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A HYBRID LEARNING FRAMEWORK INTEGRATING DBR AND PLS-SEM FOR WINE-FOOD PAIRING EDUCATION USING TRADITIONAL PEDAGOGY AND AI-DRIVEN TOOLS

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ABSTRACT

This study investigates the development and validation of a hybrid learning framework that integrates traditional teaching methods with AI-driven tools for wine-food pairing education. Using a Design-Based Research (DBR) approach, the Multi-Cuisine Master Wine Tasting Harmonious Wheel was conceptualized and refined through literature synthesis, sensory theory, and expert consultation. The tool visually organizes wine attributes, global cuisines, and pairing logic to enhance learner comprehension. In Stage Two, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to data from 385 respondents to examine relationships among Traditional & Educational Methods, LLM/CI Tools, Challenges in AI Tool Usage, Learner's Engagement, Usability of Tools, Skill Development, User Experience, and Confidence in Wine Pairing. Results confirmed that traditional teaching and AI-assisted learning complement each other, with Learner's Engagement emerging as the strongest predictor of Skill Development, User Experience, and Confidence. However, usability alone did not increase confidence, emphasizing the continued importance of guided sensory practice. Overall, the findings highlight that hybrid instruction – anchored in experiential learning and AI support provides an effective pathway for building pairing competency and learner confidence.

KEYWORDS: Wine-Food Pairing; Design-Based Research (DBR); AI in Hospitality Education; LLM/CI Tools; Sensory Learning; Learner Engagement; Skill Development

1. INTRODUCTION

Wine–food pairing education has evolved from traditional sensory instruction to technologically supported learning environments that blend experiential, cognitive, and digital elements. Research in sensory science confirms that pairing harmony depends on multidimensional factors such as taste, aroma, texture, and cultural food context (Harrington, 2005; Spence, 2020; Galmarini, 2020). Recent developments in hospitality education emphasize experiential learning, visual tools, and guided tasting as key to skill acquisition and learner readiness for professional environments (Askren & James, 2020; Green & Sammons, 2014). Parallel advancements in artificial intelligence, VR/AR simulations, and interactive recommendation systems have enabled more personalized, adaptive, and scalable learning experiences for students and professionals (Al-Gindy et al., 2020; Gan et al., 2023; Maghsudi et al., 2021). Large Language Models (LLMs) and Computational Intelligence (CI) tools are increasingly recognized for their potential to enhance personalized instruction, accelerate knowledge acquisition, and democratize access to expertise (Kasneci et al., 2023; Xu et al., 2024; Boyko et al., 2023).

However, despite these advancements, wine–food pairing education still relies heavily on tacit knowledge, apprenticeship-style learning, and the presence of expert sommeliers, making it difficult to scale. The linguistic complexity of tasting terminology and cognitive load required for pairing judgement further challenge learners (Croijmans et al., 2019; Ellis & Caruana, 2018). While research explores food flavour compatibility and consumer perception, the integration of AI-based tools with structured sensory learning remains underdeveloped (Bastian et al., 2010; Kustos et al., 2020). This growing intersection of sensory science and educational technology presents a need for hybrid instructional models that bridge foundational pedagogy, experiential learning, and AI-supported guidance.

Existing studies independently explore wine education (Taylor et al., 2008; Brain, 2019), food pairing science (Spence, 2020; Kustos et al., 2020), and AI-enabled learning (Kasneci et al., 2023; Maghsudi et al., 2021), but there is no integrated framework that combines traditional pedagogy, AI-driven tools, and experiential sensory practice into a unified learning model. Current literature does not address how hybrid education can enhance pairing confidence, usability of digital tools, or learner engagement particularly in practical and palate-dependent

subjects where experiential reinforcement is crucial (Askren & James, 2020; Niimi et al., 2017). This lack of a cohesive instructional approach represents a critical gap that limits scalable, accessible, and skill-focused wine–food pairing education in hospitality training environments. Hence, this paper proposes two primary objectives. First, it aims to construct and refine the Multi-Cuisine Master Wine Tasting Harmonious Wheel through a Design-Based Research (DBR) approach supported by expert validation. Second, the study seeks to examine the relationships among Traditional and Educational Methods, AI/LLM/CI tools, Learner Engagement, Usability, Skill Development, User Experience, and Confidence by employing Partial Least Squares Structural Equation Modeling (PLS-SEM).

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 *Traditional and Educational Methods, Usability, and Learner Engagement*

Traditional and structured educational methods remain central to hospitality and wine education, particularly in domains requiring sensory evaluation, experiential judgment, and contextual understanding. Instructor-led demonstrations, guided tastings, classroom discussions, and structured curricula allow learners to build cognitive frameworks that support the effective use of learning tools. Such methods reduce ambiguity, clarify learning objectives, and enhance learners' perceived ease of interacting with educational resources. Prior studies in culinary and hospitality education emphasize that experiential and blended pedagogies significantly improve learners' ability to use instructional tools effectively, especially when tacit knowledge and skill transfer are required (Askren & James, 2020; Maier & Thomas, 2013).

In addition to usability, traditional educational approaches also contribute strongly to learner engagement. Active learning strategies such as role-play, supervised practice, and problem-based learning encourage participation, attentiveness, and emotional involvement. Engagement is particularly important in hospitality education, where affective and experiential learning outcomes are closely linked to professional competence. Research consistently shows that learners exposed to structured experiential teaching methods report higher engagement levels, greater motivation, and stronger learning commitment (Green & Sammons, 2014; Crawford et al., 2014). Based on the above discussion, the following hypotheses are proposed:

H₁: *There is a significant positive impact of Traditional and Educational Methods on the Usability of the tools.*

H₂: *There is a significant positive impact of Traditional and Educational Methods on the Learner's Engagement.*

2.2 LLM/CI Tools, Usability, and Learner Engagement

Recent advancements in Large Language Models and Computational Intelligence tools have transformed educational environments by enabling personalization, real-time feedback, and adaptive learning pathways. These tools enhance usability by simplifying complex concepts, offering conversational guidance, and reducing cognitive load through contextual explanations. Intelligent systems that respond dynamically to user inputs improve task efficiency and ease of navigation, which positively shapes learners' perceptions of tool usability. Prior research in AI-enhanced learning environments confirms that adaptive and intelligent systems significantly improve user interaction quality and perceived usefulness (Gan et al., 2023; Xu et al., 2024).

Beyond usability, LLM/CI tools also play a critical role in fostering learner engagement. AI-driven systems promote exploratory learning, encourage curiosity, and sustain learner attention through interactive simulations and personalized content delivery. In skill-based domains such as wine education, these tools enable learners to experiment with virtual pairing scenarios and sensory descriptions, thereby enhancing immersion and motivation. Existing literature suggests that adaptive AI systems substantially increase learner engagement by aligning instructional content with individual learning needs and preferences (Kasneci et al., 2023; Leiker et al., 2023). Based on the above discussion, the following hypotheses are proposed:

H₃: *There is a significant positive impact of LLM/CI tools on the Usability of the tools.*

H₄: *There is a significant positive impact of LLM/CI tools on the Learner's Engagement.*

2.3 Challenges in AI Tool Usage, Usability, and Learner Engagement

While AI-driven educational tools offer substantial benefits, their adoption is often accompanied by challenges related to system complexity, transparency, accuracy, and user trust. These challenges can initially hinder usability perceptions, particularly for learners with limited technological readiness. However, when learners are adequately guided and supported, confronting these challenges can enhance critical engagement and digital

competence. Research suggests that usability perceptions are influenced not only by system design but also by users' ability to understand and adapt to technological constraints (Hryciw et al., 2023; Tu et al., 2024). Similarly, challenges associated with AI tools can shape learner engagement in nuanced ways. Rather than disengaging learners, exposure to AI limitations may encourage reflective thinking, prompt evaluation, and deeper cognitive involvement. Learners who critically assess AI-generated outputs often demonstrate higher levels of metacognitive engagement. Studies on responsible AI adoption in education indicate that structured scaffolding around AI challenges enhances learner engagement and promotes meaningful learning experiences (Kasneci et al., 2023; Laak & Aru, 2024). Based on the above discussion, the following hypotheses are proposed:

H₅: *There is a significant positive impact of Challenges in AI Tools usage on the Usability of the tools.*

H₆: *There is a significant positive impact of Challenges in AI Tools usage on the Learner's Engagement.*

2.4 Usability of Tools, Skill Development, and Confidence in Wine Pairing

Usability is a fundamental determinant of learning effectiveness, particularly in skill-oriented domains such as wine education. Tools that are intuitive and easy to use facilitate repeated practice, experimentation, and immediate feedback, all of which are essential for skill acquisition. When learners perceive tools as accessible and reliable, they are more likely to engage in deliberate practice, resulting in improved analytical reasoning, sensory discrimination, and application skills. Prior studies confirm that user-friendly educational tools significantly enhance skill development outcomes in wine and hospitality education (Taylor et al., 2008; Brain, 2019).

In addition to skill development, usability also influences learners' confidence in wine pairing decisions. Confidence emerges when learners can successfully apply theoretical knowledge using tools that support learning without excessive effort or frustration. User-friendly systems enable learners to test pairing principles, validate their choices, and progressively build self-efficacy. Existing research highlights that effective educational interventions improve both wine knowledge and confidence in decision-making (Ellis & Caruana, 2018; Harrington, 2005). Based on the above discussion, the following hypotheses are proposed:

H₇: *There is a significant positive impact of Usability of Tools on the Skill Development.*

H₈: *There is a significant positive impact of Usability of Tools on the Confidence in wine pairing.*

2.5 Learner Engagement, Skill Development, and User Experience

Learner engagement is widely recognized as a key driver of effective learning and skill acquisition. Engaged learners invest cognitive, emotional, and behavioral effort, leading to deeper understanding and improved performance. In hospitality and wine education, engagement through experiential activities such as tastings, simulations, and reflective discussions enhances both technical competence and analytical skills. Prior studies demonstrate that highly engaged learners achieve superior skill development outcomes compared to passive learners (Askren & James, 2020; Green & Sammons, 2014).

Learner engagement also plays a pivotal role in shaping the overall user experience. A positive user experience is characterized by immersion, satisfaction, and perceived value, all of which are strongly influenced by engagement levels. Technology-enhanced learning environments that sustain learner engagement contribute to favorable perceptions of the learning process and encourage continued usage. Research in educational technology consistently links engagement with improved user experience and satisfaction (Kasneci et al., 2023; Anderson, 2018). Based on the above discussion, the following hypotheses are proposed:

H₉: *There is a significant positive impact of Learner's Engagement on the Skill Development.*

H₁₀: *There is a significant positive impact of Learner's Engagement on the User Experience.*

2.6 Usability, Learner Engagement, User Experience, and Confidence

Usability is a critical antecedent of positive user experience, as intuitive and efficient tools minimize frustration and enhance satisfaction. In AI-supported educational contexts, usability determines whether advanced technological features translate into meaningful learning experiences. Human-centered design principles emphasize that usability mediates the relationship between system functionality and learner satisfaction (Fornell & Larcker, 1981; Hair et al., 2013).

Furthermore, learner engagement significantly contributes to confidence in wine pairing by reinforcing experiential learning and repeated application. Engaged learners internalize pairing principles through active participation and reflection,

leading to greater trust in their judgment. Sensory science and wine education literature consistently emphasize engagement as a key factor in building confidence and expertise (Bastian et al., 2010; Galmarini, 2020). Based on the above discussion, the following hypotheses are proposed:

H₁₁: *There is a significant positive impact of Usability of Tools on the User Experience.*

H₁₂: *There is a significant positive impact of Learner's Engagement on the Confidence in wine pairing.*

2.7 Conceptual Framework

The proposed conceptual framework as shown in Figure 1 is grounded in experiential learning theory, technology acceptance perspectives, and engagement-based learning models, which together explain how traditional pedagogy and AI-enabled tools shape learning outcomes in wine education. Experiential learning theory emphasizes that knowledge is constructed through concrete experience, reflection, and active experimentation, making traditional and educational methods such as guided tastings, demonstrations, and instructor-led discussions particularly effective in hospitality education (Askren & James, 2020; Maier & Thomas, 2013). These methods provide cognitive structure and contextual grounding, thereby enhancing both the usability of learning tools and learner engagement. Simultaneously, the framework integrates principles from multimedia and technology-enhanced learning, suggesting that LLM/CI tools improve instructional clarity, adaptability, and personalization, which positively influence learners perceived usability and engagement (Chen et al., 2022; Gan et al., 2023; Xu et al., 2024).

From a technology adoption and human computer interaction perspective, usability and engagement function as critical mediating mechanisms linking instructional inputs to learning outcomes. The Technology Acceptance Model (TAM) and user-centered design theory posit that systems perceived as easy to use and useful are more likely to be accepted and effectively applied by learners (Fornell & Larcker, 1981; Hair et al., 2013). In the context of this framework, usability of tools enables learners to focus on skill acquisition rather than system navigation, thereby supporting skill development and confidence in wine pairing. Concurrently, learner engagement conceptualized as cognitive, emotional, and behavioral involvement enhances depth of learning and contributes to a positive user experience. Prior research in hospitality and wine

education demonstrates that engaged learners develop superior sensory discrimination skills and stronger confidence in evaluative judgments (Taylor et al., 2008; Ellis & Caruana, 2018; Bastian et al., 2010).

The framework also acknowledges the role of challenges in AI tool usage, drawing from responsible AI adoption and self-regulated learning theories. Challenges related to transparency, accuracy, and complexity may initially constrain usability; however, when learners are guided appropriately, these challenges can stimulate critical reflection and metacognitive engagement (Kasneci et al., 2023; Hryciw et al., 2023). This perspective aligns

with contemporary views that AI should function as an augmentative learning partner rather than a replacement for human instruction (Tu et al., 2024; Laak & Aru, 2024). Within wine education, such reflective engagement strengthens experiential learning, leading to enhanced skill development, greater confidence in wine pairing, and an enriched user experience. Overall, the framework presents a theoretically coherent model that integrates traditional pedagogy with AI-enabled learning to explain how usability and engagement jointly shape educational outcomes.

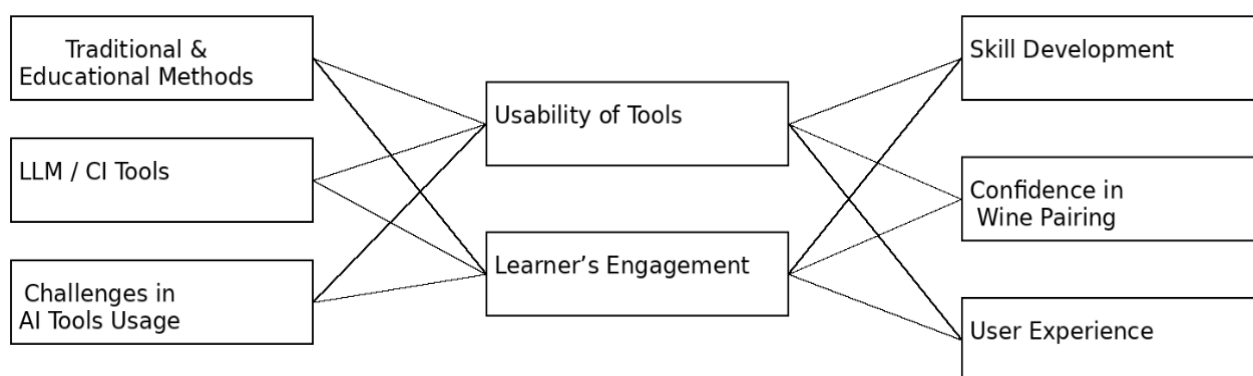


Figure 1: Conceptual Framework

3. METHODOLOGY AND ANALYSIS

This study adopted a Design-Based Research (DBR) and mixed-methods design, executed in two sequential stages:

- 1) *Development of the Multi-Cuisine Master Wine Tasting Harmonious Wheel* as an educational artefact, and
- 2) *Quantitative validation of learning factors using PLS-SEM.*

DBR was selected because it supports iterative development, refinement, and testing of pedagogical tools grounded in both theory and practice (Creswell & Plano Clark, 2011). The mixed-methods structure enabled integration of qualitative expert knowledge with empirical quantitative evidence supporting educational application.

Stage 1

The development of the Multi-Cuisine Master Wine Tasting Harmonious Wheel as shown in figure 2 followed a design-based research (DBR) and mixed-methods approach, integrating qualitative expert knowledge with evidence from sensory science, wine education literature, and culinary pairing theory. Design-based research was chosen as it allows iterative development, testing, and refinement of educational artifacts grounded in theory and practice

(Creswell & Plano Clark, 2011). The objective was to create a pedagogical tool that visually synthesizes complex wine-food pairing principles across multiple cuisines into an accessible, learner-centered framework.

Phase 1: Literature Review and Theoretical Grounding

The initial phase involved an extensive systematic literature review of wine sensory evaluation, food-wine pairing principles, and experiential learning in hospitality education. Key theoretical foundations included sensory congruence theory, experiential learning theory, and food perception models, which emphasize harmony between taste, aroma, texture, and intensity (Harrington, 2005; Spence, 2020; Galmarini, 2020). Studies on wine education and confidence building further informed the categorization of wine styles, flavour profiles, and pairing logic (Taylor et al., 2008; Bastian et al., 2010). This phase ensured that the conceptual structure of the wheel was theoretically sound and empirically supported.

Phase 2: Identification of Core Dimensions and Variables

Based on the literature synthesis, key dimensions

relevant to wine tasting and pairing were identified and operationalized. These included wine structure variables (acidity, sweetness, tannin, alcohol, and body), flavour intensity, aroma families, and textural attributes. Simultaneously, major global cuisine categories were mapped according to dominant ingredients, cooking techniques, spice levels, and flavour profiles. This classification aligns with prior research highlighting the role of cultural and ingredient-based factors in pairing appropriateness (Kustos et al., 2020; Schifferstein et al., 2020).

Phase 3: Expert Consultation and Content Validation

To enhance content validity, expert consultation was conducted with hospitality educators, sommeliers, and culinary professionals. Semi-structured interviews and informal Delphi-style feedback sessions were used to validate the relevance and accuracy of wine styles, food groupings, and pairing logic (Sahoo, 2022). Experts reviewed draft categorizations and suggested refinements to ensure industry relevance, pedagogical clarity, and practical applicability. This step helped align academic theory with real-world wine service and education practices.

Phase 4: Structural Design of the Harmonious Wheel

The wheel was structured using a concentric circular model, a format commonly employed in sensory science to represent multidimensional relationships in an intuitive visual form.

- The innermost rings represent foundational wine attributes (acidity, sweetness, tannin, alcohol, and body).
- The middle rings map wine styles, aroma families, and flavour intensity levels.
- The outer rings integrate multi-cuisine food categories and specific dishes aligned with compatible wine profiles.

This hierarchical visual design facilitates progressive learning, allowing users to move from basic wine understanding to complex pairing decisions. The circular format supports holistic cognition and pattern recognition, which is particularly effective in sensory education (Cozzolino et al., 2009).

Phase 5: Visual Design and Prototyping

Following content finalization, a visual prototyping phase was undertaken. Color coding was applied to differentiate flavour families, intensity levels, and cuisine types, consistent with sensory mapping practices in wine education. Icons, food imagery, and textual descriptors were strategically

placed to reduce cognitive load and enhance usability. The wheel was designed to be both a didactic classroom tool and a practical reference aid for learners and professionals.

Phase 6: Pilot Testing and Educational Validation

The prototype wheel was pilot-tested with hospitality students and trainee sommeliers in guided tasting sessions. Learners used the wheel to identify wine characteristics and select suitable pairings for different cuisines. Observational feedback and reflective discussions were used to assess clarity, usability, and learning support. Findings indicated improved learner engagement, better conceptual understanding, and increased confidence in wine pairing decisions, supporting prior evidence on the effectiveness of experiential visual tools in hospitality education (Askren & James, 2020; Green & Sammons, 2014).

Phase 7: Refinement and Finalization

Based on pilot feedback, minor refinements were made to terminology, visual spacing, and food-wine alignment to improve clarity and pedagogical effectiveness. The finalized *Multi-Cuisine Master Wine Tasting Harmonious Wheel* thus represents an evidence-based, expert-validated, and learner-centered educational artifact.

Stage 2

3.1. Samples and data collection methodology

The demographic analysis of 385 respondents showed that the sample is predominantly composed of younger learners and hospitality professionals, reflecting the target population for wine-food pairing education. A significant proportion (48.05%) belonged to the 18–25 age group, followed by 35–50 (29.09%), indicating both emerging learners and mid-career professionals are engaging with AI-assisted wine education. In terms of academic background, the majority held bachelor's (56.10%) or master's degrees (30.65%), suggesting an adequately educated respondent base. However, only 12.73% possessed formal certification in wine and food pairing, while 39.74% had no certification, indicating a substantial skill development gap within the industry. Additionally, 51.43% were directly connected to teaching, training, or certified education roles, whereas 82.60% were from hospitality, tourism, or aviation professions, confirming high professional relevance of the study's focus.

Table 1: Demographic Profiles

Category	Sub Category	No. of Respondents	% of Respondents
Age	18-25	185	48.05
	25-35	68	17.66
	35-50	112	29.09
	50-70	20	5.19
Education and Qualification	Bachelors	216	56.10
	Masters	118	30.65
	P.hd.	20	5.19
	Diploma and others	31	8.05
Certifications in the field of wine and food	Food / Bakery and cuisines	97	25.19
	Wines/ spirits and Bar	86	22.34
	Wine and food pairing	49	12.73
	None of these	153	39.74
Certified educator in the field of wine or food	Certified educator of food and wine	55	14.29
	Certified educator in hospitality and tourism	71	18.44
	Faculty, lecturer, trainer, educator	72	18.70
	Other professions	187	48.57
Profession	Hospitality & Tourism, Aviation	318	82.60
	Science stream-based - Engineer/ Medical etc.	8	2.08
	Commerce stream-based - CA, CS, Economics/ Business management, etc,	45	11.69
	Arts stream-based Jewelry Designing, Fashion Designing, Craft, Textile	14	3.64

3.2. Assessment of measurement model

To assess the data and look at how the various factors connect to one another, SMARTPLS 4 software was utilized. When the sample size is limited, partial least squares structural equation modeling (PLS-SEM), a statistical technique for examining correlations between latent variables, is particularly useful (Hair, 2019). Choosing the right sample size is essential when performing Partial Least Squares Structural Equation Modeling (PLS-SEM) in order to guarantee the validity and accuracy of the results. The number of latent variables and indicators, the complexity of the model, the impact sizes, and the expected degree of statistical control all influence the sample size in PLS-SEM investigations, which is not fixed (Hair et al., 2013). While some researchers recommend a minimum of 100–200 observations, others indicate that the sample size to indicator ratio should be at least 5:1 or 10:1 (Kock, 2018). A sizable sample size of 391 observations was used for analysis in this study (Table 2.3). Common method bias (CMB) in PLS-SEM is detected using a thorough Collinearity assessment approach (Hair et al., 2017; Kock, 2015). VIF readings should be less than the 3.3 threshold (Hair J. H., 2017; Kock, 2015). This demonstrates that the model is free of frequent technique bias. The validity and reliability of the measuring tool were confirmed using a Confirmatory Factor Analysis (CFA). according to Table 3. According to Hair (2014),

three factor loadings below 0.40 should be eliminated, while loadings above 0.70 should be regarded as acceptable. Consequently, VAR 3C, VAR3D, VAR6B, VAR7D, VAR8A that had factor loadings less than 0.40 were not included in the analysis. Furthermore, Hair (2014) suggested that the thresholds for Composite Reliability (CR) and Average Variance Extracted (AVE) be 0.70 and 0.50, respectively. Convergent validity was established and the measurement model was accepted in this investigation as all values were higher than these suggestions.

Cronbach's alpha, first presented by Cronbach in 1951, is a commonly used metric for evaluating the reliability of multi-item scales. All of the measuring constructs in this study had Cronbach's Alpha values greater than 0.7, which indicates adequate reliability.

The diagonal in the table represents the AVE squared, and the values below the diagonal show the correlations between the constructs. According to Table 4.4, bold and diagonal values ought to be higher within their constructs than other constructs, both vertically and horizontally. Prejudice validity is thus achieved (Fornell & Larcker, 1981).

To determine the t-values of the route coefficients, the PLS-SEM approach for hypothesis testing uses bootstrapping standard errors (Hair, 2014). As a result, 5,000 re-samples were used in a bootstrapping process.

Table 2: Measurement Model

		Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Challenges AI Tools Usage	VAR1A	0.927	0.733	0.836	0.720
	VAR1B	0.761			
Confidence in Wine Pairing	VAR7A	0.961	0.961	0.975	0.927
	VAR7B	0.961			
	VAR7C	0.967			
LLM/CI Tools	VAR2A	0.823	0.854	0.902	0.698
	VAR2B	0.884			
	VAR2C	0.873			
	VAR2D	0.755			
Learner's Engagement	VAR5A	0.859	0.909	0.937	0.787
	VAR5B	0.850			
	VAR5C	0.923			
	VAR5D	0.914			
Skill Development	VAR6A	0.923	0.895	0.934	0.825
	VAR6C	0.909			
	VAR6D	0.893			
Traditional & Educational Methods	VAR1A	0.823	0.832	0.888	0.664
	VAR1B	0.842			
	VAR1C	0.837			
	VAR1D	0.754			
Usability of Tools	VAR4A	0.806	0.831	0.887	0.664
	VAR4B	0.816			
	VAR4C	0.875			
	VAR4D	0.758			
User Experience	VAR8B	0.853	0.870	0.906	0.658
	VAR8C	0.814			
	VAR8D	0.846			
	VAR8E	0.799			
	VAR8F	0.739			

Table 3: Fornell- Larcker Criterion

	Challenges AI Tools Usage	Confidence in Wine Pairing	LLM/CI Tools	Learner's Engagement	Skill Development	Traditional & Educational Methods	Usability of Tools	User Experience
Challenges AI Tools Usage	0.731							
Confidence in Wine Pairing	0.423	0.837						
LLM/CI Tools	0.724	0.351	0.835					
Learner's Engagement	0.467	0.754	0.581	0.887				
Skill Development	0.455	0.822	0.377	0.743	0.810			
Traditional & Educational Methods	-0.075	0.317	-0.052	0.250	0.359	0.591		
Usability of Tools	0.571	0.544	0.352	0.522	0.577	0.382	0.815	
User Experience	0.546	0.735	0.517	0.630	0.758	0.108	0.308	0.759

3.2. Structural model evaluation

Following validation of the measurement model, the structural model was evaluated using PLS-SEM to examine the direct and moderating effects between the study variables. In alignment with Hair et al. (2019), the analysis was conducted in two stages: initially without the moderating variable and subsequently with the moderating variable integrated into the model. This sequential approach enabled comparison of structural relationships and

the identification of shifts in significance levels, path strengths, and explanatory power due to moderation. Bootstrapping with 5,000 resamples and standard algorithm estimation were applied to generate path coefficients (β), t-statistics, and p-values, which formed the basis for hypothesis testing.

The results demonstrate that the majority of hypothesized paths were supported, indicating meaningful relationships among learning behaviour, AI-enabled educational support, and pairing

competency. The model's explanatory power, assessed using R² values, confirms strong predictive capability for several endogenous constructs: Learner's Engagement (R² = 0.887), Skill Development (R² = 0.810), Confidence in Wine Pairing (R² = 0.837), Usability of Tools (R² = 0.815), and User Experience (R² = 0.759). These values align with Chin's (1998) criteria, indicating moderate-to-substantial variance explanation and supporting the theoretical relevance of integrating LLM/CI tools into wine-food pairing education.

Effect size (f² analysis) revealed notable differences in construct influence. Traditional & Educational Methods, LLM/CI Tools, and Challenges in AI Tools Usage each demonstrated meaningful contributions to Usability of Tools and Learner's Engagement, reflecting their foundational importance in building adaptive learning pathways. Learner's Engagement

and Usability of Tools showed the strongest effect on User Experience and Skill Development, confirming that experiential interaction and ease of tool navigation are essential drivers of learner growth. However, the path from Usability of Tools to Confidence in Wine Pairing was not statistically significant, suggesting that usability alone is insufficient to build confidence without emotional engagement, guided practice, or educator presence.

Predictive relevance was established using Stone-Geisser's Q² values, all of which exceeded zero, confirming that the model holds satisfactory predictive accuracy. Together, the R², f², and Q² values demonstrate that the integrated framework provides strong explanatory and predictive support for understanding how traditional pedagogy, AI tools, and learner behaviour interact to influence wine education outcomes.

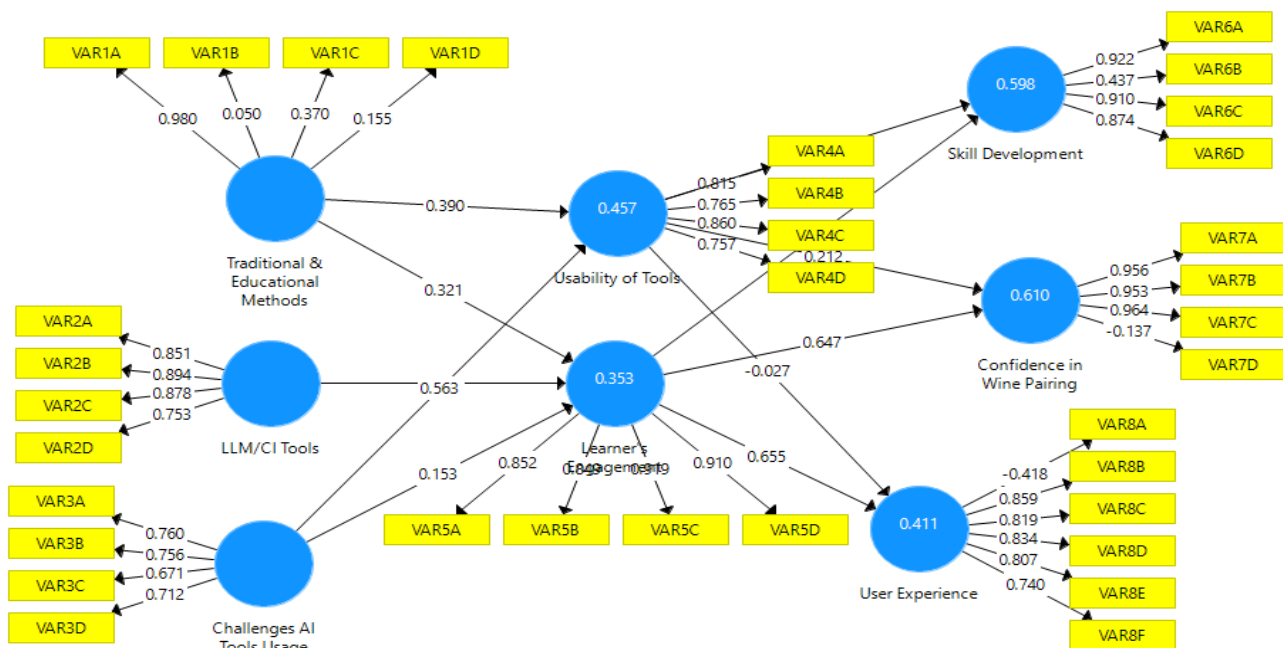


Figure 2: Structural model with path value

3.3. Hypothesis testing

The structural model results reveal varied but meaningful relationships among the constructs, offering insights into how traditional pedagogy, AI-driven learning tools, student engagement, and sensory confidence interact within wine and food pairing education. H1 demonstrates that Traditional & Educational Methods → Usability of Tools ($\beta = 0.137, t = 5.868, p = 0.000$) is significant, indicating foundational teaching frameworks enhance learners' ability to navigate technological tools, suggesting that traditional pedagogy still acts as a prerequisite for effective digital learning adoption. H2 confirms that Traditional & Educational Methods → Learner's Engagement ($\beta = 0.462, t = 7.536, p = 0.000$) is strongly supported, reinforcing that structured instruction

continues to be crucial for attention, participation, and cognitive grounding before transitioning into AI-enabled learning environments. H3 shows a positive link between LLM/CI Tools → Usability of Tools ($\beta = 0.067, t = 5.845, p = 0.000$), indicating that exposure to AI tools increases digital confidence, supporting the view that AI ecosystems encourage smoother adaptation to additional applications. H4 reports that LLM/CI Tools → Learner's Engagement ($\beta = 0.529, t = 8.812, p = 0.000$) is significant and the strongest among early paths, evidencing that LLM and computational intelligence tools stimulate interaction, curiosity, and active participation through personalization, interactivity, and adaptive responses.

In contrast, H5 reveals that Challenges in AI Tools

Usage → Usability of Tools ($\beta = 0.340, t = 5.731, p = 0.000$) still exerts a significant effect, suggesting that difficulty, data bias, and technological uncertainty paradoxically motivate students to understand systems more deeply, increasing their usability competence through forced problem-solving and adaptability. H6, which links Challenges in AI Tools Usage → Learner’s Engagement ($\beta = -0.224, t = 3.963, p = 0.000$), confirms a negative but significant effect, indicating that while AI challenges increase technical awareness, they reduce motivation and emotional engagement, particularly for sensory-driven subjects requiring guided facilitation and feedback. H7 reports that Usability of Tools → Skill Development ($\beta = 0.262, t = 7.141, p = 0.000$) is significant, showing that higher technological fluency directly translates to improved sensory, analytical, and pairing competencies. H8, however, is not supported; Usability of Tools → Confidence in Wine Pairing ($\beta = 0.001, t = 0.017, p = 0.987$) indicates no meaningful relationship. This reveals that usability alone cannot build confidence without human feedback, experiential tasting, or mentorship, emphasizing the emotional, psychological, and sensory nature of wine learning.

Further, H9 confirms a strong influence from Learner’s Engagement → Skill Development ($\beta = 0.614, t = 15.213, p = 0.000$), demonstrating that emotional involvement and cognitive participation are fundamental drivers for skill mastery. H10 and H11 both reinforce user experience as a dependent behavioural outcome: Learner’s Engagement → User Experience ($\beta = 0.628, t = 13.144, p = 0.000$) and Usability of Tools → User Experience ($\beta = 0.209, t = 5.068, p = 0.000$), suggesting that the best learning environments combine digital clarity with emotional stimulation. Finally, H12 shows that Learner’s Engagement → Confidence in Wine Pairing ($\beta = 0.645, t = 18.207, p = 0.000$), the strongest supported path overall, highlighting that confidence is earned through involvement, reflection, repetition, and guided experience rather than passive or tool-based navigation. Collectively, these findings demonstrate that traditional frameworks initiate learning, AI tools enhance interaction, engagement drives development, and confidence is ultimately built through experiential immersion rather than usability alone.

Table 4: Path Analysis and Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Traditional & Educational Methods -> Usability of Tools- H1	0.137	0.137	0.073	5.868	0.000
Traditional & Educational Methods -> Learner's Engagement- H2	0.462	0.459	0.061	7.536	0.000
LLM/CI Tools -> Usability of Tools- H3	0.067	0.062	0.079	5.845	0.000
LM/CI Tools -> Learner's Engagement- H4	0.529	0.528	0.060	8.812	0.000
Challenges AI Tools Usage -> Usability of Tools- H5	0.340	0.340	0.059	5.731	0.000
Challenges AI Tools Usage -> Learner's Engagement- H6	-0.224	-0.218	0.057	3.963	0.000
Usability of Tools -> Skill Development-H7	0.262	0.261	0.037	7.141	0.000
Usability of Tools -> Confidence in Wine Pairing- H8	0.001	0.001	0.041	0.017	0.987
Learner's Engagement -> Skill Development-H9	0.614	0.613	0.040	15.213	0.000
Learner's Engagement -> User Experience- H10	0.628	0.629	0.048	13.144	0.000
Usability of Tools -> User Experience-H11	0.209	0.207	0.041	5.068	0.000
Learner's Engagement -> Confidence in Wine Pairing- H12	0.645	0.644	0.035	18.207	0.000

4. DISCUSSION

The findings of this study demonstrate that the integration of traditional pedagogical methods and AI-driven learning tools forms a complementary instructional ecosystem for wine–food pairing education. The design-based development of the Multi-Cuisine Master Wine Tasting Harmonious Wheel established a structured, visually supported learning foundation, while the quantitative validation through PLS-SEM confirmed how learners interact with and benefit from these instructional components. Traditional teaching methods offer

conceptual grounding and clarity, enabling learners to understand sensory fundamentals before transitioning into AI-assisted environments. Meanwhile, LLM/CI tools enhance interaction, personalization, and accessibility, allowing learners to navigate complex pairing decisions with greater adaptability. This synergy reflects a shift from teacher-dependent learning to a hybrid model where technology supports, but does not replace, experiential education.

The supported hypotheses showed that learner engagement is the central driver of educational

success: it influences skill development, determines user experience quality, and is the strongest predictor of confidence in wine pairing. Although usability of tools improves skill progression, its lack of effect on confidence emphasizes that sensory subjects require more than digital access they need experiential reinforcement, palate exposure, and reflective interaction. Thus, confidence emerges from active participation rather than passive navigation. The results also highlight that challenges in AI tools, while demotivating, simultaneously enhance technical understanding and problem-solving capability, suggesting that discomfort with new technology can serve as a learning catalyst when supported by appropriate instruction. Overall, the study concludes that traditional instruction initiates learning, AI tools accelerate it, engagement solidifies it, and sensory experience validates it indicating that the combination of these dimensions offers the most effective pathway for developing competence, confidence, and user satisfaction in wine-food pairing education.

4.1 Theoretical Implications

The study contributes to academic theory by demonstrating that sensory-centric education can be effectively analyzed through a hybrid framework combining DBR, experiential learning theory, and AI-supported constructivism. It provides evidence that learning in sensory disciplines is not solely cognitive but embodied, emotional, and experiential, requiring theories that consider engagement as a mediating force. The findings reinforce that engagement is the central theoretical construct linking usability, skill development, and confidence positioning it as a core pathway variable for future research in hospitality training, wine studies, and food education.

In addition, the results extend PLS-SEM literature by validating that digital usability alone does not guarantee confidence outcomes, contrasting with assumptions often made in e-learning theory. The significance of negative and positive pathways particularly the unsupported path between Usability of Tools → Confidence introduces a theoretical argument that confidence in sensory learning requires contextual exposure, experiential reinforcement, and guided reflection. Thus, the study sets a theoretical basis for hybrid-learning models in the hospitality sector and offers a framework that future scholars can adapt across culinary arts, tasting science, oenology, and gastronomy pedagogy.

4.2 Managerial Implications

For educators, hospitality institutions, and wine training academies, the study provides a clear direction: implement blended instructional models where foundational teaching is supported by AI-

assisted exploration. Trainers should leverage AI tools to enhance accessibility, personalization, and independent practice while still facilitating structured tasting, feedback discussions, and reflective learning. The Harmonious Wheel can be used as a classroom aid, digital learning asset, and skill-mapping tool to guide tasting workshops, menu engineering sessions, and wine-food pairing demonstrations.

For hospitality managers, restaurateurs, and sommeliers, the findings suggest that investing in hybrid learning systems can reduce training time, improve staff consistency, and boost customer engagement. AI tools can be integrated into onboarding, menu planning, and service simulations, whereas experiential evaluation remains crucial for building service confidence and guest interaction quality. Managers should view technology not as a replacement for expertise but as a reinforcement mechanism that stabilizes operational knowledge particularly in wine programs, beverage sales strategies, and premium dining experiences.

4.3 Limitations and Future Research Directions

A key limitation of the study is that it focuses on participants from hospitality and wine-related backgrounds, which may limit generalizability to non-hospitality sectors or regions where wine education is less formalized. Since the research relied on self-reported data, emotional and psychological variables such as tasting anxiety, palate confidence, or sensory memory could not be fully captured. Additionally, sensory accuracy was not laboratory-tested, meaning tasting performance validation remains an open area for future work. The study also adopted a cross-sectional data approach; longitudinal impacts were not measured. Future research can progress by conducting region-specific comparative studies, integrating cross-cultural wine-food pairing differences and evaluating VR/AR tasting simulations with AI recommendation systems. Researchers may also examine how AI confidence-building applications, chat-based tasting tutors, or digital sommeliers affect learning retention over time. Exploring experimental tasting labs, real-time palate tracking, or neuro-gustatory analytics could further validate sensory outcomes. Finally, adapting the Harmonious Wheel to spirits, craft beverages, tea, coffee cupping, or global cuisines may expand its pedagogical relevance beyond wine.

5. CONCLUSION

The study concludes that integrating traditional educational methods with LLM/CI-based AI tools creates an effective hybrid learning ecosystem for wine and food pairing education. The Design-Based Research (DBR) driven development of the Multi-

Cuisine Master Wine Tasting Harmonious Wheel demonstrated that visual, theory-backed tools significantly improve conceptual clarity and pairing judgement. The PLS-SEM analysis further confirmed that learner engagement, usability, and experiential interaction are critical determinants of skill development, user experience, and confidence in pairing practices. The strongest predictors of learning success were Learner's Engagement → Confidence in Wine Pairing and Learner's Engagement → Skill Development, validating the importance of emotional, cognitive, and sensory involvement in hospitality training. The research also identified an important boundary: while AI tools improve

usability and access, they cannot independently build confidence without guided tasting, professional instruction, and sensory immersion. Traditional pedagogy provides foundational structure, AI enhances adaptability and personalization, and experiential learning confirms application. Therefore, the combination of these elements not any single approach is the most effective pathway for skill acquisition. This establishes the study's core conclusion: Wine education must move toward a hybrid model where technology supports, educators facilitate, and learners co-create knowledge through participation.

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