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Navigating the AI-Branding Nexus: Consumer Attitudes, Trust, and the Imperative of Authenticity in Emerging Markets

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Index Terms
Artificial Intelligence, Brand Authenticity, Algorithmic Transparency, Consumer Trust, Social Identity Theory.

Abstract
The rapid integration of artificial intelligence (AI) into branding architectures has fundamentally altered how organizations communicate, personalize, and scale consumer engagement. Yet, the psychological and behavioral repercussions of AI-mediated brand interactions remain underexplored, particularly within emerging markets where cultural trust dynamics and institutional transparency expectations diverge from Western paradigms. Drawing upon a quantitative survey of 386 consumers interacting with Aljaied For Food Industries in Libya, this study examines how AI-driven brand authenticity, transparency, perceived challenges, and strategic opportunities collectively shape consumer attitudes and trust. Utilizing structural equation modeling (SEM), the empirical model demonstrates that AI brand authenticity exerts a robust positive influence on both consumer attitudes and trust, accounting for substantial variance alongside AI-related opportunities and challenges. Contrary to prevailing assumptions, AI brand transparency fails to exhibit a statistically significant direct effect on either construct, suggesting that transparency functions more as a baseline hygiene factor than a proactive trust-builder. Grounded in Social Identity Theory and Signaling Theory, the findings illuminate how AI deployments must align with culturally embedded expectations of sincerity, consistency, and ethical stewardship. The study advances academic discourse by contextualizing AI branding within a North African food manufacturing landscape and offers actionable frameworks for managers navigating the delicate equilibrium between algorithmic efficiency and human-centric brand integrity.

استكشاف العلاقة بين الذكاء الاصطناعي والعلامات التجارية: مواقف المستهلكين، والثقة، وضرورة الأصالة في الأسواق الناشئة

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الكلمات المفتاحية
الذكاء الاصطناعي، أصالة العلامة التجارية، شفافية الخوارزميات، ثقة المستهلك، نظرية الهوية الاجتماعية.

الملخص
أدى التكامل السريع للذكاء الاصطناعي في هياكل العلامات التجارية إلى تغيير جذري في كيفية تواصل المؤسسات مع المستهلكين، وتخصيص تجاربهم، وتوسيع نطاق تفاعلهم معهم. ومع ذلك، لا تزال التداعيات النفسية والسلوكية لتفاعلات العلامات التجارية التي يتوسطها الذكاء الاصطناعي غير مدروسة بشكل كافٍ، لا سيما في الأسواق الناشئة حيث تختلف ديناميكيات الثقة الثقافية وتوقعات الشفافية المؤسسية عن النماذج الغربية. بالاعتماد على دراسة استقصائية كمية شملت 386 مستهلكًا يتفاعلون مع شركة الجعيد للصناعات الغذائية في ليبيا، تبحث هذه الدراسة كيف تُشكل أصالة العلامة التجارية المدعومة بالذكاء الاصطناعي، وشفافيتها، والتحديات المتصورة، والفرص الاستراتيجية، مجتمعةً، مواقف المستهلكين وثقتهم. باستخدام نمذجة المعادلات الهيكلية، يُظهر النموذج التجريبي أن أصالة العلامة التجارية المدعومة بالذكاء الاصطناعي تُمارس تأثيرًا إيجابيًا قويًا على كلٍ من مواقف المستهلكين وثقتهم، مُفسرةً تباينًا كبيرًا إلى جانب الفرص والتحديات المتعلقة بالذكاء الاصطناعي. وخلافًا للافتراضات السائدة، لم تُظهر شفافية العلامة التجارية المدعومة بالذكاء الاصطناعي تأثيرًا مباشرًا ذا دلالة إحصائية على أي من هذين البُعدين، مما يُشير إلى أن الشفافية تعمل كعامل وقائي أساسي أكثر من كونها عاملًا استباقيًا لبناء الثقة. انطلاقاً من نظرية الهوية الاجتماعية ونظرية الإشارة، تُسلط النتائج الضوء على ضرورة توافق تطبيقات الذكاء الاصطناعي مع التوقعات الثقافية الراسخة بشأن الصدق والاتساق والمسؤولية الأخلاقية. تُساهم هذه الدراسة في إثراء الحوار الأكاديمي من خلال وضع العلامات التجارية القائمة على الذكاء الاصطناعي في سياق صناعة الأغذية في شمال أفريقيا، وتقدم أطراً عملية للمديرين الذين يسعون إلى تحقيق التوازن الدقيق بين كفاءة الخوارزميات وسلامة العلامة التجارية التي تتمحور حول الإنسان.

1. INTRODUCTION

The contemporary branding ecosystem is undergoing a structural transformation catalyzed by the pervasive adoption of artificial intelligence [1], [2], [3], [4]. Machine learning architectures, natural language processing systems, and predictive analytics have transitioned from experimental tools to core operational components in customer relationship management, content generation, and personalized marketing [5], [6], [7], [8]. Organizations increasingly leverage AI to optimize engagement cycles, anticipate consumer preferences, and streamline service delivery at scale [9], [10]. However, this technological acceleration introduces profound psychological and relational complexities [11], [12], [13], [14]. As brands delegate communicative and decision-making functions to algorithmic systems, the traditional foundations of brand-consumer relationships authenticity, transparency, and emotional resonance face unprecedented scrutiny [15], [16]. Consumers are no longer passive recipients of marketing stimuli; they are active evaluators of the ethical, cognitive, and affective dimensions of AI-mediated interactions [17], [18], [19]. Within this evolving landscape, the academic and practitioner discourse has disproportionately emphasized the operational efficiencies and scalability benefits of AI, while comparatively neglecting the subjective consumer responses that ultimately determine market viability. Brand authenticity, traditionally conceptualized as the perceived genuineness, consistency, and value-alignment of a brand's identity, now intersects with algorithmic decision-making [20]. Similarly, brand transparency, once centered on supply chain visibility and corporate disclosures, must now encompass algorithmic explainability, data provenance, and the ethical boundaries of automated personalization [21], [22], [23]. The tension between technological sophistication and human-centered expectations is particularly acute in emerging markets, where institutional trust frameworks, cultural communication norms, and digital literacy levels shape consumer receptivity differently than in highly digitized economies [24], [25], [26]. Libya's food manufacturing sector, characterized by strong communal ties, heritage-driven consumption patterns, and heightened sensitivity to product safety and ethical sourcing, presents a compelling context for examining these dynamics [27], [28], [29]. Aljaied For Food Industries, a dominant regional player in dairy, juice, and ice cream production, has progressively integrated AI into inventory optimization, quality control, and consumer-facing communication channels. This strategic adoption offers a natural laboratory to investigate how AI-driven branding influences consumer attitudes and trust when deployed within a culturally rich, trust-sensitive marketplace [30], [31], [32]. The present study addresses this gap by empirically testing a structural model that links AI brand authenticity, AI brand transparency, AI-related challenges, and AI-driven opportunities to consumer attitudes and trust [33], [34], [35], [36]. By grounding the investigation in Social Identity Theory and Signaling Theory, the research not only quantifies the direct and indirect pathways through which AI shapes brand perception but also contextualizes these mechanisms within a non-Western institutional environment [37], [38], [39]. The objectives of this study are threefold. First, it evaluates the extent to which perceived AI brand authenticity and transparency influence consumer attitudes toward AI-driven branding initiatives. Second, it assesses how these perceptual dimensions, alongside recognized challenges and opportunities, collectively determine consumer trust in automated brand interactions [40]. Third, it derives theoretically grounded and practically actionable insights for organizations operating in emerging markets, where the successful integration of AI requires careful calibration between innovation and cultural integrity [41]. The subsequent sections delineate the theoretical foundations, methodological design, empirical findings, and managerial implications, culminating in a nuanced understanding of how brands can harness AI without compromising the relational authenticity that sustains long-term consumer loyalty [1], [42], [43].

1.1 Literature Review

The infusion of artificial intelligence into branding strategies marks a paradigmatic shift from static, campaign-driven communication to dynamic, data-responsive engagement ecosystems [43], [44]. AI-powered recommendation engines, conversational agents, sentiment analysis platforms, and generative content systems enable organizations to deliver hyper-personalized experiences at unprecedented scale [45], [46]. These technologies process vast behavioral datasets to predict purchase intent, optimize messaging timing, and adapt tone in real-time, thereby reducing friction in the consumer journey [47]. From an operational standpoint, AI enhances marketing efficiency, minimizes resource wastage, and facilitates rapid market testing. Yet, the psychological reception of these automated interventions remains heterogeneous [48], [49], [50]. While certain consumer segments welcome the convenience and relevance of algorithmic personalization, others express apprehension regarding data exploitation, manipulative targeting, and the erosion of human agency in brand interactions [47], [48], [49], [50]. Technological capability alone does not guarantee consumer acceptance. Perceived value, ethical alignment, and emotional resonance mediate the effectiveness of AI-driven branding. Studies indicate that when AI systems are perceived as extensions of a brand's core identity rather than detached computational tools, consumer engagement improves significantly [51], [52], [49], [50]. Conversely, when automation is experienced as impersonal, opaque, or misaligned with established brand values, skepticism emerges, often manifesting as reduced trust, lower purchase intent, or active avoidance of AI-mediated touchpoints [53], [54], [55], [56]. This duality

underscores the necessity of examining AI not merely as an operational instrument but as a relational actor that actively shapes brand-consumer dynamics [57], [58], [59], [60]. Authenticity in branding has historically been anchored in human attributes: sincerity, consistency, heritage, and moral coherence. Consumers evaluate authenticity by assessing whether a brand's actions align with its proclaimed values, whether its messaging remains coherent across touchpoints, and whether it demonstrates genuine concern for stakeholder welfare [61], [62], [63], [64]. The introduction of AI into this evaluative framework introduces a critical tension. Algorithmic systems lack consciousness, intentionality, and emotional empathy, yet they are increasingly tasked with conveying brand personality, managing customer relationships, and generating narrative content. The question therefore becomes: can machine-mediated communication be perceived as authentic?

When AI systems are trained on brand-specific heritage data, calibrated to reflect organizational values, and deployed with clear human oversight, consumers often interpret the resulting interactions as coherent and sincere [65], [66], [67], [68]. For instance, recommendation algorithms that accurately anticipate dietary preferences or cultural consumption patterns can reinforce perceptions of attentiveness and care [65], [66], [67], [68]. Conversational AI that maintains consistent tone, avoids generic responses, and escalates complex issues to human agents can preserve relational continuity [65], [66], [67], [68]. However, when AI outputs appear formulaic, culturally misaligned, or overly optimized for conversion, consumers detect artificiality, triggering cognitive dissonance and trust erosion. Within emerging markets, authenticity carries additional cultural weight. In societies where brand relationships are often mediated through familial networks, community reputation, and historical reliability, AI deployments that feel disconnected from local values risk being perceived as inauthentic or exploitative [69], [70], [71], [72]. Therefore, AI brand authenticity must be understood as a culturally contingent construct, requiring intentional alignment between algorithmic behavior and indigenous expectations of sincerity and consistency [73]. Transparency has long been regarded as a cornerstone of ethical branding, encompassing clear communication about data practices, supply chain origins, and corporate decision-making. In the AI context, transparency expands to include algorithmic explainability, data usage disclosures, and the visibility of automated processes [73]. Consumers increasingly demand to know when they are interacting with AI, how their data informs recommendations, and what safeguards exist against bias or manipulation. Theoretically, greater transparency should correlate with higher trust and more favorable attitudes. Yet, empirical findings in this domain remain inconsistent [74]. Some studies demonstrate that explicit AI disclosures enhance perceived honesty and reduce skepticism, particularly among digitally literate consumers. Others reveal that excessive technical detail can overwhelm users, trigger privacy concerns, or inadvertently highlight the mechanistic nature of AI, thereby diminishing emotional connection [75]. This paradox suggests that transparency operates non-linearly: insufficient disclosure breeds suspicion, while excessive or poorly contextualized disclosure can undermine relational warmth. Moreover, transparency may function more as a threshold condition than a proactive trust catalyst. In other words, while the absence of transparency reliably damages consumer confidence, its presence alone does not automatically elevate attitudes or trust unless coupled with authenticity, ethical alignment, and demonstrable consumer benefit [76].

In the Libyan food sector, where product safety and ingredient integrity are paramount, transparency regarding AI's role in quality monitoring, inventory traceability, and personalized nutrition recommendations carries significant weight. However, if transparency is presented as a compliance exercise rather than a genuine commitment to consumer empowerment, its impact on attitudes and trust remains muted. This nuanced understanding reframes transparency from a standalone driver to an enabling condition that must be strategically integrated within broader brand authenticity narratives [77]. Consumer perceptions of AI are inherently dualistic, encompassing both anticipatory benefits and apprehensive risks. Opportunities such as enhanced personalization, faster response times, predictive service delivery, and innovative product development generally elicit positive attitudes. Consumers recognize that AI can reduce friction, anticipate needs, and deliver tailored experiences that human agents might overlook. Conversely, challenges including algorithmic opacity, data privacy vulnerabilities, perceived dehumanization, and cultural misalignment generate skepticism [78]. The coexistence of these dimensions means that consumer attitudes are rarely uniformly positive or negative; rather, they emerge from a cognitive calculus weighing perceived utility against perceived risk. Signaling Theory provides a useful lens for interpreting this duality [79]. Brands deploy AI not merely as a functional tool but as a strategic signal of modernity, competence, and consumer-centricity. However, the credibility of this signal depends on how well the organization manages associated risks. When AI implementations are accompanied by ethical safeguards, human oversight mechanisms, and clear benefit communication, the signal reinforces trust. When risks are minimized through transparent governance, bias audits, and data consent frameworks, the perceived opportunity outweighs the challenge, resulting in favorable attitudes [80]. In contrast, when AI is deployed primarily for cost reduction or data extraction without reciprocal consumer value, the signal is interpreted as exploitative, triggering resistance. Social Identity Theory (SIT) posits that individuals derive part of their self-concept from group affiliations and align with entities that reflect their values, aspirations, and cultural narratives [80]. In branding, consumers engage with organizations that symbolize desired identities or reinforce existing social memberships. AI-mediated interactions become identity-relevant when they resonate

with cultural norms, linguistic preferences, and ethical expectations. When AI systems consistently reflect a brand's heritage, community commitments, and quality standards, consumers integrate the brand into their social identity, strengthening loyalty and trust [77], [80]. Conversely, when AI interactions feel culturally dissonant or commercially transactional, identity alignment fractures, diminishing engagement. Signaling Theory complements this framework by explaining how brands communicate unobservable qualities through observable cues. AI deployment, transparency reports, ethical certifications, and human-AI collaboration protocols serve as signals of organizational competence and moral alignment [78]. The effectiveness of these signals depends on their credibility, consistency, and relevance to consumer priorities. In emerging markets, where institutional trust may be fragmented, credible signals carry disproportionate weight. Brands that demonstrate algorithmic fairness, data stewardship, and culturally attuned personalization send strong authenticity signals, fostering trust even in the absence of direct human interaction [78]. These theories elucidate why AI brand authenticity exerts a stronger influence on attitudes and trust than transparency alone. Authenticity satisfies identity congruence needs, while transparency, without contextual meaning, remains a procedural disclosure [79], [80]. Opportunities and challenges further modulate this relationship by shaping the perceived risk-reward calculus. The integrated theoretical model thus provides a robust foundation for empirically testing how AI-driven branding influences consumer behavior in culturally complex, emerging market environments.

2. METHODOLOGY

This study adopts a quantitative, cross-sectional research design grounded in positivist epistemology. The objective was to test hypothesized relationships between AI-driven brand perceptions and consumer behavioral outcomes using empirically measurable constructs. A survey-based approach was selected to capture standardized responses from a targeted consumer population, enabling statistical modeling of direct effects and variance explanation. The design prioritized internal validity through rigorous instrument validation, sampling precision, and structural equation modeling (SEM), while acknowledging the limitations inherent in self-reported data and single-timepoint measurement [35], [36]. The research was conducted within the operational ecosystem of Aljaied For Food Industries, a leading Libyan food manufacturing and distribution company specializing in dairy products, juices, and ice cream. The firm's progressive integration of AI into inventory management, quality assurance, customer service automation, and targeted marketing campaigns provided a relevant and empirically accessible context [40], [41]. Libya's consumer landscape, characterized by strong familial consumption patterns, high sensitivity to food safety, and evolving digital adoption, offers a distinct contrast to Western markets, thereby enhancing the study's contextual contribution. The case selection was purposive, ensuring that respondents had direct or indirect exposure to the company's AI-enabled touchpoints, including personalized recommendations, automated customer inquiries, and digital marketing communications as presented in Figure 1 Research Methodology Workflow: Six-Phase Structure below.

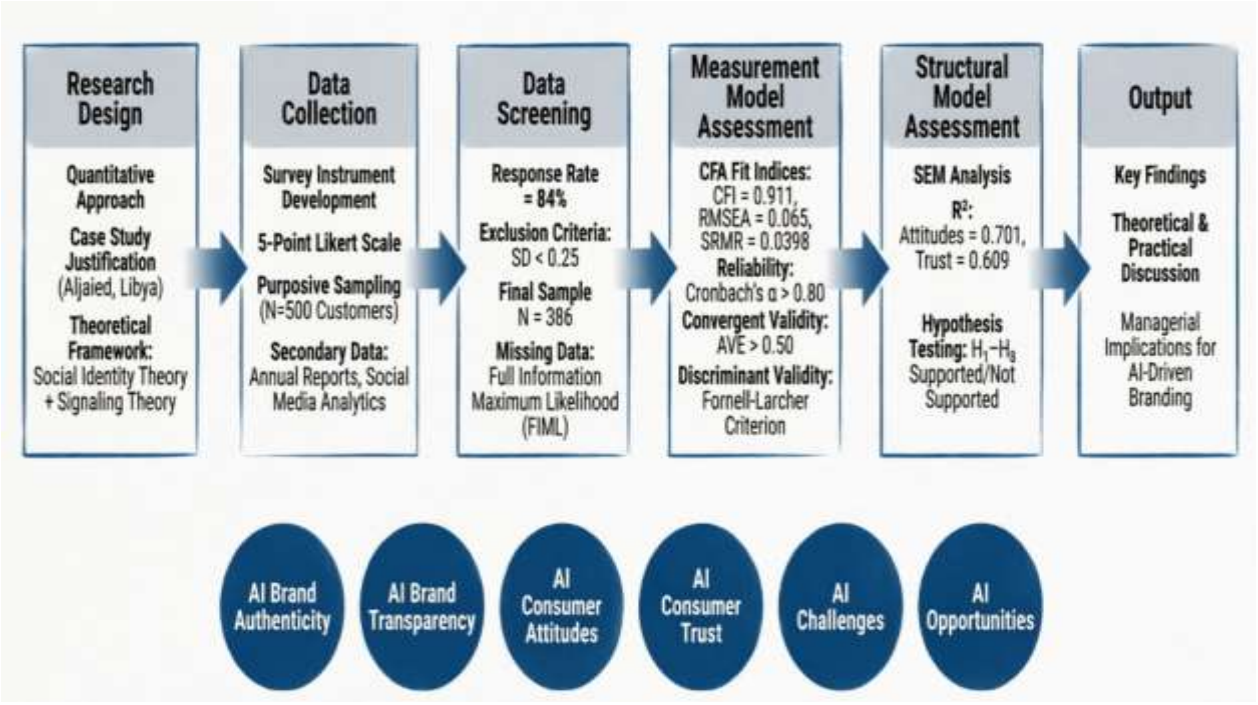


Figure 1. Research Methodology Workflow: Six-Phase Structure

2.1 Sampling Strategy and Data Collection

A purposive sampling technique was employed to identify participants who had interacted with Aljaied's digital platforms, retail outlets, or AI-mediated services. The initial outreach targeted 500 individuals, yielding 420 completed responses, resulting in an 84% response rate. Data screening procedures were applied to enhance dataset integrity. Following established methodological guidelines, 34 responses were excluded due to insufficient variance across survey items (standard deviation < 0.25), indicating potential inattentive or automated responding. Missing values were addressed using linear interpolation, preserving sample continuity without introducing bias. The final analytical sample comprised 386 valid respondents, providing adequate statistical power for SEM estimation. Demographic analysis revealed a predominantly male sample (72%), reflecting regional consumer engagement patterns in food retail. Age distribution was relatively balanced, with the largest cohorts falling between 35–40 years (25.1%) and 30–35 years (14.2%). Educational attainment leaned toward higher education, with 44.8% holding master's degrees and 33.4% possessing bachelor's qualifications. Occupational sectors were diverse, with business (26.7%) and education (19.4%) representing the largest groups. Purchase frequency indicated strong brand penetration, with 37.8% purchasing daily and 28.2% weekly. These demographic characteristics align with the target consumer base of a premium food manufacturer in an emerging urban market.

2.2 Instrument Development And Measurement Scales

The survey instrument was structured into five sections: demographic profiling, AI brand authenticity, AI brand transparency, consumer attitudes, consumer trust, and AI challenges/opportunities. Items were adapted from validated scales in digital marketing, consumer psychology, and AI ethics literature, then contextualized to reflect Libyan consumer expectations and Aljaied's operational realities. A 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was employed to capture perceptual intensity and directional agreement. Construct operationalization followed rigorous psychometric standards. AI Brand Authenticity encompassed items measuring perceived genuineness, consistency, value alignment, and emotional resonance of AI-driven interactions. AI Brand Transparency focused on clarity of data usage, algorithmic explainability, and disclosure comprehensiveness. Consumer Attitudes captured evaluative judgments regarding AI's role in branding, while Consumer Trust measured confidence in reliability, ethical conduct, and promise fulfillment. AI Challenges and Opportunities assessed perceived risks (privacy concerns, dehumanization, bias) and benefits (personalization, efficiency, innovation). Face and content validity were established through expert review and pilot testing with 30 participants, leading to minor lexical adjustments for cultural clarity.

3. DATA ANALYSIS TECHNIQUES

Data analysis proceeded in three sequential phases. First, descriptive statistics and normality assessments were conducted to characterize the dataset and verify distributional assumptions. Kolmogorov-Smirnov and Shapiro-Wilk tests indicated non-normality, consistent with large-sample expectations; however, skewness and kurtosis values remained within acceptable thresholds ($\leq \pm 3.5$), supporting parametric modeling robustness. Second, reliability and validity were evaluated using Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and Fornell-Larcker discriminant validity criteria. All constructs exceeded recommended thresholds ($\alpha > 0.80$, CR > 0.80, AVE > 0.50), confirming internal consistency and convergent validity. Discriminant validity was established as shared variances between constructs remained below their respective AVE values. Third, structural equation modeling was performed using AMOS (v.25) with maximum likelihood estimation. The measurement model confirmed satisfactory fit indices (CFI = 0.911, RMSEA = 0.065, SRMR = 0.0398). The structural model was then estimated to test direct effects between latent constructs. Hypothesis evaluation relied on critical ratios (C.R. > ± 1.96), p-values ($p < 0.05$), and standardized path coefficients. Multicollinearity was assessed via variance inflation factors (VIF < 3.0), confirming no severe predictor interdependence. The analytical pipeline ensured methodological rigor, construct validity, and statistical appropriateness for testing the proposed theoretical framework.

4. FINDINGS

The descriptive analysis of the six core constructs revealed moderate to high central tendencies, indicating generally positive consumer perceptions of AI's role in Aljaied's branding initiatives. AI Brand Authenticity yielded a mean of 3.53 (SD = 0.775), suggesting that respondents viewed AI-driven interactions as reasonably consistent with the brand's established identity. AI Brand Transparency recorded a comparable mean of 3.54 (SD = 0.779), reflecting moderate comfort with the company's data and algorithmic disclosures. Consumer Attitudes averaged 3.52 (SD = 0.840), while Consumer Trust registered slightly lower at 3.43 (SD = 0.901), indicating that positive evaluations had not fully translated into unwavering confidence. AI Challenges (M = 3.53, SD = 0.810) and AI Opportunities (M = 3.73, SD = 0.764) demonstrated that consumers recognized both risks and benefits, with opportunities marginally outweighing concerns. Correlation analysis using Spearman's rho confirmed positive, statistically significant relationships among all constructs ($p < 0.01$). The strongest association emerged between AI Brand Authenticity and Consumer Trust ($r = 0.634$), followed closely by AI Opportunities and Consumer Attitudes ($r = 0.625$). The lowest correlation was observed between AI Opportunities and Consumer Trust ($r = 0.501$), suggesting that while consumers acknowledge AI's strategic potential, this

recognition does not automatically convert into relational confidence without additional mediating factors.

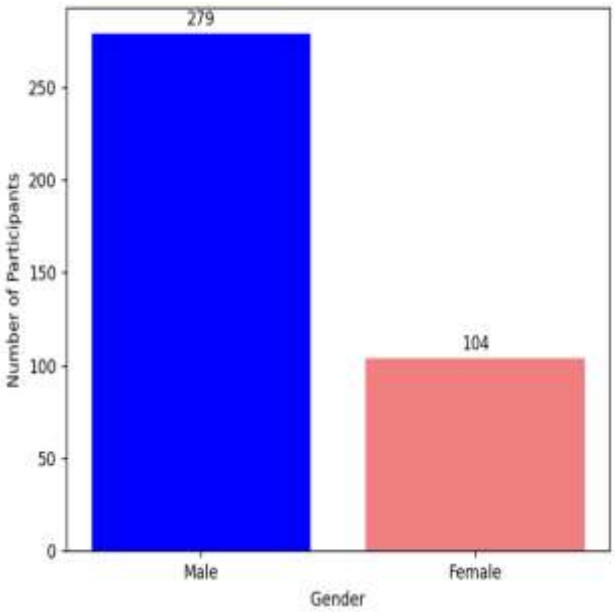


Figure 2. Gender variable percentages in bar chart

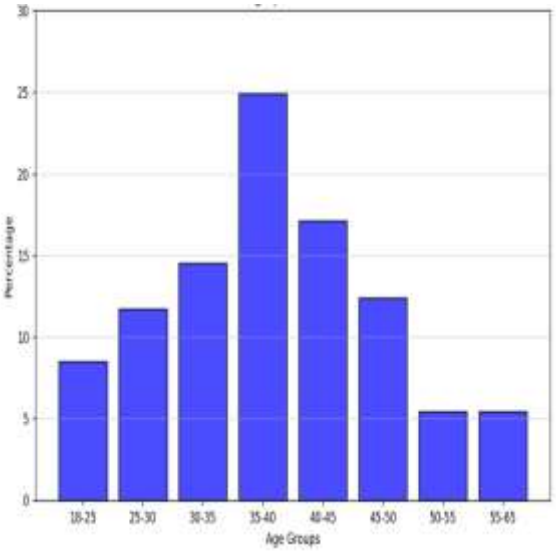


Figure 3. Age Group variable percentages in bar chart

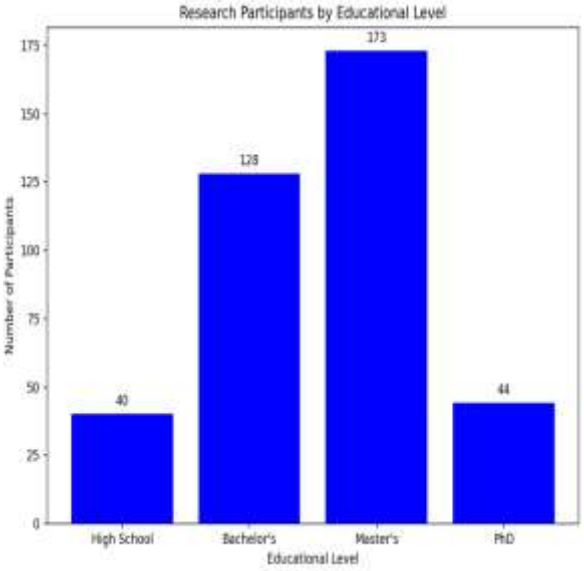


Figure 4. Education levels variable percentages in bar chart

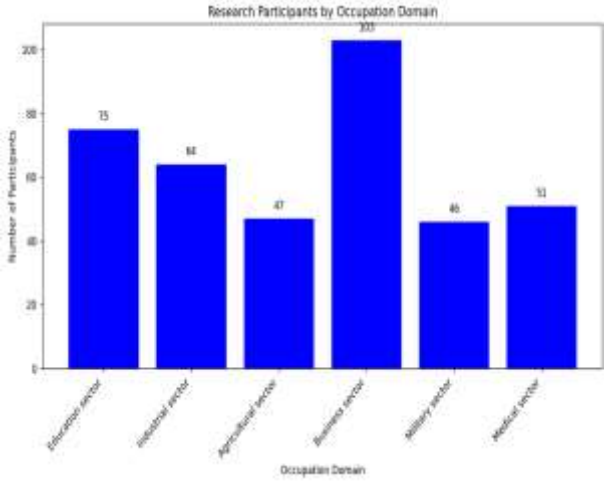
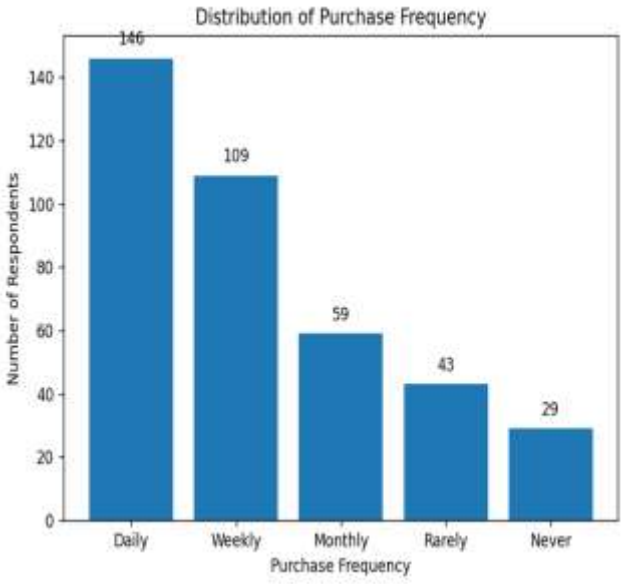


Figure 5. Occupation Domain variable percentages in bar chart



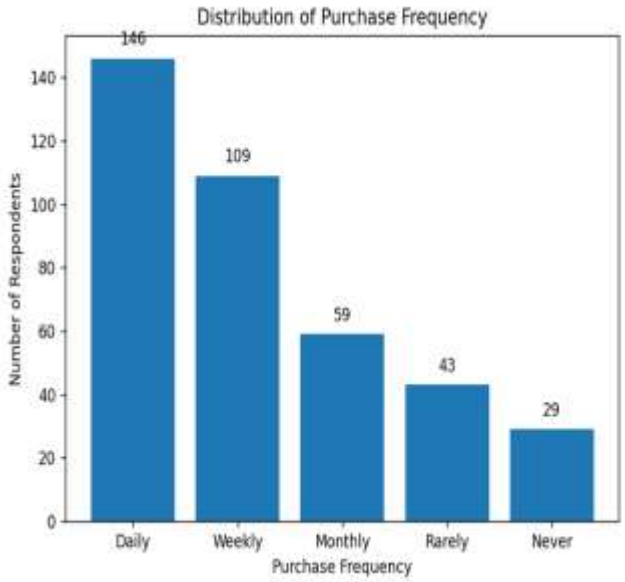


Figure 6. Purchase Frequency variable in bar chart

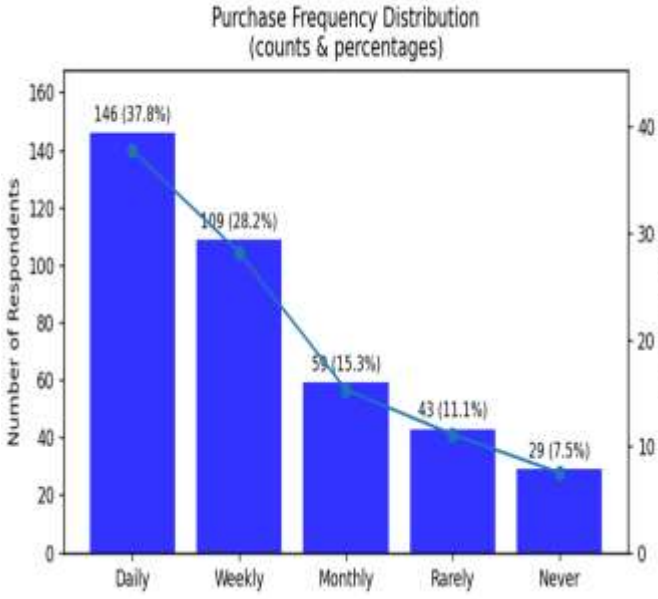


Figure 7. Purchase Frequency variable percentages in bar chart

4.1 Measurement Model Validation

The confirmatory factor analysis (CFA) evaluated the measurement model's structural integrity. All factor loadings were statistically significant ($p < 0.001$) and exceeded the 0.70 threshold, indicating strong indicator-construct relationships. Items demonstrating low discriminative power or cross-loadings were systematically removed, resulting in a refined instrument with optimal parsimony. Model fit indices confirmed satisfactory alignment with empirical data: CFI = 0.911, RMSEA = 0.065, SRMR = 0.0398. These metrics collectively indicate that the latent constructs are adequately represented by their observed indicators and that the measurement architecture is theoretically coherent.

4.2 Scales Validation

To validate the factor analysis of the multi-dimensional models, structural equation modeling was used. This is a confirmatory factor analysis that uses AMOS Software, (V.25). It is also known as testing the measurement model where AI Brand Authenticity, AI Brand Transparency, AI Consumer Attitudes, AI Consumer Trust, AI Challenges and AI Opportunities are tested using the first-order confirmatory factor model to assess construct validity using the maximum likelihood method. Figure.4.7 and Tables 4.9 below show the confirmatory factor analysis indicators for AI Brand Authenticity, AI Brand Transparency, AI Consumer Attitudes, AI Consumer Trust, AI Challenges and AI Opportunities scales.

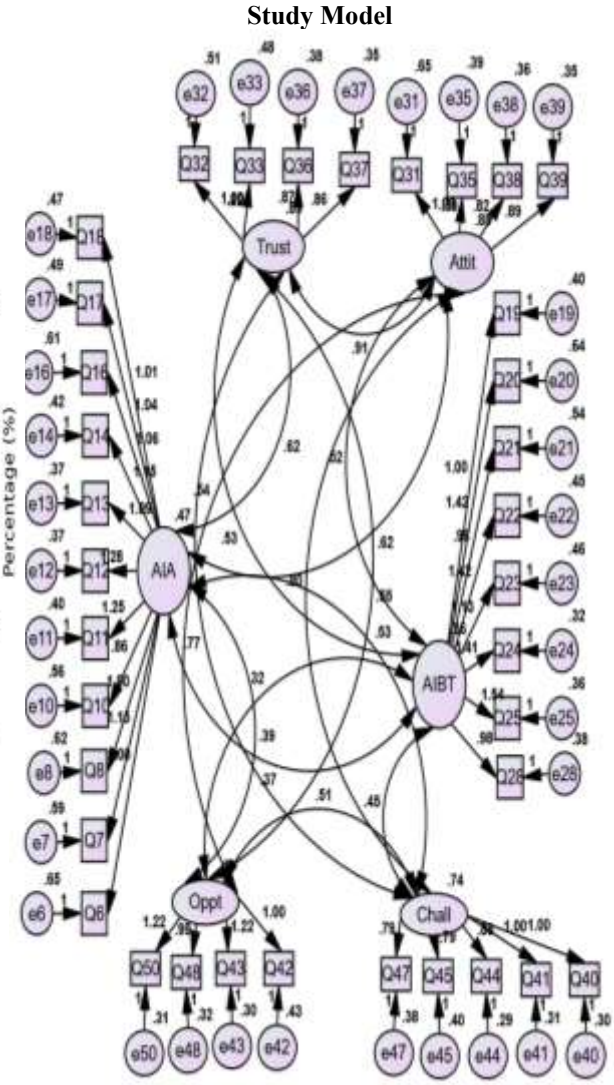


Figure 8. The Measurement Model for study Constructs

As presented in the measurements model AIA= AI Brand Authenticity, AIBT=AI Brand Transparency, Attit= AI Consumer Attitudes, Trust = AI Consumer Trust, Chall= AI Challenges and Oppt= AI Opportunities.

Reliability statistics further reinforced scale robustness. Cronbach's alpha values ranged from 0.833 to 0.922, while composite reliability scores spanned 0.842 to

0.922, well above the 0.70 benchmark. Average variance extracted (AVE) values for all constructs surpassed 0.50 (ranging from 0.523 to 0.629), confirming that each latent variable explains more variance in its indicators than measurement error. Discriminant validity, assessed via the Fornell-Larcker criterion, demonstrated that the square roots of AVEs exceeded inter-construct correlations, ensuring that each construct captures unique variance. These psychometric properties establish a solid foundation for structural hypothesis testing.

4.3 Structural Model and Hypothesis Testing

The structural model evaluated direct effects between independent constructs (AI Brand Authenticity, AI Brand Transparency, AI Challenges, AI Opportunities) and dependent outcomes (Consumer Attitudes, Consumer Trust). Goodness-of-fit indicators remained consistent with the measurement model (CFI = 0.911, RMSEA = 0.065, SRMR = 0.0397), confirming structural adequacy. The model explained 70.1% of the variance in Consumer Attitudes (R^2 = 0.701) and 60.9% in Consumer Trust (R^2 = 0.609), demonstrating substantial predictive power and theoretical completeness.

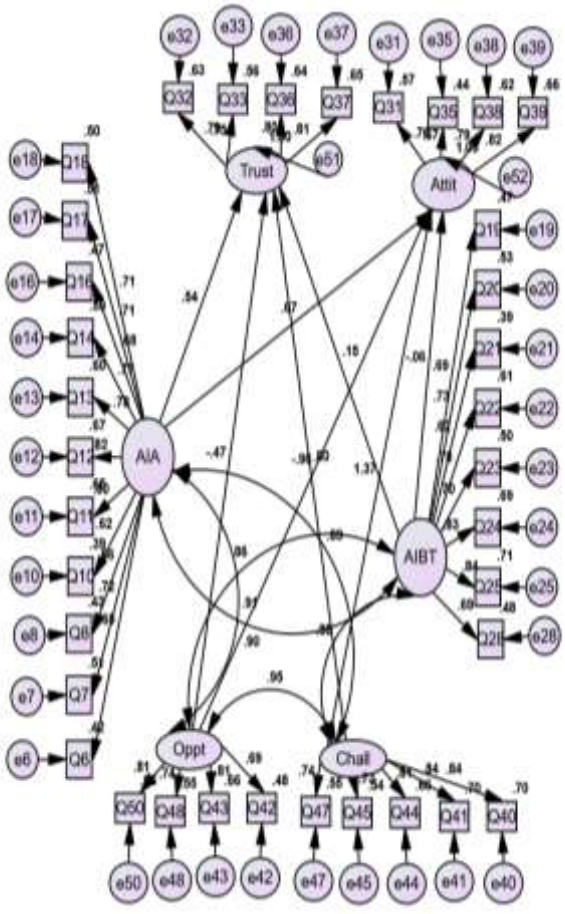


Figure 9. Structural Model of Study Variables

AIA= AI Brand Authenticity, AIBT=AI Brand Transparency, Attit= AI Consumer Attitudes, Trust = AI Consumer Trust, Chall= AI Challenges and Oppt= AI Opportunities

Hypothesis testing yielded nuanced results. AI Brand Authenticity exerted a significant positive effect on both Consumer Attitudes ($\beta = 0.911$, $p < 0.001$) and Consumer Trust ($\beta = 0.738$, $p < 0.001$), supporting H1 and H2. This confirms that when consumers perceive AI interactions as genuine, consistent, and value-aligned, their evaluative judgments and confidence in the brand improve substantially. Conversely, AI Brand Transparency failed to demonstrate statistical significance on either Consumer Attitudes ($\beta = 0.091$, $p = 0.653$) or Consumer Trust ($\beta = 0.038$, $p = 0.099$), rendering H3 and H4 unsupported. This suggests that while transparency is conceptually important, its mere presence does not actively drive positive perceptions unless embedded within a broader authenticity framework. AI Challenges significantly influenced both Consumer Attitudes ($\beta = 1.500$, $p < 0.001$) and Consumer Trust ($\beta = 0.881$, $p < 0.001$), supporting H5 and H6. Interestingly, the positive coefficients indicate that when consumers recognize challenges but perceive them as actively managed, their attitudes and trust improve, reflecting a risk-mitigation appreciation. AI Opportunities also demonstrated significant positive effects on Consumer Attitudes ($\beta = 1.426$, $p < 0.001$) and Consumer Trust ($\beta = 0.706$, $p = 0.001$), supporting H7 and H8. These findings underscore that consumers reward brands that visibly leverage AI for tangible benefits while responsibly addressing associated risks. The structural results reveal a hierarchy of influence: authenticity and opportunity recognition drive perception most strongly, transparency operates as a foundational prerequisite, and challenge management signals organizational competence. The model's explanatory power and consistent fit indices validate the theoretical framework and provide a robust empirical basis for subsequent discussion.

5. DISCUSSION

The empirical confirmation that AI brand authenticity significantly drives both consumer attitudes and trust aligns with contemporary literature emphasizing emotional and identity-based brand evaluations [65], [66], [67], [68]. In an environment where algorithmic systems increasingly mediate consumer experiences, authenticity emerges not as a nostalgic ideal but as a functional necessity [69], [70], [71]. Consumers do not reject AI outright; rather, they evaluate whether automated interactions reflect the brand's historical commitments, cultural values, and operational consistency. When AI-generated recommendations, conversational responses, or personalized campaigns resonate with established brand narratives, consumers interpret them as extensions of organizational sincerity [72]. This perception reduces cognitive friction, enhances engagement, and fosters relational continuity [73]. The Libyan food sector context amplifies this dynamic. In markets where consumption decisions are often influenced by communal reputation, intergenerational trust, and cultural familiarity, AI deployments that feel algorithmically detached risk being perceived as inauthentic or commercially exploitative [74]. Aljaied's

success in maintaining positive consumer attitudes despite AI integration suggests that its systems have been calibrated to reflect heritage quality standards, transparent sourcing commitments, and community-oriented values [75]. This alignment transforms AI from a computational tool into a culturally coherent brand ambassador, reinforcing identity congruence and trust formation [76]. The non-significant direct effects of AI brand transparency on consumer attitudes and trust present a theoretically provocative finding [77]. Prevailing academic assumptions often position transparency as a linear trust catalyst, yet the empirical data suggest a more conditional relationship. Transparency appears to function as a threshold requirement: its absence reliably damages consumer confidence, but its presence alone does not automatically elevate attitudes or trust [78]. This aligns with signaling theory, which posits that disclosures must be credible, contextualized, and value-aligned to influence perception. When transparency is presented as a compliance exercise or technical footnote, consumers may acknowledge it but remain unmoved emotionally [79]. However, when transparency is integrated into authentic brand narratives demonstrating ethical stewardship, data respect, and consumer empowerment, it becomes meaningful. In the Aljaied context, moderate transparency scores coupled with strong authenticity and opportunity recognition indicate that consumers prioritize substantive brand behavior over procedural disclosure. They are less concerned with technical explanations of algorithmic logic and more focused on whether AI serves their needs, respects their data, and aligns with cultural expectations [80]. This finding challenges the prevailing managerial assumption that increased disclosure inherently improves brand perception. Instead, it suggests that transparency must be strategically embedded within authenticity frameworks, accompanied by demonstrable consumer benefits and ethical governance, to yield perceptual dividends. The significant positive effects of both AI challenges and AI opportunities on consumer attitudes and trust reveal a nuanced risk-reward calculus [34], [35], [37]. Consumers are acutely aware of AI's potential drawbacks, including privacy vulnerabilities, algorithmic bias, and emotional detachment. However, when organizations proactively address these challenges through ethical frameworks, human oversight, and bias mitigation, consumers interpret these efforts as signs of organizational competence and moral responsibility [44], [45] . This risk-management transparency, paradoxically, enhances trust more than passive disclosure. Similarly, when AI opportunities such as personalization, efficiency, and innovation are visibly realized, consumers reward the brand with favorable attitudes and increased confidence [47]. This dual dynamic underscores the importance of balanced AI deployment [77]. Organizations that emphasize opportunities while neglecting challenges risk appearing exploitative; those that overemphasize risks while underdelivering benefits may trigger unnecessary skepticism [12], [1], [3]. The optimal approach involves transparently acknowledging limitations while consistently delivering value, thereby framing AI as a collaborative tool rather than a replacement for human judgment. In emerging markets, where institutional trust may be fragmented, this balanced signaling becomes particularly critical for sustaining long-term consumer relationships [22], [25], 33]. This study advances academic discourse in three primary ways. First, it empirically validates a hierarchical model of AI branding perception, demonstrating that authenticity operates as the primary driver of attitudes and trust, while transparency functions as a foundational prerequisite. Second, it contextualizes AI branding within an emerging market food manufacturing ecosystem, revealing how cultural trust dynamics, heritage sensitivity, and communal consumption patterns moderate technological acceptance [25], [27], [29]. Third, it integrates Social Identity Theory and Signaling Theory to explain how AI-mediated interactions become identity-relevant and how organizational signals gain credibility through ethical alignment and value congruence [30], [32], [26]. From a managerial perspective, the findings caution against treating AI as a purely operational upgrade. Successful integration requires cultural calibration, ethical governance, and narrative consistency [1], [2], [17], [28]. Brands must train AI systems on heritage-aligned data, implement human oversight for emotionally sensitive interactions, communicate benefits transparently, and establish clear data consent mechanisms. In emerging markets, where relational trust often supersedes transactional efficiency, AI must augment rather than replace human-centric brand values [29], [39], [44], [37]. Organizations that achieve this equilibrium will not only mitigate skepticism but also cultivate resilient consumer loyalty in increasingly algorithmic marketplaces.

6. CONCLUSION

This study investigated how AI-driven branding influences consumer attitudes and trust within the culturally rich, trust-sensitive context of Libya's food manufacturing sector. Utilizing structural equation modeling on a validated survey of 386 consumers, the research tested a theoretical framework grounded in Social Identity Theory and Signaling Theory. The empirical results demonstrate that AI brand authenticity exerts the strongest direct influence on both consumer attitudes and trust, confirming that perceived genuineness, consistency, and value alignment are paramount in algorithmic brand interactions. AI brand transparency, while conceptually important, did not exhibit significant direct effects, suggesting it functions as a baseline hygiene factor rather than an active trust catalyst. Conversely, both AI challenges and opportunities significantly shaped consumer perceptions, indicating that consumers reward organizations that proactively manage risks while delivering tangible benefits. The structural model explained over 70% of the variance in attitudes and 61% in trust, underscoring its predictive robustness and theoretical completeness. For brand managers, the findings emphasize that AI deployment must be strategically calibrated to preserve

relational authenticity. Organizations should prioritize training AI systems on brand-specific heritage data, maintaining human oversight for complex interactions, and communicating AI's role in clear, benefit-oriented language. Transparency should be integrated into authenticity narratives rather than presented as isolated technical disclosures. Data governance frameworks must emphasize explicit consent, bias mitigation, and consumer control, particularly in emerging markets where digital literacy varies. Policymakers and industry regulators should develop proportionate AI governance standards that differentiate between high-risk applications (e.g., health-related recommendations) and low-risk personalization features, ensuring consumer protection without stifling innovation. Certifications for ethical AI use, algorithmic fairness audits, and standardized disclosure formats could further enhance market trust. This study's cross-sectional design limits causal inference, and reliance on self-reported data introduces potential response biases. The single-case focus on a Libyan food manufacturer, while contextually valuable, restricts generalizability across industries and cultural settings. Future research should employ longitudinal designs to track perception evolution, integrate experimental methodologies to isolate transparency and authenticity effects, and conduct cross-cultural comparisons to examine how institutional trust and digital literacy moderate AI acceptance. Additionally, exploring AI-human collaboration models, neurophysiological response measurements, and regulatory impact assessments would deepen understanding of how AI branding evolves in dynamic, globally interconnected markets. Artificial intelligence is no longer an emerging technology; it is an embedded reality shaping how brands communicate, personalize, and scale. Yet, technological capability alone cannot sustain consumer relationships. Authenticity, ethical alignment, and culturally attuned deployment remain the foundational pillars of brand trust in an algorithmic era. Organizations that recognize AI as a relational actor rather than a computational tool will navigate the digital transformation successfully. By harmonizing innovation with integrity, brands can harness AI's transformative potential while preserving the human-centric values that ultimately drive consumer loyalty and market resilience.

REFERENCES

Aljarah, A., Ibrahim, B., & López, M. (2025). In AI, we do not trust! The nexus between awareness of falsity in AI-generated CSR ads and online brand engagement. Internet Research, 35(3), 1406-1426.

Arora, J., Bali, S., Aggarwal, N., Mamgain, G., & Sharma, T. (2025). AI-Driven Personalization Of Brand Voice: Enhancing Customer Engagement And Brand Identity. International Journal of Environmental Sciences, 935-943.

Ben Dalla, L., Medeni, T. M., Zbeida, S. Z., & Medeni, İ. M. (2024). Unveiling the Evolutionary Journey based on Tracing the Historical Relationship between Artificial Neural Networks and Deep Learning. *The International Journal of Engineering & Information Technology (IJEIT)*, *12*(1), 104-110.

Bensalem, S., & Boudaoud, B. (2024). Ethical Algorithms: Balancing the Power of AI in Marketing with Consumer Trust-Case Studies of International Experiences. مجلة إدارة الأعمال والدراسات الاقتصادية, 10(1), 349-360.

Bensalem, S., Boudaoud, B., & Merrakchi, A. (2024). Symbiosis or Surveillance? Exploring the Relationship between AI, Big Data, and Consumer Privacy in Digital Marketing. افاق للعلوم, 9(4), 192-208.

Bentler, P. M. (1992). On the fit of models to covariances and methodology to the Bulletin. Psychological bulletin, 112(3), 400.

Bialkova, S. (2024). Data management. In The rise of AI user applications: Chatbots integration foundations and trends (pp. 167-186). Cham: Springer Nature Switzerland.

Blösser, M., & Weihrauch, A. (2024). A consumer perspective of AI certification–the current certification landscape, consumer approval and directions for future research. European Journal of Marketing, 58(2), 441-470.

Browne, M. W. and Cudeck R. (1993). Alternative ways of assessing model fit. In Bollen, K. A., & Long, J. S. (Eds.). (1993). Testing structural equation models (Vol. 154). Sage.

Browne, M. W. and Cudeck R. (1993). Alternative ways of assessing model fit. In Bollen, K. A., & Long, J. S. (Eds.). (1993). Testing structural equation models (Vol. 154). Sage.

Brüns, A., & Meißner, M. (2024). Perceived genuineness in AI-mediated brand communications . Journal of Interactive Marketing, 65, 1–14.

Brüns, A., & Meißner, M. (2024). Perceived genuineness in AI-mediated brand communications. Journal of Interactive Marketing, 65, 1–14.

Brüns, J. D., & Meißner, M. (2024). Do you create your content yourself? Using generative artificial intelligence for social media content creation diminishes perceived brand authenticity. Journal of Retailing and Consumer Services, 79, 103790.

Bulmer, S., Palakshappa, N., Dodds, S., & Harper, S. (2024). Sustainability, brand authenticity and Instagram messaging. Journal of Business Research, 175, 114547.

Byrne Barbara, M. (2016). Structural equation modeling with AMOS: basic concepts, applications, and programming. Routledge.

Byrne Barbara, M. (2016). Structural equation modeling with AMOS: basic concepts, applications, and programming. Routledge.

Charfou, A. R., & Naji, J. (2024). The Era of Ai-Generated Video Production: Exploring Consumers' Attitudes.

Chen, Y., Wang, H., Hill, S. R., & Li, B. (2024). Consumer attitudes toward AI-generated ads: Appeal types, self-efficacy and AI's social role. Journal of Business Research, 185, 114867.

Cicek, M., Gursoy, D., & Lu, L. (2025). Adverse impacts of revealing the presence of "Artificial Intelligence (AI)" technology in product and service descriptions on purchase intentions: the mediating role of emotional trust and the moderating role of perceived risk. Journal of Hospitality Marketing & Management, 34(1), 1-23.

Collier, J. (2020). Applied structural equation modeling using AMOS: Basic to advanced techniques. Routledge.

Collier, J. (2020). Applied structural equation modeling using AMOS: Basic to advanced techniques. Routledge.

Crisci, A. (2024). Business-To-Business Brand Authenticity in the Age of Artificial Intelligence: Best Practices for Discussing Emotionally Charged Issues on Social Media From Top Technology Companies.

Crisci, L. (2024). Personalisation paradoxes in AI advertising. Marketing Science Review, 39(3), 55–73.

Dalla, L. O. B., Karal, Ö., & Degirmenciyi, A. (2025). Leveraging LSTM for Adaptive Intrusion Detection in IoT

Networks: A Case Study on the RT-IoT2022 Dataset implemented On CPU Computer Device Machine.
Dalla, L. O. B., Medeni, T. D., & Medeni, İ. T. (2024). Evaluating the Impact of Artificial Intelligence-Driven Prompts on the Efficacy of Academic Writing in Scientific Research. *المجلة الأفروآسيوية للبحث العلمي (AAJSR)*, 48-60.
Dalla, L. O. F. B. (2020). Convolutional Neural Network Baseline Model Building for Person Re-Identification..
Dalla, L. O. F. B. (2020). Dorsal Hand Vein (DHV) Verification in Terms of Deep Convolutional Neural Networks with the Linkage of Visualizing Intermediate Layer Activations Detection..
Hawa Ahmed Alrawayati, Ümit Tokeşer. (2025).Spectral Integral Variation of Graph Theory. Asian Journal of Mathematics and Computer Research.32, Issue, 2. Pages(151-160). https://www.elibrary.ru/item.asp?id=82163806
Alrawayati, H., & Tökeşer, Ü. (2021). PARKINSON'S DISEASE DIAGNOSIS BASED ON THE CONVOLUTIONAL NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION ALGORITHM. *Asian Journal of Mathematics and Computer Research*, *28*(1), 26-37.
Hawa Ahmed Alrawayati, Ümit Tokeşer. (2025).Spectral Integral Variation of Graph Theory. Asian Journal of Mathematics and Computer Research.32, Issue, 2. Pages(151-160). https://www.elibrary.ru/item.asp?id=82163806.
Hawa Alrawayati (2020). Development of High Efficiency Optimization Algorithm based on New Topology in Particle Swarm Optimization for Parkinson's Disease. IOSR Journal of Mathematics (IOSR-JM). 8
Bentler, P. M. (1992). On the fit of models to covariances and methodology to the Bulletin. Psychological Bulletin, 112(3), 400.
Byrne, B. M. (2016). Structural equation modeling with AMOS: Basic concepts, applications, and programming. Routledge.
Collier, J. (2020). Applied structural equation modeling using AMOS: Basic to advanced techniques. Routledge.
Huang, Q., & Maracic, J. (2024). Consumer perception of Deepfake Technology in Marketing: An abductive study on consumer attitude, trust and brand authenticity. Journal of Interactive Marketing.
Kirkby, A., Baumgarth, C., & Henseler, J. (2023). To disclose or not disclose, is no longer the question–effect of AI-disclosed brand voice on brand authenticity and attitude. Journal of Product & Brand Management, 32(7), 1108–1122.
Spence, A. M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355–374.
Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), The social psychology of intergroup relations (pp. 33–47). Brooks/Cole.
Vo, C., et al. (2024). Authenticity cues in AI chatbots. Computers in Human Behavior, 139, 107490.
Wang, X., & Qiu, X. (2024). The positive effect of artificial intelligence technology transparency on digital endorsers: Based on the theory of mind perception. Journal of Retailing and Consumer Services, 78, 103777.
Hawa Alrawayati. (2016). (المعادلة التكاملية ونواة المؤثر) Integral Equation and Kernel Operator.76 – 63 .مجلة الساتل - جامعة مصراته
Dalla, L. O. B., Essgaer, M., Jetlawei, S. S., EL-sseid, M., Alsharif, A., & Agila, A. A. A. (2026). Local Precision and Global Harmony: A Comparative Literature Review (LR) Framework for Taylor and Fourier Series in Engineering Modeling. *Al-Farooq Journal of Sciences*, *2*(1), 275-304.
Hawa Alrawayati. (2016). Integral Equation and Kernel Operator. Al-Satel Journal - Misrata University. 63-76
Hawa Alrawayati. (2013). (المؤثرات الخطية المحدودة على فضاء هلبرت) • Finite linear operators on Hilbert spaces.-184.مجلة جامعة الزيتونة 193
Chantar, H., Tubishat, M., Essgaer, M., & Mirjalili, S. (2021). Hybrid binary dragonfly algorithm with simulated annealing for feature selection. *SN computer science*, *2*(4), 295.
Siraj, F., & Abdoulha, M. A. (2009, May). Uncovering hidden information within university's student enrollment data using data mining. In *2009 Third Asia International Conference on Modelling & Simulation* (pp. 413-418). IEEE.
Siraj, F., & Abdoulha, M. A. (2007). Mining enrolment data using predictive and descriptive approaches. *Knowledge-Oriented Applications in Data Mining*, 53-72.
Alssager, M., & Othman, Z. A. (2016). Taguchi-based parameter setting of cuckoo search algorithm for capacitated vehicle routing problem. In *Advances in Machine Learning and Signal Processing: Proceedings of MALSIP 2015* (pp. 71-79). Cham: Springer International Publishing.
Alssager, M., Othman, Z. A., Ayob, M., Mohemad, R., & Yuliansyah, H. (2020). Hybrid cuckoo search for the capacitated vehicle routing problem. *Symmetry*, *12*(12), 2088.
Omar, A., Essgaer, M., & Ahmed, K. M. (2022, July). Using machine learning model to predict Libyan telecom company customer satisfaction. In *2022 International Conference on Engineering & MIS (ICEMIS)* (pp. 1-6). IEEE.
Ben Dalla, L. O. F., Medeni, T. D., Medeni, I. T., & Ulubay, M. (2025). Enhancing Healthcare Efficiency at Almasara Hospital: Distributed Data Analysis and Patient Risk Management. Economy: Strategy and Practice, 19(4), 54–72. https://doi.org/10.51176/1997-9967-2024-4-54-72
Dalla, L. O. F. B. (2020). Modeling by using Generic Modeling Environment (GME) Domain specific modeling language (DSL) for agile software development (ASD) types.
Бен Далла Л., Медени Т.Д., Медени И.Т., Улубай М. Повышение эффективности здравоохранения в больнице Алмасара: анализ распределенных данных и управление рисками для пациентов. Economy: strategy and practice. 2024;19(4):54-72. https://doi.org/10.51176/1997-9967-2024-4-54-72
FARAJ, L. O. (2017). OBSERVATIONS ON EVOLUTION OF LEAN SOFTWARE DEVELOPMENT (LSD). 88 pages.https://tez.yok.gov.tr/UlusalTezMerkezi/tezDetay.jsp?id=R_EJxYiWWNffOuWM4F4eXQ&no=fiwArXgOvJPKmFC-nX3H-w
Dalla, L. O. F. B. (2020). IT security Cloud Computing. . In 2020 IT security Cloud Computing Applications Conference (ITSCC) (pp. 1-10). IEEE. https://doi.org/10.16377/ITSCC50717.2020.9259880
Degirmenci, A., & Karal, O. (2022). iMCOD: Incremental multi-class outlier detection model in data streams. Knowledge-Based Systems, 258, 109950. https://doi.org/10.1016/j.knosys.2022.109950
Alssager, M., & Othman, Z. A. (2016). Cuckoo search algorithm for capacitated vehicle routing problem. *Journal of Theoretical and Applied Information Technology*, *88*(1), 11.
Siraj, F., & Ali, M. (2011). *Mining enrollment data using descriptive and predictive approaches* (pp. 53-72). InTech—Open Access Company.
Dalla, L. O. B., Karal, Ö., Degirmenci, A., EL-Sseid, M. A. M., Essgaer, M., & Alsharif, A. (2025). Edge Intelligence for Real-Time Image Recognition: A Lightweight Neural Scheduler Via Using Execution-Time Signatures on Heterogeneous Edge Devices. *Scientific Journal for Publishing in Health Research and Technology*, 74-85.
Alssager, M., & Nasir, I. (2021). Evaluation of using Google Classroom as a Tool for Asynchronous E-learning at Sebha University. *Journal of Pure & Applied Sciences*, *20*(1), 44-49.

ALSSAGER, M., & OTHMAN, Z. A. (2014). SIMULATED ANNEALING ALGORITHM USING ITERATIVE COMPONENT SCHEDULING APPROACH FOR CHIP SHOOTER MACHINES. *Journal of Theoretical & Applied Information Technology*, *65*(2).

Siraj, F., & Abdoulha, M. A. (2009, May). Uncovering hidden information within university's student enrollment data using data mining. In *2009 Third Asia International Conference on Modelling & Simulation* (pp. 413-418). IEEE.

Karal, Ö., & Dalla, L. O. F. B. (2025). Lung Nodule Characterization in CT Scans Using Hybrid 3D Attention U-Net Segmentation and Transfer Learning-Based Classification Approach. Comprehensive Science Journal, 10(37), 2907-2921.

Alssager, M., Othman, Z. A., & Ayob, M. (2017). Cheapest insertion constructive heuristic based on two combination seed customer criterion for the capacitated vehicle routing problem. *Int. J. Adv. Sci. Eng. Inf. Technol*.

Ghumeid, N. A., & Essgaer, M. (2024, May). Addressing the Libyan Arabic dialect identification: a comparative study of ensemble classification methods. In *2024 IEEE 4th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)* (pp. 579-584). IEEE.

DALLA, L. B. (2020). The Sustainable Efficiency of Modeling a Correspondence Undergraduate Transaction Framework by using Generic Modeling Environment (GME. Ben Dalla. International Journal of Engineering and Modern Technology E-ISSN 2504-8848 P-ISSN 2695-2149 . Vol 6 No 1 2020 www.iiardpub.org

Dalla, L. O. B., Karal, Ö., Degirmenci, A., EL-sseid, M. A. M., Essgaer, M., & Alsharif, A. (2025). A comprehensive literature review (LR) on optimization algorithms of sewage water treatment processes. Comprehensive Science Journal, 10(37), 3204-3220.

Dalla, L. O. F. B., & AHMAD, T. M. A. (2024). Integration of Artificial Bee Colony Algorithm with Deep Learning for Predictive Maintenance in Industrial IoT.

Ben Dalla, L., Medeni, T. M., Agila, A. A., & Medeni, İ. M. (2024). Architectural Synergy: Investigating the Role of Artificial Neural Networks in Enabling Deep Learning. *The International Journal of Engineering & Information Technology (IJEIT)*, *12*(1), 96-103.

Ramadhan, H. R. S., Osman, M. O. M., Dalla, L. O. F. B., Rashid, T. A., Albaraesi, M. J. S., El-Sseid, M. A. M., & Alnnale, T. (2025). A New Approach of the Machine Learning Framework Integrating Policy Design to Predict Renewable Electricity Penetration in Resource-Constrained Settings. Comprehensive Science Journal, 10(Supplement 38), 2929-2950

Albaraesi, M. J. S., Ali, M. A. M. A., Dalla, L. O. B., EL-sseid, M. A. M., Medeni, T. D., Medeni, İ. T., & Alnnale, T. (2025). Random construction in the city of Al-Bayda during the period 2011-2022 and its irregular expansion and its impact on the urban landscape. Comprehensive Science Journal, 10 (Supplement 38), 2590-2614.

A-abdullatef, M. M., Osman, M. O. M., Elghaffi, F. S. A., Dalla, L. O. B., Agila, A. A. A., & Alsharif, A. (2025). LATENT: Low-Latency Anomaly Tracking in National Electricity Time-Series Using Hybrid LSTM-Regression Architectures–A Case Study of Bangladesh's PGCB Grid. Comprehensive Science Journal, 9(36), 1891-1912.

Jetlawei, S. S., Dalla, L. O. B., Karal, Ö., Degirmenci, A., El-Sseid, M. A. M., Essgaer, M., & Alsharif, A. (2025). Temporal Intelligence and Algorithmic Equity: A Multi-Phase Framework for Predictive Student Success in Higher Education. Comprehensive Science Journal, 9(36), 1574-1595.https://doi.org/10.65405/f0xx5p02

Dalla, L. O. F. B. (2020). Lean Software Development Practices and Principles in Terms of Observations and Evolution Methods to increase work environment productivity. *International Journal of Engineering and Modern Technology*, *6*(1), 23-45.

Dalla, L. O. F. B., & AHMAD, T. M. A. (2024). IMPROVE DYNAMIC DELIVERY SERVICES USING ANT COLONY OPTIMIZATION ALGORITHM IN THE MODERN CITY BY USING PYTHON RAY FRAMEWORK.

Karal, Ö. (2020). Performance comparison of different kernel functions in SVM for different k value in k-fold cross-validation. In 2020 Innovations in Intelligent Systems and Applications Conference (ASYU) (pp. 1-5). IEEE. https://doi.org/10.1109/ASYU50717.2020.9259880

Ben Dalla, L., Medeni, T. M., Zbeida, S. Z., & Medeni, İ. M. (2024). Unveiling the Evolutionary Journey based on Tracing the Historical Relationship between Artificial Neural Networks and Deep Learning. *The International Journal of Engineering & Information Technology (IJEIT)*, *12*(1), 104-110.

Essgaer, M., & Beitalmal, A. (2026). Insights into Journal Performance and Submission Trends: A Quantitative Analysis of JOPAS Data from 2017 to 2024. *Journal of Pure & Applied Sciences*, *25*(1), 7-13.

Alssager, M., & Khalifa, H. (2019). Toward improving Sebha University in world universities ranking.