixed with calcium lactate

Stir until dissolved

Inject milk into a mold

Frozen at -8ºC for least 24 hours

Remove from mold

Dissolve in sodium alginate solution

Sweet-noodles in milk balls

Figure 1 Process for producing Sweet-noodles in milk balls

RESULTS AND DISCUSSION

Study of the optimized condition of sweet-noodle milk ball

A statistical experiment design based on the response surface methodology to central composite design (CCD) was planned. The two independent variables were concentrations of alginate (X_1) and soaking time (X_2). The total runs of the experiment was described on Table 1. The physical properties of all the sweet-noodle milk balls were examined (Table 1). The result showed that the differential concentration of sodium alginate and soaking time effect to physical properties of sweet-noodle milk ball, in which the quality of the gel is dependent on the concentration of alginate, the concentration of calcium and time to soaking in solution (Le Roux et al., 1999). As the concentration of alginate constant, increasing in soaking time, the weight and thickness of the sweet-noodle milk balls increased while the size of sphere decreased. Also, as the soaking time constant, increasing in alginate content, the thickness of the film and weight increased but size decreased. In all the parameters that were studied, the size of the sweet-noodle milk ball was greatly affected.

The fitting of all the examined to various models (linear, two factorials, quadratic and cubic) and their subsequently analysis of variance (ANOVA) were shown on the table 2. The analysis of variance shown that model of the weight, size and thickness equations could be used to predict the result because a lack of fit were not significant and the coefficient R^2 of the response in the range 0.76 - 0.81 which shown the possibilities. As size of sphere was greatly affected by the concentration of alginate and soaking time and its coefficient R^2 was highest (0.81). In the present study, the model of size would be use to find the suitable condition to produce sweet-noodle milk ball. Fitting of the examined size data to various models, their subsequently ANOVA showed that the size was most suitably described with quadratic polynomial model.

$$\text{Size (mm)} = 10.07+19.64*X_1-5.32*X_2-4.77*X_1*X_2+0.48*X_1^2+1.41*X_2^2$$

Where X_1 is the concentration of alginate; X_2 the soaking time. Coefficient value of determination (R^2) was 0.81 ($p<0.05$).

Response surface and contour plot that described the effect of sodium alginate soaking time on the size of sweet-noodle milk balls were shown on Figure 3. The effects of sodium alginate concentration and soaking time on the size of sweet-noodle milk balls were found to be significant, with both variables directly influencing the diameter of the formed spheres. This phenomenon is chiefly attributable to the augmented cross-linking interactions between alginate and calcium ions, which culminates in a more robust gel membrane encasing the liquid core, thereby facilitating an increase in the size of the milk spheres (Paoletti and Donati, 2022). While prolonged soaking times enhance the cross-linking process, leading to larger bead sizes and improved structural integrity, The interaction time with calcium ions is crucial for achieving the desired gel strength and size (Li et al., 2015). Additionally, the rheological properties of the polysaccharide solution play a crucial role in the reverse spherification process (Hu et al., 2025). Furthermore, a low-viscosity environment facilitates the diffusion of Ca^{2+} ions into the alginate matrix, improving the efficiency of gel formation and enhancing the spherification process as a whole (Bennacef et al., 2021). Conversely, the excessive viscosity not only hinders the immersion of the ice ball but also limits the diffusion of Ca2+, reducing the rate and success rate of spherification (Nair et al., 2020). Gelation of alginate becomes more pronounced with higher concentrations and longer interaction times, resulting in a thicker gel membrane (Sen, 2017). In addition, the ratio of mannuronic acid (M) to guluronic acid (G) in sodium alginate significantly affects the gel network formation (Stewart et al., 2014). The G blocks can form crosslinking with the presence of divalent cations leading to the formation of alginate gel (El Hariri El et al., 2022; George & Abraham, 2006). The duration of interaction between alginate and calcium ions affects bead size, as extended contact promotes cross-linking and strengthens gel connectivity, leading to larger and more structured hydrogel beads (Tsai et al., 2017). In this study, the optimal conditions for producing sweet-noodle milk balls were found to be a sodium alginate concentration of 1.50% and a soaking time of 3 minutes. Under these conditions, the experimentally obtained bead size was 15.93 mm. The predictive equation derived from the response surface model was then validated, yielding a predicted size of 15.43 ± 0.49 mm. This result confirms the accuracy and reliability of the model for estimating the outcome under optimal processing conditions.

Table 1 The experiment design and the response of the central composite design factors.

RUN	Alginate (%)	Time (min)	Weight (g)	Size (mm)	Color L^*	a^*	b^*	Thickness (mm)
1	1.00	5.00	31.10	15.80	64.30	1.17	3.66	0.03
2	1.25	5.41	30.89	15.54	64.00	0.79	3.73	0.03
3	1.25	2.59	32.04	15.26	63.81	0.20	3.31	0.02
4	1.00	3.00	31.11	12.82	53.48	0.91	2.12	0.03
5	1.25	4.00	32.82	13.04	66.28	0.74	4.10	0.05
6	1.50	3.00	32.40	16.52	45.20	0.80	2.45	0.04
7	1.50	5.00	31.73	14.01	66.27	0.66	3.16	0.03
8	1.60	4.00	29.76	12.96	44.68	1.32	1.12	0.04
9	0.90	4.00	29.28	12.31	58.15	2.37	2.17	0.03
10	1.25	4.00	29.54	11.55	50.10	0.10	2.24	0.03
11	1.25	4.00	30.95	12.33	60.32	0.53	3.96	0.03
12	1.25	4.00	30.10	13.33	63.07	2.83	2.74	0.02
13	1.25	4.00	31.59	14.10	64.94	1.04	3.82	0.02

Table 2 Analysis of variance of alginate and time that effect the physical properties of sweet-noodle milk ball.

Source	p-value Prob>F						
	df	weight	size	L	a	b	thickness
Model	5	0.0186**	0.0173**	0.1130**	-	0.0917 ns	0.0008**
A-alginate	1	0.9874	0.1774	0.2084	-	0.4099	0.0004
B-time	1	0.9236	0.9525	0.6067	-	0.4754	0.0562
AB	1	0.9938	0.0247	0.0393	-	0.1359	-
A^2	1	0.0021	0.9273	-	-	0.0162	-
B^2	1	0.0144	0.0030	-	-	0.5968	-
Lack of Fit	3	0.2201ns	0.7660 ns	0.4807 ns	0.9196 ns	0.9076ns	0.4965 ns
R^2	-	0.80	0.81	0.46	0.00	0.68	0.76

** Significant at $p<0.05$

Figure 2 Sweet-noodles in milk balls product

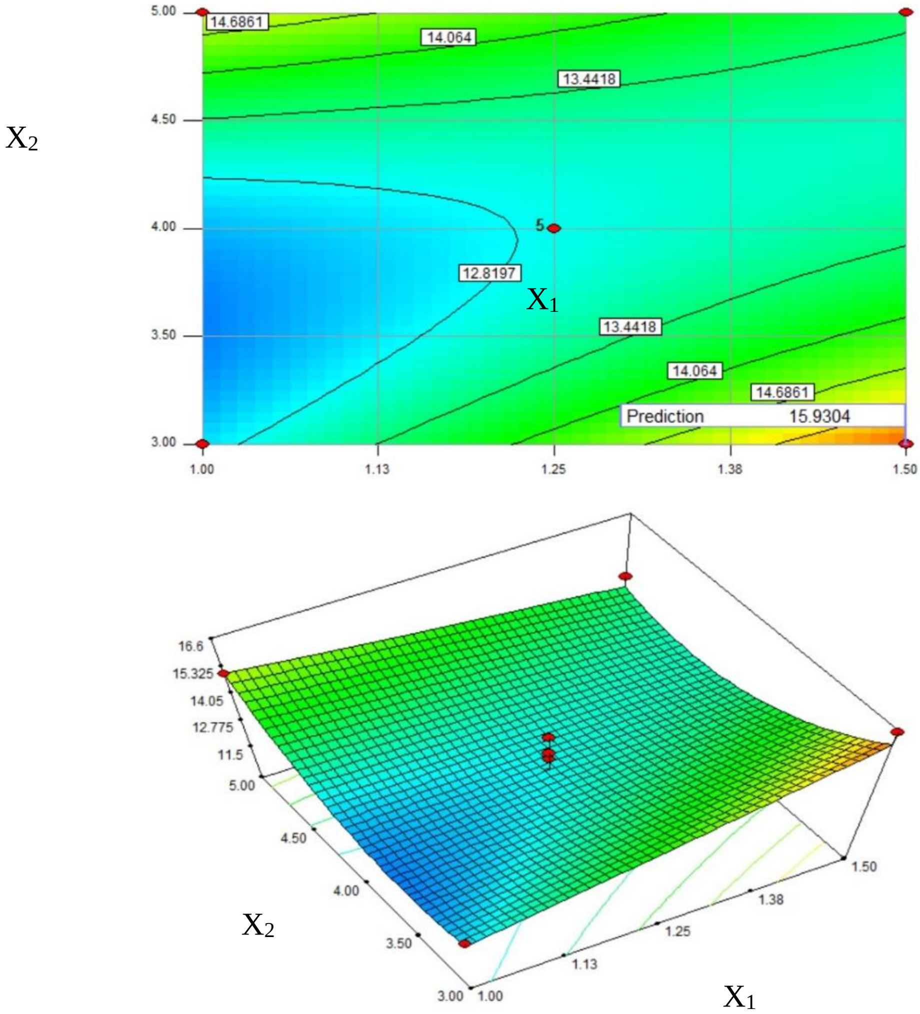

Figure 3 Response surface (a) and contour plot (b) showed the effect of alginate and soaking time on the size of sweet-noodle milk ball.

CONCLUSIONS

The production of sweet-noodle milk balls by using the reverse spherification technique was studied. The effect of sodium alginate and soaking time for the preparation of sweet-noodle milk ball were determined using response surface methodology (RSM). The model of size would be used to find the suitable condition to produce sweet-noodle milk balls. The optimal production condition was alginate concentration of 1.50% and a soaking time of 5 minutes. The predicted responses for this production condition was 15.43 ± 0.49 mm which was similar to that from the experiment.

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The use of artificial intelligence methods to predict income and expense trends from semi-unstructured data for accounting planning for pineapple farmers in Phitsanulok province

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ABSTRACT

This study examined the use of artificial intelligence (AI), specifically Natural Language Processing (NLP), to predict income and expense trends for pineapple farmers in Ban Yang Subdistrict, Nakhon Thai District, Phitsanulok Province. The research focused on processing semi-unstructured accounting data, mainly from PDF files, provided by 30 farmers with prior accounting experience. A custom NLP algorithm was used to classify financial records into payment and income categories. Three time series forecasting models—Prophet, LSTM, and ARIMA—were applied to comparatively predict future trends. LSTM excels at capturing complex long-term patterns, Prophet effectively models seasonal and event-driven fluctuations, and ARIMA is well suited for identifying linear trends and short-term changes. The results showed that ARIMA outperformed both LSTM and Prophet in terms of accuracy and explanatory power. ARIMA achieved the lowest Mean Absolute Error (MAE) of 34.1084 and the highest R-squared (R^2) of 0.9901, indicating superior prediction performance. LSTM had a MAE of 71.0920 and an R^2 of 0.9511, showing good accuracy but with higher MAE and lower R^2 compared to ARIMA. Prophet had the highest MAE of 603.8044 and the lowest R^2 of -3.2273, reflecting poor performance. Based on these results, ARIMA is identified as the most suitable model for this dataset. ARIMA's performance improved with longer forecast periods. For a 10-day forecast, it showed relatively low accuracy. As the forecast period extended to 20 and 30 days, accuracy and explanatory power increased, with the best results observed for the 30-day forecast. These findings suggest that ARIMA performs better for longer-term predictions. Future work could optimize the model and incorporate additional features for improved accuracy.

Keywords: artificial intelligence, income and expense accounting trend, semi-unstructured data; pineapple farmer

INTRODUCTION

Accounting for income and expenses is crucial for managing finances in farming, especially for pineapple farmers in Phitsanulok Province, where weather conditions and fluctuating prices impact their earnings. By tracking income and expenses, such as costs for fertilizers, seeds, and labor, farmers can assess their operations and plan their finances more effectively. However, some farmers may lack the necessary knowledge or tools to manage financial data efficiently. External factors, such as market fluctuations or weather conditions, can also affect the accuracy of income and expense forecasts. Therefore, adopting accounting practices in agriculture requires a simplified approach that emphasizes the importance of farm records for evaluating performance and supporting decision-making (Singh, 2024). Despite the challenges, accounting remains a valuable tool for managing finances efficiently and mitigating risks from uncontrollable factors.

Household accounting for farmers has been continuously promoted, as good financial management is an important factor affecting the economic stability of farming households. The recording of income and expenses in the form of unstructured data and semi-unstructured data refer to data that is not organized or structured clearly, making it challenging to manage and utilize the information (Tredinnick and Laybats, 2024). This is in contrast to structured data, which is stored in standardized formats, such as tables or databases with clearly defined fields, making management and analysis easier (Bhatt et al.,2024). When data is stored in an unstructured form, such as handwritten notes or documents without proper organization, finding the necessary information can become difficult

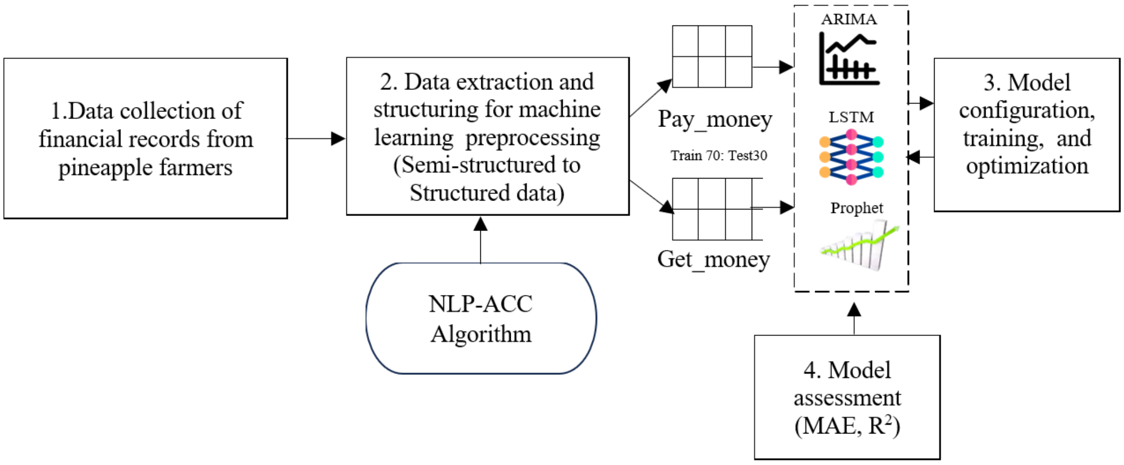

Figure 1. Research methodology steps diagram

and time-consuming. For example, if someone wants to know past expenses or look up income from product sales in different seasons, semi-unstructured data can make it impossible to retrieve the information quickly, requiring significant time to compile and analyze the results. If the data can be organized using artificial intelligence-related analytical techniques (Cao et al.,2024), it can be categorized into clear sections, such as income from product sales, expenses for materials and inputs, or other costs, making data management and analysis more efficient. Moreover, having organized data helps farmers track their financial status more effectively and accurately evaluate the performance of their agricultural operations.

At present, research works have developed various techniques for extracting semi-unstructured data and transforming it into structured data, which is highly significant in an era where data is abundant and complex. Artificial Intelligence (AI) technology has become a key tool in enhancing the efficiency and accuracy of managing this type of data. One of the critical techniques is Natural Language Processing (NLP), which enables computers to analyze text in various formats, such as documents, emails, or social media posts. NLP enables the extraction of key information, such as names, dates, and keywords, from textual data, organizing it into clear structures. It also helps analyze sentiment trends on social media, providing an automated approach to knowledge discovery and information extraction (VanGessel, 2024). Another prominent technique is Computer Vision, which is used to process image or video data. AI in this area can detect objects in images, read text using Optical Character Recognition (OCR), and convert image data into a format suitable for further analysis, such as digitizing information from image-based documents. Additionally, machine learning models are used in processes after transforming semi-unstructured data into structured data for clustering, classification, and prediction of data trends. These models are essential for extracting valuable insights from large-scale or semi-unstructured data to forecast sales, stock prices, or changes in a business's financial status. Predictive models analyze historical data to identify patterns, which they then use to predict future events (Dhawas et al.,2024).

This paper discusses the use of Natural Language Processing (NLP) techniques to organize and understand semi-unstructured financial data by matching expected accounting keywords. It focuses on identifying and categorizing key terms in financial documents, such as revenue and income statements. Additionally, predictive models, such as linear regression and time series algorithms, are used to forecast future financial outcomes based on historical data. This approach aims to improve traditional manual accounting methods, particularly for pineapple farmers in Phitsanulok Province, by automating the categorization and analysis of financial data, ultimately saving time and improving the tracking of income, expenses, and profits.

MATERIALS AND METHODS

From Figure 1, This research methodology began with the collection of financial data from pineapple farmers, including income, expenses, and related accounting information. The data are transformed from semi-structured formats into well-structured data using the NLP-ACC algorithm, making them suitable for machine learning preprocessing. Next, the LSTM model was configured, trained, and optimized, as it is effective in capturing complex and long-term data patterns. The ARIMA model focuses on analyzing linear trends and short-term fluctuations, while the Prophet model captures seasonal patterns and special events. The data were split into 70% for training and 30% for testing to accurately evaluate the models' performance. Finally, the results from each model were assessed using metrics such as MAE and R^2 to measure forecasting accuracy and suitability.

Data collection for accounting management methods of pineapple farmers

This research aimed to investigate the accounting practices and use of accounting formulas among 30 pineapple farmers in Ban Yang Subdistrict, Nakhon Thai District, Phitsanulok Province. The participants were selected using purposive sampling, focusing on farmers with prior experience in accounting. The data collection focused on how these farmers document their income and expenses, calculate production costs, and apply accounting formulas to assess their profits and losses. The data collection was conducted from October to November 2024.

The results of the data collection can be summarized by stating that most farmers believe accounting plays a vital role for pineapple farmers, enabling them to effectively manage and control their finances and production activities. The process begins with the preparation of income and expense accounts, which involves recording data on revenue from selling fresh produce and processed products, as well as expenditures such as fertilizer costs, pesticide costs, and labor expenses. Detailed record-keeping allows farmers to accurately track their expenses and net profits.

Additionally, categorizing production costs into fixed and variable costs helps farmers better understand the structure of their expenses. This classification also facilitates cost-per-unit calculations, which can be used to analyze profit and loss for each production cycle. Recording assets such as land and agricultural tools, along with liabilities like loans or other financial obligations, is another critical step in resource management.

Financial data analysis, such as calculating net profit and liquidity, enables farmers to plan their long-term finances more effectively. Moreover, leveraging technology, such as accounting applications or Excel programs, adds convenience and accuracy to data recording and numerical calculations using the common accounting formulas outlined in Equations 1–3.

$$\text{Total Income} = \text{Sum of all incomes} \tag{1}$$

$$\text{Total Expenditure} = \text{Sum of all expenditures} \tag{2}$$

$$\text{Net Income or Loss} = \text{Total Income} - \text{Total Expenditure} \tag{3}$$

From the study of accounting practices among farmers, it was found that fewer farmers recorded accounting data for revenue and payment summarization in the initial stages. They used an accounting form created by the Cooperative Audit Department (2009) as a structured data format, which was then input into Excel software. The summarized accounting data of the 30 farmers is presented as an average structured accounting record in Table 1. Additionally, some farmers used semi-unstructured data formats, such as text files on smartphone applications and Microsoft Word documents. While these methods are more convenient for the farmers, they lack a standardized structure. This reliance on informal formats reflects the farmers' limited accounting proficiency and the lack of user-friendly tools tailored to their needs. As a result, converting such unstructured data (Figure 2) into a format suitable for machine learning forecasting poses a significant challenge.

An example of semi-unstructured data records from farmers, who recorded data in text files on smartphone applications and document files in Microsoft Word, poses a challenge for structuring the data in the machine learning prediction process, as illustrated in Figure 2. From Figure 2, it is shown as a prototype of the farmers' accounting records in the form of semi-unstructured data in text files. This presents a challenge in building an understanding and tracking the data, such as lists of dates, income and expenditure types, and amounts. For this data collection process, 150 semi-unstructured accounting data samples can be collected from 30 farmers for testing the performance of data extraction using NLP techniques and creating a dataset for developing predictive models using machine learning algorithms. However, when this semi-unstructured data is transformed into structured data, it can be enhanced to develop accounting trends for farmers, which can be used in artificial intelligence models to predict future agricultural accounting risk states.

Using natural language processing (NLP) techniques to understand semi-unstructured accounting data

Review of NLP techniques for understanding semi-unstructured data from related research works

In the field of Natural Language Processing (NLP), several new techniques have been developed to improve the efficiency of analyzing and handling text data. One of the key techniques is word embedding proposed by Mikolov et al. (2013) , which transforms words or phrases into mathematical vectors that capture the meaning of the words in context. Models like Word2Vec or GloVe are used, helping words with similar meanings to be located close together in vector space. For example, the words "expense" and "payment" will have similar vector values. This technique allows NLP models to better understand the relationships between words in a deeper and more efficient way.

Table 1. Average structured accounting data recording of 30 farmers

Date	**Average income (Baht)**	**Average expenditure (Baht)**
Feb 2, 2024	2,750 (Carry-forward cash balance)	-
Mar 3, 2024	-	250 (Household expenses)
Mar 5, 2024	2,000 (Farm wages)	400 (Household expenses)
Mar 8, 2024	1,500 (Mushroom nursery wages)	500 (Kitchen supplies)
Mar 10, 2024	20,000 (Loan)	7,000 (Agricultural equipment)
Mar 12, 2024	-	3,500 (Fertilizers)
Mar 15, 2024	30,000 (Loan)	20,000 (Bank deposit)
Mar 15, 2024	-	2,400 (Fertilizers and pesticides)
Mar 20, 2024	-	8,000 (Soil preparation)
Mar 22, 2024	5,000 (Pineapple sales)	700 (Transport costs)
Mar 25, 2024	-	100 (Medical expenses)
Mar 28, 2024	-	

"On March 3, 2024, the farmer paid 200 Baht for food, gave 300 Baht to their child, and paid 100 Baht for electricity and water bills. On March 8, 2010, the farmer received 1,500 Baht for wages from building a mushroom nursery, paid 300 Baht for food, and spent 500 Baht on kitchen supplies.

On March 15, 2024, the farmer borrowed 30,000 Baht and deposited 20,000 Baht into the bank, spent 2,400 Baht on fertilizers and pesticides, paid 100 Baht for car fuel, and spent another 300 Baht on food.

On March 20, 2024, the farmer paid 8,000 Baht for plowing soil preparation and 200 Baht for food. On March 25, 2010, the farmer went to see a doctor, spending 100 Baht for medical expenses and another 200 Baht for food. On March 28, 2010, the farmer gave 300 Baht to their child."

Figure 2. Semi-unstructured accounting data recording of farmers**.**

Another widely used technique is sentiment analysis proposed by Pang and Lee (2008), which aims to analyze the opinions or emotions expressed in text. This technique is particularly useful for evaluating feedback on products or services. For instance, the text "This product is great" would be classified as a positive sentiment, while "The product is damaged" would be classified as negative. Sentiment analysis enables a better understanding of the emotions and opinions of people online effectively.

Text summarization is another important technique proposed by Nallapati et al. (2017). that helps create concise summaries from large volumes of information, such as summarizing news articles or financial reports. By using models like Sequence-to-Sequence or Transformer, it can produce abstractive summaries (using new words), making the content easier to understand and quicker to process without having to read all the data.

Topic modeling is a technique used to identify hidden topics in large datasets of text. This method proposed by Blei and Lafferty (2007), does not require prior input and is used, for example, to classify financial transactions according to the type of product or service. Models such as Latent Dirichlet Allocation (LDA) or Correlated Topic Model (CTM) can help find relevant topics from vast amounts of data efficiently.

Lastly, Named Entity Recognition (NER) proposed by Finkel et al. (2005), is a technique used to identify important information within text, such as names, places, dates, or monetary amounts. For example, in the sentence "Paid 500 baht for kitchen equipment on March 8, 2010," the model can identify "500 baht" and "March 8, 2010" as key entities. This technique helps extract specific, meaningful data from text more accurately.

These five techniques are crucial for developing and enhancing the performance of NLP, helping to analyze and understand text data with greater precision and efficiency.

Development of NLP techniques for understanding semi-unstructured accounting data

The operation of this code involves the collaboration of multiple libraries, which enables efficient extraction of data from PDF files, translation, word similarity checking, and saving data into CSV files. The process is classified into 4 steps as follows:

Opening and reading the PDF file

The pypdf library is used to open the PDF file named 'doc3.pdf' with the command PdfReader('doc3.pdf') to read the data from the file. The code checks the total number of pages in the PDF using len(reader.pages), which tells the total number of pages in the file. Then, the code selects the desired page using reader.pages[i], which extracts the text from the chosen page and stores it in the text variable. This text is then split into words using text.split(), which breaks the text into individual words and stores them in the list selected_text_split. The content from the PDF page is stored in the dictionary datax, with the page number as the key.

Language translation

In this step, the googletrans library is used, which is a tool for language translation. The translator.translate() function is used to translate words from Thai into English. This translation is important for converting Thai data in the PDF into English for easier processing. The translated word is stored in the translated_previous_value variable for use in the next step.

Checking word similarity

After translation, the code uses the difflib library and the get_close_matches() function to compare the translated word with words in a predefined dictionary. This dictionary contains words related to payment (e.g., "pay", "payment", "settle") and income (e.g., "receive", "income", "profit"). The get_close_matches() function checks how similar the translated word is to the words in the dictionary, considering a similarity threshold of 70% (using the cutoff=0.7 parameter). If the translated word is sufficiently similar to a word in the dictionary, the data is categorized into appropriate lists (e.g., pay_money or get_money). In this process, difflib.get_close_matches function from Python's Standard Library identifies close matches for a given word within a list using the SequenceMatcher algorithm. It compares similarity ratios to provide a ranked list of matches that meet or exceed a specified threshold, as shown in Equation 4.

$$Similarity\ Raio = \frac{2.M}{T_a + T_b} \qquad (4)$$

From Equation 4, M is Number of matching elements, T_a is Total elements in the first sequence and T_b is Total elements in the second sequence.

Saving data into CSV files

After translating the words and categorizing the data, the code uses the csv library to save the data into CSV files. The csv.writer() function is used to write the data into the file. The code opens a new CSV file and uses writer.writerow() to write the header of the file and writer.writerows() to write the data in each row. The data saved includes both the translated text and the information related to payments and income, which is stored in separate CSV files based on category (e.g., corrected_data.csv, pay_money.csv, and get_money.csv). After the structured accounting data is stored in the .CSV files, the data (pay_money.csv and get_money.csv) will be processed using the accounting formulas provided in Equations 1–3 with time series algorithms for predicting the future accounting status. The algorithm is outlined in the procedure shown in Table 2.

Developing predictive accounting trend models using machine learning algorithms

After extracting the semi-unstructured accounting data recorded by farmers, it is categorized into two accounting types: pay_money and get_money, using the developed algorithm shown in Table 2. The categorized data in the CSV file is then organized into lists of payments and receipts, grouped by date, to create a suitable dataset for processing with time series algorithms, including Prophet, LSTM, and ARIMA. The structure of the categorized data is shown below.

Table 1: pay_money

Date	Description	Amount
2025-01-01	Purchased fertilizer	500
2025-01-02	Paid for labor	700
2025-01-04	Bought seeds	300

Figure 3. Pay money data table.

Table 2: get_money

Date	Description	Amount
2025-01-01	Sold rice	1,200
2025-01-03	Sold vegetables	800
2025-01-05	Received government aid	1,000

Figure 4. Get_money data table.

In processing the accounting data recorded by farmers in CSV files, following the data structures—including dates and related amounts shown in Figures 3 and 4, the data are imported using Python’s Pandas library. This process prepares the data into a suitable format for management and analysis by converting the date columns into datetime types, enabling various models to accurately process the information.

To compare the performance of time series modeling and linear regression modeling systematically, we can break the process into three main stages:

Data preparation

The data preparation for time series modeling starts by organizing the data in chronological order, ensuring that the data is sorted by date and filling in any missing values. Then, the data is split into 70% for the training set and 30% for the testing set to preserve the chronological order and prevent data leakage, where future data would be used to predict the past.

Model configuration

The time series algorithms, including Prophet, LSTM, and ARIMA were defined with the following model configuration.

Facebook prophet

Prophet is based on an additive time series decomposition approach. Prophet is optimized for large datasets with strong seasonal patterns and is designed to handle seasonality and holidays. The model adjusts trends, seasonality, and events using either an additive or multiplicative approach. Its accuracy can be improved by fine-tuning parameters related to seasonality, holidays, and changepoints based on the data characteristics.

LSTM (Long Short-Term Memory)

LSTM is a type of recurrent neural network (RNN) that is highly effective at handling sequential data and capturing long-term dependencies in time series.

Optimized method: To enhance LSTM performance, several hyperparameters can be tuned, including the number of layers, units per layer, learning rate, batch size, and sequence length for the input data. The process begins by scaling the data using MinMaxScaler to normalize it within the range of 0 to 1. A 5-point lag sequence is then created to predict the next value in the series. The data is reshaped into a 3D format, suitable for LSTM processing, where the input data structure follows the shape (samples, time steps, features). The LSTM model consists of two layers, each with 50 units, and uses the 'tanh' activation function. To reduce the risk of overfitting, two Dropout layers with a rate of 0.2 are included. Finally, a Dense layer is used to output the predicted value. This optimization approach helps ensure accurate predictions while minimizing overfitting.

ARIMA (Autoregressive Integrated Moving Average)

ARIMA is a statistical model used for time series forecasting, consisting of three main components: 1) AR (Autoregressive): This component utilizes the relationship between the current value and past values of the data to predict future values. For example, if today's result is related to the result of the previous day, this relationship will be used to forecast the next value, 2) I (Integrated): This component is used to make the data stationary or reduce its randomness by differencing the data over time. Differencing helps eliminate trends and make the data more stable over time, and 3) MA (Moving Average): This component uses a moving average of past prediction errors or residuals to forecast future values. This helps the model handle volatility in the data by averaging out past errors.

The auto Arima function automatically selects the best ARIMA model by testing different combinations of autoregressive (AR), moving average (MA), and differencing parameters, and choosing the model with the lowest Akaike Information Criterion (AIC). It uses seasonal=False to exclude seasonality and stepwise=True for efficient model selection. Warnings are suppressed with suppress_warnings=True, and errors are ignored during training with error_action="ignore". The model is then trained using arima_model.fit(train['y']), and predictions are made for the test period with arima_model_fit.predict(n_periods=len(test)), comparing the forecasted values with actual data.

Experiment Method

Performance assessment of the NLP-ACC algorithm

The performance of the NLP-ACC algorithm is assessed by examining its capability to process 150 semi-unstructured accounting data samples. The evaluation is based on the percentage of matches, which shows how accurately the algorithm detects relevant data in comparison to the total number of expected elements.

Performance assessment of predictive accounting trend models

The extracted payment accounting dataset from semi-unstructured data is used to assess the performance of time series algorithms. This dataset consists of 365 samples, split into 256 training samples (70%) and 109 testing samples (30%) for building and evaluating the predictive model. Additionally, the best model's performance in predicting data for 10, 20, and 30 days is tested. To assess the predictive model's performance, we use two main metrics:

R^2: Measures the ability of the model to explain the variance in the data. A high R^2 means the model explains the data well, but it does not always mean the model will predict well, as it may be due to overfitting, as shown in Equation 8.

$$R^2 = 1 - \frac{RSS}{TSS} \quad (8)$$

MAE (Mean Absolute Error) : a metric used to evaluate the accuracy of a forecasting model. It is

Table 2. Pseudocode for developing NLP techniques to understand semi-unstructured accounting data

Algorithm: NLP-Based Approach for Semi-Unstructured Accounting Data (NLP-ACC)

Step	Action
1	Initialize the PDF reader using PdfReader('doc3.pdf')
2	Get the total number of pages in the PDF using len(reader.pages)
3	Select the desired page by iterating through reader.pages[i]
4	Extract the text from the selected page using text = page.extract_text()
5	Split the extracted text into words using text.split()
6	Store the split words in the list selected_text_split
7	Store the content from the page in the dictionary datax using the page number as the key
8	Initialize the translator using Translator()
9	For each word in selected_text_split, translate it using translator.translate(word, src='th', dest='en'):
10	{
11	Store the translated word in the translated_previous_value variable
12	}
13	Define two lists: pay_money (e.g., "pay", "payment", "settle") and get_money (e.g., "receive", "income", "profit")
14	For each translated word (translated_previous_value), compare it to the dictionary using get_close_matches():
15	{
16	Set the similarity threshold to 70% (cutoff=0.7)
17	If the translated word is similar to a word in the dictionary, categorize the data:
18	{
19	If related to payment:
20	{
21	Add it to pay money
22	}Else {
23	Add it to get_money
24	}
25	}
26	Open a CSV file for each category (corrected_data.csv, pay_money.csv, get_money.csv)
27	Use csv.writer() to create a CSV writer object
28	Write the header in the CSV file using writer.writerow()
29	Write the categorized data into the file using writer.writerows()

calculated by determining the difference between the predicted values and the actual values at each data point and then finding the average of these differences., as shown in Equation 9.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i) \qquad (9)$$

RESULTS AND DISCUSSION

Performance Assessment Results of the NLP-ACC Algorithm

The performance evaluation of the NLP-ACC algorithm in detecting the collected semi-unstructured accounting data from the farmers is as follows.

From Table 3, the NLP-ACC algorithm can process the accounting data recorded by farmers effectively, with an average matching percentage of 90.66%. This indicates that the algorithm performs well in detecting the expected data. Although some data categories have lower matching percentages, the overall results demonstrate the algorithm's strong performance in detecting information from semi-unstructured accounting records.

Performance assessment results of predictive accounting trend models

The extracted payment accounting dataset from semi-unstructured data is used to comparatively assess time series algorithms. This dataset consists of 365 samples, split into 256 training samples (70%) and 109 testing samples (30%) for building and evaluating the predictive model's performance. In assessing the predictive model's performance, we use two main metrics:

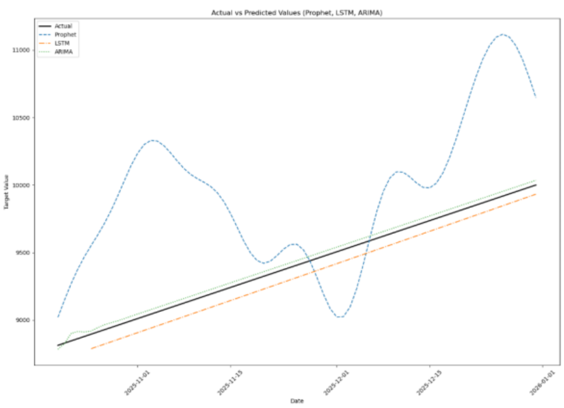

Figure 5. Comparison of predicted and actual values at the date points of the time series algorithms.

Table 3: Performance of the NLP-ACC algorithm in detecting collected semi-unstructured accounting data recordings

Expected Data	Collected Semi-Unstructured Accounting Data Recordings (Number of Detected)	Extracted Data Using NLP-ACC Algorithm (Number of Detected)	Match (%)
Food payment	126	120	95.24
Give money	149	130	87.25
Car fuel	185	150	81.08
Medical expenses	141	135	95.74
Kitchen supplies	157	140	89.17
Tap water	161	150	93.17
Wages	176	165	93.75
Loan	154	130	84.42
Deposit	130	120	92.31
Fertilizers/Pesticides	149	140	93.96
Plowing	159	145	91.19
Average Summarization	**153.36**	**138.64**	**90.66**

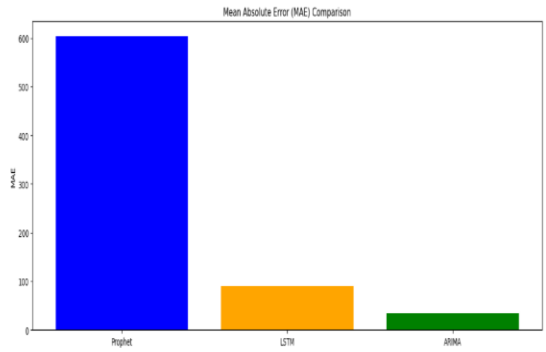

Figure 6. Comparison of MAE of the algorithms.

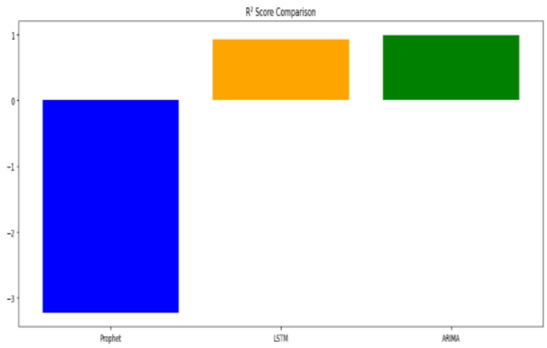

Figure 7. Comparison of R^2 of the algorithms.

Figure 5 – 7, the comparison of prediction results from the Prophet, LSTM, and ARIMA models applied to the payment accounting dataset clearly demonstrates varying performance levels, with Mean Absolute Error (MAE) and R-squared (R^2) used to assess each model's prediction accuracy and ability to explain the data.

MAE, or Mean Absolute Error, indicates the average prediction error of each model. In this case, the ARIMA model has the lowest MAE of 34.1084, showing the highest prediction accuracy as it predicts values closest to the actual data. LSTM has a MAE of 71.0920, indicating good accuracy but with slightly more error than ARIMA. Prophet has the highest MAE of 603.8044, reflecting the greatest prediction error, as its predictions deviate most from the actual values.

Another metric, R-squared (R^2), measures the model's ability to explain data variance. A value closer to 1 indicates a better explanation of the data, while a negative value suggests poor explanatory power. ARIMA has an R^2 of 0.9901, showing that it captures the data characteristics very well and explains the data variance effectively. LSTM has an R^2 of 0.9511, still demonstrating good explanatory power but slightly lower than ARIMA. Prophet has an R^2 of -3.2273, which is a negative value, indicating that it cannot explain the data at all and fails to capture its variance.

From the comparison of both MAE and R^2, it can be concluded that ARIMA is the most effective model for this dataset. Not only does it have the highest accuracy, but it also explains the data well. While LSTM shows good prediction capability, its higher MAE and lower R^2 suggest that it still struggles in comparison to ARIMA. Prophet, on the other hand, shows both high prediction error and poor explanatory power, making it the least suitable model for this dataset. Therefore, ARIMA is the most appropriate model for this data at present.

The performance of ARIMA as the best model is tested for predicting data for 10, 20, and 30 days, as shown in the results in Figure 8.

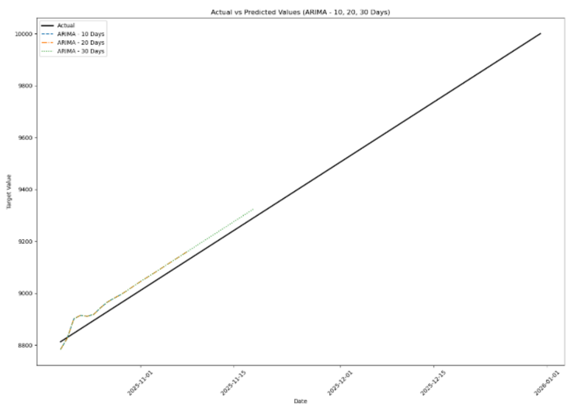

Figure 8. The performance of the ARIMA model in predicting data for different time periods.

From Figure 8, the performance of the ARIMA model in predicting data for 10, 20, and 30 days varies with the prediction period. For the 10-day forecast, the model exhibits a relatively low performance, with an MAE of 33.3129 and an R^2 of 0.4205, indicating limited accuracy and explanatory power.

However, as the forecast period extends to 20 days, the MAE increases slightly to 33.4816, but the R^2 improves to 0.8654, suggesting a better fit and more accurate predictions. The 30-day forecast shows a slight increase in MAE to 33.6254, but the R^2 continues to rise to 0.9414, reflecting the model's highest accuracy and explanatory power for this period. Overall, these results indicate that the ARIMA model performs better with longer prediction periods, particularly in terms of its explanatory capability, as reflected by the increasing R^2 values.

The experimental results show that the ARIMA model achieved the best performance because it was efficiently fine-tuned using the auto_arima function, which automatically selects the best parameters by testing various values based on the Akaike Information Criterion (AIC) (Ali and Masmoudi, 2025). This approach simplifies the parameter selection process and results in more accurate predictions compared to the LSTM and Prophet models. ARIMA exhibited the lowest error and highest accuracy, especially for long-term forecasting. Overall, ARIMA is the most suitable model for this dataset, with potential for further improvement through additional fine-tuning and feature enhancement.

CONCLUSIONS

This study applied AI, specifically Natural Language Processing (NLP), to predict income and expense trends for pineapple farmers in Phitsanulok Province using semi-unstructured accounting data. The NLP-ACC algorithm effectively detected the data, achieving a high matching rate. Time series forecasting models—Prophet, LSTM, and ARIMA—were compared, with ARIMA showing the best performance in terms of accuracy and explanatory power, outperforming both LSTM and Prophet. The performance of the ARIMA model varied with the prediction period. For shorter forecasts, the model showed lower accuracy, but as the forecast period increased, both the accuracy and explanatory power improved, with the best results seen for longer prediction periods. This suggests that ARIMA performs better for longer-term predictions.

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