ABRJ
American Based Research Journal
ISSN Online (2304-7151)

https://www.abrj.org/
Impact Factor 2.30

Examining the Factors Affecting Marketers Willingness to Adopt AI Technologies for Marketing Campaigns in industrial Automation industry in Egypt

A research Submitted in partial fulfilment of the requirements of the Doctor of Business Administration Degree -ESLSCA BUSINESS SCHOOL-

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Abstract
The rapid advancement of Artificial Intelligence (AI) has opened new avenues in marketing, particularly in content creation and personalization. Despite global trends, the adoption of AI technologies in Egypt's industrial automation sector remains limited and underexplored. This study aims to investigate the factors influencing marketers' intention to adopt and use AI tools within this context. Drawing on an extended version of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the research incorporates Perceived Behavioral Control (PBC) as a mediating variable and Perceived Risk (PR) as a moderator to improve the model's contextual fit. A mixed-method approach was adopted, combining expert interviews and a structured survey of 400 professionals working in industrial marketing. Quantitative analysis using factor analysis, regression, mediation, and moderation techniques revealed that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions significantly influence Behavioral Intention (BI). Furthermore, PBC was found to mediate the relationship between these predictors and intention, while PR significantly moderated their effect. Notably, Behavioral Intention was also a strong predictor of actual AI usage. These findings offer valuable theoretical insights by validating an extended UTAUT2 model in an emerging B2B market and provide actionable recommendations for marketers and policymakers to support responsible and strategic AI integration

Keywords: *AI adoption; Marketing campaign; perceived behavioral control; perceived risk; industrial marketing; Egypt*

1. Introduction

The rapid integration of Artificial Intelligence (AI) is reshaping the marketing landscape, revolutionizing how businesses create, personalize, and deliver content. Tools such as automated content generation, predictive analytics, chatbots, and customer segmentation are now pivotal for enhancing marketing precision, efficiency, and innovation (Chatterjee et al., 2021; Dwivedi et al., 2021). Beyond operational improvements, these technologies significantly elevate personalization and customer engagement (Salloum, 2023). Yet, despite this global momentum, AI adoption in developing economies particularly in B2B industrial marketing remains inconsistent and underexplored (Thompson et al., 2023). Egypt, with its Vision 2030 digital transformation agenda, presents a timely and relevant case. While the government champions AI as a key driver of modernization (OECD, 2021), adoption is slowed by structural challenges like limited infrastructure, digital skill gaps, and organizational resistance (Thompson et al., 2013).

To better understand adoption dynamics in this context, the study extends the widely used UTAUT2 model (Venkatesh et al., 2012), which explains user behavior toward technology. Recognizing its limitations in complex, non-Western, and B2B settings (Oliveira et al., 2016; Sharma et al., 2022), the model is expanded by incorporating two critical constructs: Perceived Behavioral Control (PBC) capturing users' confidence and autonomy in using AI (Ajzen, 1991), and Perceived Risk (PR) encompassing concerns about data security, job loss, and trust in algorithms (Featherman & Pavlou, 2003). This enhancement responds to scholarly calls to adapt UTAUT2 to emerging technologies and under-researched environments (Dwivedi et al., 2019; Venkatesh et al., 2022). Focusing on Egypt's industrial automation marketing sector, the study employs a quantitative, survey-based method to examine how UTAUT2 factors, PBC, and PR shape behavioral intention and actual AI usage in content marketing. It delivers both a theoretical contribution by validating an enriched UTAUT2 model in a novel context, and practical guidance for marketers, leaders, and policymakers working to advance AI in resource-constrained B2B environments.

2. Literature Review

2.1 Artificial Intelligence (AI) Adoption in Marketing

Artificial Intelligence (AI) is fundamentally reshaping the marketing landscape by automating content creation, enabling hyper-personalization, segmenting customers, and optimizing campaigns through data-driven insights (Chatterjee, 2022; Islam et al., 2024; Wang, 2020). Advanced tools like GPT models, Natural Language Processing (NLP), and Generative Adversarial Networks (GANs) empower marketers to craft targeted, high-quality content with speed and precision (Chung et al., 2023; Rieder & Gröppel-Klein, 2023). These capabilities are driving measurable gains in campaign effectiveness, customer engagement, and marketing ROI (Lee & Chae, 2023; Kapoor & Dwivedi, 2023).

While adoption is accelerating in B2C sectors within developed markets, uptake remains uneven in B2B contexts and emerging economies. In countries like Egypt, where AI is central to national digital transformation efforts under Vision 2030 (OECD, 2021), adoption in sectors such as industrial automation marketing is still limited. Structural challenges such as poor infrastructure, limited digital literacy, and organizational resistance continue to hinder progress (Rana, 2023; Al-Darmaki & Zaidi, 2023). These issues are compounded by heightened concerns around cost, job displacement, data security, and algorithmic bias, especially in high-stakes, high-risk decision environments (Barnes, 2021; Ranaweera & Ranaweera, 2023).

To better understand these complexities, scholars advocate for extending traditional adoption frameworks like UTAUT2 by incorporating context-sensitive variables such as Perceived Behavioral Control and Perceived Risk (Venkatesh et al., 2022; Jahanshahi & Farid, 2021). Doing so can offer more accurate insights into the behavioral dynamics influencing AI adoption in B2B and resource-constrained settings, ensuring that strategies are both effective and ethically grounded.

2.2 Theoretical Foundation: UTAUT2 Model

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), developed by Venkatesh et al. (2012), expands on the original UTAUT framework by integrating new constructs such as hedonic motivation, price value, and habit. These additions enhance the model's ability to explain user behavior in both consumer and professional settings. UTAUT2 has since been widely employed in studies involving AI-related technologies and remains one of the most reliable frameworks for understanding individual acceptance of emerging tools (Venkatesh et al., 2022).

However, growing evidence suggests that while UTAUT2 is robust, it may not fully capture the nuances of complex B2B environments, especially in non-Western and high-risk markets (Wang et al., 2024; García de Blanes Sebastián, 2022). As such, recent scholarship supports incorporating additional psychological and contextual variables. Perceived Behavioral Control (PBC) derived from Ajzen’s (1991) Theory of Planned Behavior reflects users' confidence and autonomy in handling new technologies. Perceived Risk (PR) accounts for the concerns associated with data security, ethical use, and the trustworthiness of algorithmic decisions (Dixit et al., 2025; Paraskevi & Saprikis, 2023). These enhancements are essential for capturing the dynamics of technology adoption in environments marked by uncertainty and complexity.

2.3 UTAUT2 Constructs and Hypothesis Development

The UTAUT2 framework retains four foundational constructs from its predecessor while integrating three new elements to improve behavioral prediction. These variables relate to Behavioral Intention (BI) and ultimately to Use Behavior (UB).

2.3.1 Core Constructs and Hypotheses

- **Performance Expectancy (PE):** Refers to the degree to which AI is expected to improve work performance and marketing outcomes (Venkatesh, Thong, & Xu, 2012).
  - *H1:* There is a significant positive relationship between PE and BI to adopt AI technologies in marketing.
- **Effort Expectancy (EE):** Denotes perceived ease of using AI technologies (Venkatesh et al., 2012).
  - *H2:* There is a significant positive relationship between EE and BI to adopt AI technologies.
- **Social Influence (SI):** Indicates the extent to which organizational or peer pressure influences adoption behavior (Venkatesh et al., 2012).
  - *H3:* There is a significant positive relationship between SI and BI to adopt AI technologies.
- **Facilitating Conditions (FC):** Represents the availability of resources and organizational support for AI adoption (Venkatesh et al., 2012).
  - *H4:* There is a significant positive relationship between FC and BI to adopt AI technologies.

2.3.2 Additional UTAUT2 Variables

- **Hedonic Motivation (HM):** The degree of enjoyment derived from using the technology.
- **Price Value (PV):** The balance between the perceived benefits of AI and its associated costs.
- **Habit (HB):** The extent to which AI adoption becomes routine behavior due to prior exposure or learning.

2.3.3 Outcome Constructs

- **Behavioral Intention (BI):** The individual’s intention to use AI in future tasks (Venkatesh et al., 2012).
- **Use Behavior (UB):** Actual engagement with AI tools, influenced by BI and FC.

- *H8: BI positively affects the actual use of AI in marketing content creation.*

2.3.4 Moderating Variable: Experience

Experience serves as a moderator within UTAUT2, especially critical in B2B AI contexts. Marketers with greater exposure to AI tools may perceive higher benefits and lower risks (Williams et al., 2015).

- *H6:* Experience moderates the relationship between core UTAUT2 variables (PE, EE, SI, FC) and BI, strengthening the effect for users with more prior experience.

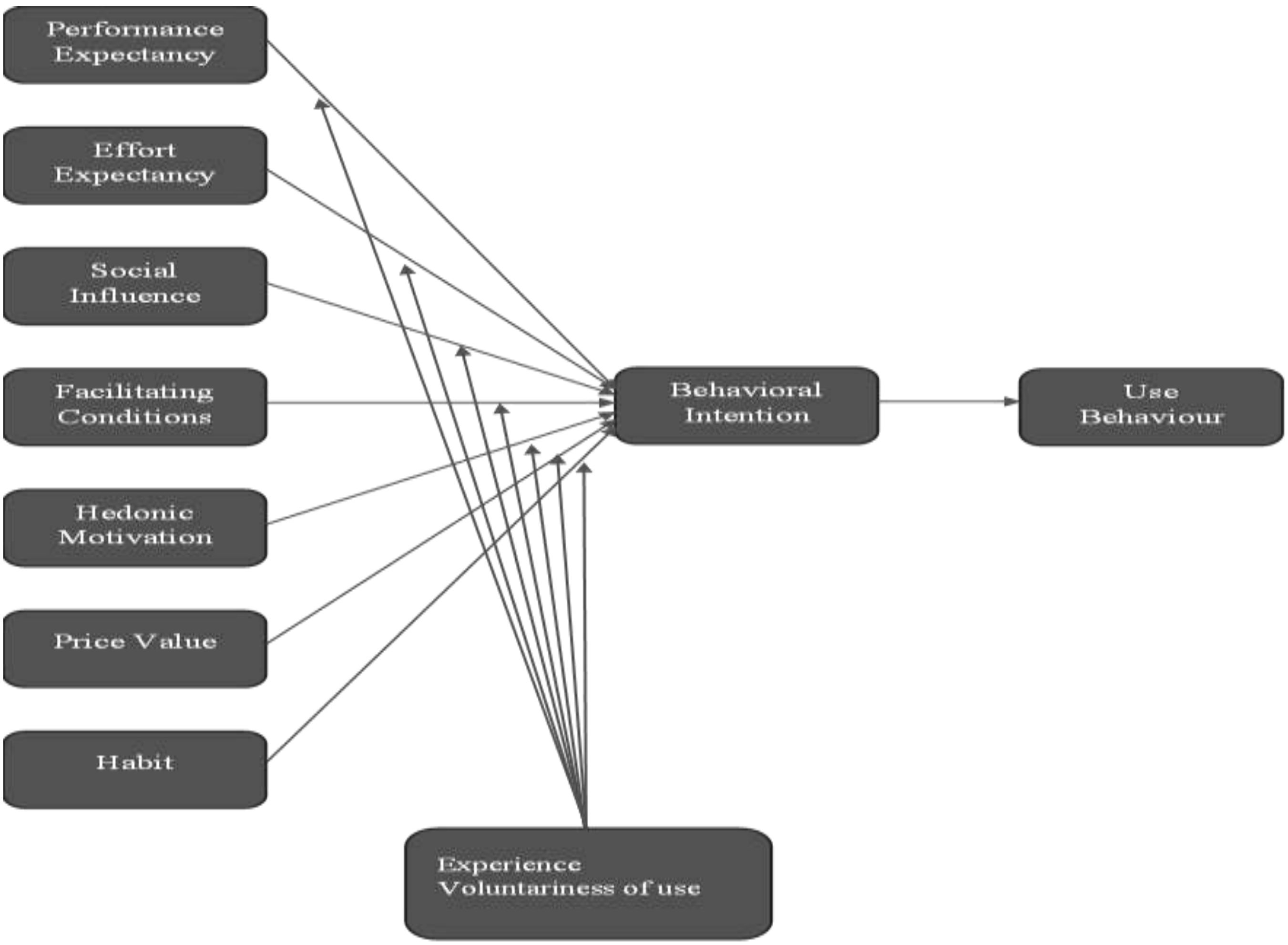

Figure 2.1 Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) (Venkatesh et al. 2012)

2.4 Extending UTAUT2 for Industrial Automation Contexts

2.4.1 Incorporating Perceived Behavioral Control (PBC)

Perceived Behavioral Control (PBC), as conceptualized by Ajzen (1991), addresses an individual’s belief in their capability to use technology, considering both internal confidence and external resource availability. In industrial B2B marketing, where the complexity of AI tools may be high, PBC becomes a key psychological enabler. Prior studies indicate that PBC may act as a mediator, influencing how constructs like performance expectancy and effort expectancy translate into behavioral intention and use (Singh & Ahmed, 2021; Alshurideh et al., 2023).

- *H5:* PBC mediates the relationship between PE, EE, SI, FC, and BI.

2.4.2 Addressing Perceived Risk (PR)

AI deployment in marketing introduces various perceived risks, including privacy violations, data misuse, job displacement, and algorithmic bias. These risks can deter adoption despite evident benefits. Research shows that risk aversion moderates the relationship between perceived usefulness and adoption behavior (Oliveira et al., 2016; Islam et al., 2024). In contexts like Egypt where regulatory structures, institutional trust, and digital infrastructure are still maturing, these concerns become more pronounced (Alice & Ebuka, 2024).

Additionally, the B2B nature of industrial automation involves complex decision-making processes, extended sales cycles, and higher financial stakes. UTAUT2 does not fully account for sectoral maturity or institutional pressure factors essential in developing economies (Kumar et al., 2024).

- *H7:* Perceived Risk moderates the relationship between PE, EE, SI, FC, and PBC with BI, such that higher perceived risk weakens these relationships.

2.4.3 Rational behind need for Model Extension

- The study adapts the UTAUT2 model to better reflect the realities of AI adoption in Egypt's industrial marketing sector.
- Perceived Behavioral Control (PBC) is added as a mediator to account for marketers' confidence and ability to use AI tools.
- Perceived Risk (PR) is introduced as a moderator to address concerns such as data privacy, job security, and AI reliability.
- These extensions capture contextual, psychological, and trust-related barriers often seen in emerging markets and high-risk B2B environments.
- The model update aligns with scholarly calls to tailor UTAUT2 to specific industries and regions for greater relevance and predictive power (Dwivedi et al., 2019; Venkatesh et al., 2022).
- Overall, this enriched framework enhances both theoretical development and practical application of AI adoption models in underexplored settings.

3. THE CONCEPTUAL MODEL

From the preceding literature review, the researchers propose the following conceptual model, built upon seven key constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Perceived Behavioral Control (PBC), Perceived Risk (PR), and Behavioral Intention (BI). These constructs were theoretically defined and discussed in Section Two.

As outlined earlier, the foundational structure of this model is based on the UTAUT2 framework (Venkatesh et al., 2012), which identifies PE, EE, SI, and FC as primary predictors of behavioral intention. To enhance the model's applicability to the B2B industrial automation sector in Egypt, where adoption challenges are both technological and psychological, the authors extend UTAUT2 by integrating Perceived Behavioral Control (PBC) adapted from Ajzen's (1991) Theory of Planned Behavior as a mediating variable. PBC reflects the degree of control and confidence marketers perceive in adopting AI-based solutions.

Moreover, the model introduces Perceived Risk (PR) as a moderating construct to account for individual differences in risk sensitivity, especially concerning AI-related issues like data privacy, job security, and trust in automation systems (Featherman & Pavlou, 2003; Oliveira et al., 2016). The authors hypothesize that PR moderates the strength of the relationships between UTAUT2 predictors (PE, EE, SI, FC), PBC, and the resulting behavioral intention.

Thus, the proposed model positions PBC as a mediator and PR as a moderator, offering a nuanced, context-specific framework to explore how AI adoption intentions are shaped within Egypt's industrial B2B marketing sector.

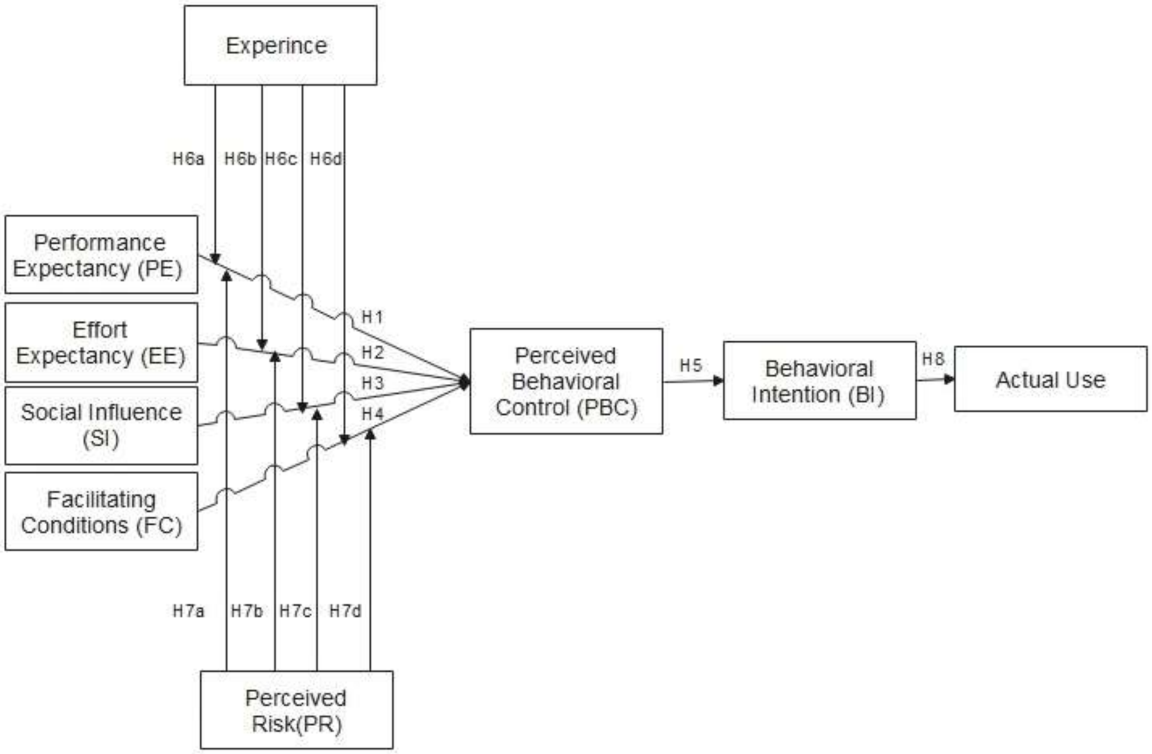

Figure 3.1 the proposed conceptual framework used in this study for AI adoption in marketing within Egypt's industrial automation sector.

4. The Research Methodology

4.1 Research Design

This research adopted a mixed-methods design to explore AI adoption in marketing content creation within Egypt's industrial automation sector. It began with qualitative interviews involving seasoned marketing professionals, whose insights were used to tailor the conceptual framework particularly through the integration of Perceived Behavioral Control and Perceived Risk (Venkatesh et al., 2012; Ajzen, 1991).

In the quantitative phase, a structured questionnaire was distributed to 400 marketers, drawing on both literature and interview findings. The study followed a deductive, theory-driven approach, testing hypotheses derived from the extended UTAUT2 model using statistical analysis.

By incorporating PBC as a mediator and PR as a moderator, the study not only confirmed the influence of core adoption factors like Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions but also provided contextual insights into adoption behavior in emerging markets (Bryman, 2016; Oliveira et al., 2016; Islam et al., 2024). This dual-phase design enhanced both the theoretical relevance and practical applicability of the findings for Egypt's evolving B2B digital landscape.

4.2 Research Population and Sampling

This study focused on marketing professionals in Egypt's industrial automation sector, particularly those involved in digital, strategic, or content-related marketing where AI technologies are being adopted or explored. The target population spanned both local and multinational firms based in key economic zones such as Cairo, Alexandria, the Suez Canal Zone, and 10th of Ramadan City.

Due to the lack of a centralized registry for professionals in this niche domain, a non-probability convenience sampling approach was employed. Participants were recruited via LinkedIn, industry directories, and professional networks. The final dataset comprised 400 valid survey responses, exceeding the statistical reliability benchmark for large populations (Sekaran, 2003), and included roles such as marketing managers, brand strategists, digital content creators, and AI campaign analysts.

Additionally, for the qualitative phase, purposive sampling was used to select 10 senior marketing experts with proven experience in AI integration and digital transformation. Their insights were instrumental in contextualizing the research model and fine-tuning the measurement instrument to reflect the unique dynamics of Egypt's industrial marketing landscape.

4.3 Data Collection Instruments and Procedures

This study adopted a two-phase data collection strategy to ensure both depth and breadth in understanding AI adoption within Egypt's industrial marketing sector.

a) Qualitative Instrument – Semi-Structured Interviews

The research began with in-depth interviews involving ten senior marketing professionals. These semi-structured discussions provided rich, contextual insights into how AI technologies are applied in real-world marketing scenarios. Crucially, this phase helped validate and adapt the UTAUT2 framework by incorporating Perceived Behavioral Control (PBC) and Perceived Risk (PR), making it more relevant to the Egyptian B2B context. The expert feedback also informed refinements in language, clarity, and industry relevance for the subsequent survey instrument.

b) Quantitative Instrument – Structured Questionnaire

In the second phase, a self-administered online survey was distributed via LinkedIn, email, and industry-specific forums. The final questionnaire included 34 closed-ended items covering all study variables independent, mediating, moderating, and dependent and was divided into three sections:

- **Section 1 – Screening Questions:** Confirmed participants were actively involved in marketing and AI-related activities.
- **Section 2 – Measurement Items:** Used **5-point Likert scales** to assess constructs such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, PBC, PR, Behavioral Intention, and Actual Usage.
- **Section 3 – Demographics:** Collected participant details including age, gender, education, job title, sector, and income.

All questionnaire items were adapted from validated instruments found in the works of Venkatesh et al. (2012), Ajzen (1991), and Featherman & Pavlou (2003), and were localized to reflect the industrial and cultural context of Egypt.

c) Pilot Study and Instrument Validation

A **pilot test** was conducted with 10 professionals from the target sector to evaluate clarity, flow, digital usability, and internal consistency. Based on their feedback:

- Wording was simplified for clarity.
- Items were reduced from 5 to 3–4 per construct to avoid survey fatigue.
- The Perceived Risk construct retained 4–5 items due to its conceptual weight.

Reliability was preliminarily tested using Cronbach's Alpha, with all constructs exceeding the acceptable threshold ($\alpha \geq 0.70$), supporting their inclusion in the final instrument. This careful process ensured that the questionnaire was reliable, context-appropriate, and theoretically grounded for the large-scale data collection.

4.4 Sampling Strategy

Due to the lack of a centralized registry for marketing professionals in Egypt's industrial automation sector, this study used a non-probability sampling approach, specifically convenience sampling. Participants were recruited through professional channels such as LinkedIn, industry events, and referrals, reflecting the sector's niche and dispersed nature.

Guided by Sekaran's (2003) recommendation of a minimum sample size of 384 for large populations, a total of 400 valid responses were collected from professionals engaged in roles like digital marketing, brand strategy, and content creation many of whom actively use or oversee AI in marketing.

For the qualitative phase, purposive sampling was employed to select ten senior marketing experts with hands-on experience in AI deployment, digital transformation, or industrial B2B campaigns. Their targeted insights enriched the contextual relevance and theoretical framing of the study.

Summary of Sampling Approach:

Table 4.1 Summary of Sampling Approach

Element	Details
Research Population	Marketing professionals in the Egyptian industrial automation sector
Sampling Method	Non-probability sampling
Sampling Criteria	Convenience sampling (quantitative), purposive sampling (qualitative)
Sample Size	400 survey responses, 10 expert interviews
Valid Responses	390 valid survey responses after data cleaning
Response Rate	Approximately 78% (based on ~500 surveys distributed)

5. Qualitative Analysis

To gain in-depth insight into the contextual and psychological dimensions influencing AI adoption in marketing, this study employed thematic analysis a method well-suited for capturing rich, qualitative patterns. This approach was ideal for examining interviews with senior marketing professionals in Egypt's industrial automation sector, whose reflections offered critical perspectives on behavioral and organizational drivers behind AI use.

Guided by Braun and Clarke's (2006) six-phase framework, the analysis systematically explored themes mapped to the UTAUT2 model and its extensions Perceived Behavioral Control (PBC) and Perceived Risk (PR). This method enabled the study to surface underlying attitudes, challenges, and contextual realities that may be obscured in purely quantitative designs.

5.1 Phases of Thematic Analysis (Braun & Clarke, 2006)

- **Familiarization**: In-depth review of transcripts to grasp key narratives around AI usability, benefits, and readiness.
- **Coding**: Labeling significant responses using constructs like Effort Expectancy, **Facilitating Conditions**, and emergent topics like Data Security.
- **Theme Identification**: Grouping related codes under broader conceptual themes (e.g., Performance Expectancy, Organizational Resistance).
- **Theme Review**: Ensuring clarity, distinctiveness, and coherence across themes by refining overlaps.
- **Theme Definition**: Articulating the scope of each theme and aligning it with the study's research questions and theoretical framework.
- **Reporting**: Synthesizing results into a coherent narrative supported by quotations and organized visuals.

This rigorous yet adaptable method allowed the study to contextualize AI adoption from the lived experiences of practitioners, enhancing both the depth and relevance of the findings.

5.2 Expert Interview Analysis

The table below presents a summary of the marketing experts interviewed, highlighting their job titles within the industrial automation sector in Egypt.

Expert Number	Job Title
E1	Marketing Director
E2	Senior Marketing Manager
E3	Marketing Strategist
E4	Digital Marketing Specialist
E5	Head of Content Creation
E6	Marketing Operations Manager
E7	Chief Marketing Officer (CMO)
E8	Brand Manager
E9	Marketing Analytics Lead
E10	Senior Digital Content Specialist

Table 5.1 Experts job titles

5.3 Extracted Codes and Themes from the Interviews

The table below details the extracted codes and corresponding themes from the expert interviews.

Code	Theme
"Increases productivity significantly"	Performance Expectancy
"AI helps me achieve better outcomes"	Performance Expectancy
"Simplifies complex tasks"	Effort Expectancy

“Reduces time spent on routine tasks”	Effort Expectancy
“Peers encouraged AI adoption”	Social Influence
“AI usage aligns with industry trends”	Social Influence
“Organization provides essential tools”	Facilitating Conditions
“Technical support is available”	Facilitating Conditions
“I feel capable of handling AI tools”	Perceived Behavioral Control
“Confidence in using AI”	Perceived Behavioral Control
“Long experience with tech helps”	Experience
“Past work with analytics was useful”	Experience
“Concern about data privacy”	Perceived Risk
“Worry about job displacement”	Perceived Risk

Table 5.2 the Extracted Codes and Themes from the Interviews with the Experts

5.4 Qualitative Analysis Conclusion

Thematic analysis revealed nuanced insights into the drivers and barriers shaping AI adoption among marketing professionals in Egypt’s industrial automation sector. Anchored in the extended UTAUT2 framework, key constructs including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Perceived Behavioral Control (PBC) proved central to influencing marketers’ behavioral intentions and actual AI usage.

Experts underscored AI’s value in improving efficiency and decision-making, highlighting Performance Expectancy as a strong motivator. Ease of use (Effort Expectancy) and support from peers or leadership (Social Influence) were also critical, alongside robust infrastructure and organizational readiness (Facilitating Conditions).

Importantly, PBC emerged as a mediating factor, where marketers’ confidence in using AI tools influenced how positively they translated favorable perceptions into actual intentions. Experience moderated these dynamics, with prior exposure to AI increasing adoption likelihood. Meanwhile, Perceived Risk linked to concerns over privacy, job displacement, or reliability tempered adoption enthusiasm, even when other factors were positive.

These findings validate the relevance of the extended UTAUT2 model in B2B, emerging market contexts and point to the importance of building trust, technical proficiency, and support systems to foster effective AI integration in marketing strategies.

6. Statistical Analysis and Results

This section outlines the key analytical steps and findings from the study’s mixed-method design. After collecting quantitative data through a structured survey, a series of statistical tests were conducted to assess the proposed hypotheses based on the extended UTAUT2 framework. These included descriptive statistics to profile respondents, along with reliability and validity tests to confirm the strength of the measurement model.

More advanced techniques regression, mediation, and moderation analyses were applied to evaluate the relationships among key variables. Specifically, Perceived Behavioral Control (PBC) was tested as a mediator, and Perceived Risk (PR) as a moderator, providing richer insight into the behavioral mechanisms driving AI adoption in Egypt's industrial automation marketing landscape. The results below confirm the study's hypotheses and lay the foundation for interpretation and managerial recommendations.

6.1 Descriptive Data Analysis

This section presents the core descriptive analyses conducted on the collected dataset (N = 402), including reliability testing, factor analysis, demographic profiling, and descriptive statistics. Reliability and factor analyses were performed to validate the internal consistency and construct alignment of the survey instrument. Demographic variables such as gender, age, education, occupation, and income were examined to understand respondent distribution. Descriptive statistics, using a 5-point Likert scale, assessed central tendencies (mean, median, mode), dispersion (range, standard deviation), and percentiles to summarize participant responses and identify general data trends without evaluating inter-variable relationships.

6.1.1 Reliability Analysis

To ensure the questionnaire's internal consistency, Cronbach's alpha was used as the primary reliability metric. This measure evaluates how well the items within each construct align to reflect the same underlying concept (Tavakol & Dennick, 2011; Alice & Ebuka, 2023). According to established guidelines, alpha values above 0.70 indicate acceptable reliability, with values between 0.7 and 0.9 considered strong, and those above 0.9 reflecting excellent consistency (George & Mallery, 2003; Hinton et al., 2004). All constructs in this study surpassed the minimum threshold, affirming the instrument's reliability and its readiness for further statistical analysis.

Type of variable	Variables	Number of Questions	Cronbach's Alpha	Test Result
Independent 1	Performance Expectancy (PE)	3 (1-10-19)	0.79	High Reliability
Independent 2	Effort Expectancy (EE)	4 (2-11-34- 27)	0.84	High Reliability
Independent 3	Social Influence (SI)	4 (3-12-20-8)		High Reliability
Independent 4	Facilitating Conditions (FC)	4 (4-13-21-29)	0.85	High Reliability
Mediator 1	Perceived Behavioral Control (PBC)	4 (5-14-22-32)	0.87	High Reliability
Moderator 1	Experience	3 (6-15-23)	0.77	High Reliability
Moderator 1	Perceived Risk	5 (7-16-24-31-33)	0.89	High Reliability
Dependent 1	Behavioral Intention (BI)	4 (8-17-25-32)	0.87	High Reliability
Dependent 2	Usage of AI Technologies	3 (9-18-26)	0.75	High Reliability

Table 6.1 the outcome of the reliability analysis for each variable

According to the Cronbach's alpha test, all the variable acquired an alpha value between 0.75 and 0.89, which indicates high reliability. The high reliability outcome is accepted to continue the rest of the analysis; hence, the questionnaire has a high internal consistency.

6.1.2 Factor Analysis

Factor analysis is a method of data reduction to find out the minimum set of questions for each variable that was used and to find the loading of each question into its corresponding variable (Hair et al., 2010). The same question could be loaded into more than one variable; however, the higher loading will be taken into consideration (Kaiser, 1974). The factor analysis confirms the correct loading of each question into its correct variable. The first test used in factor analysis is the Kaiser-Meyer-Olkin (KMO) test, which is used to check the adequacy of the data collected (Field, 2013), as shown in Table 6.2.

The test		Value
Kaiser-Meyer-Olkin	Measure of Sampling Adequacy	0.814
Bartlett's Test of Sphericity	Approx. Chi-Square	1644.93
	D.F	561
	Sig.	0.00

Table 6.2 KMO and Bartlett's Test

The sig value is .00 which is lower than 0.05, hence, the KMO test is significant. According to Table 6.2, the KMO value is 0.964 which is higher than 0.7, hence, the factor analysis method is appropriate for data reduction. The principal component method was used to extract the required components.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	3.59	10.57	10.57	3.59	10.57	10.57	2.39	7.02	7.02
2	2.39	7.02	17.59	2.39	7.02	17.59	2.24	6.58	13.61
3	1.77	5.19	22.78	1.77	5.19	22.78	1.99	5.85	19.45
4	1.55	4.55	27.33	1.55	4.55	27.33	1.78	5.23	24.68
5	1.40	4.10	31.43	1.40	4.10	31.43	1.7	5.00	29.68
6	1.32	3.90	35.33	1.32	3.90	35.33	1.48	4.35	34.03
7	1.28	3.76	39.09	1.28	3.76	39.09	1.46	4.29	38.32
8	1.27	3.73	42.82	1.27	3.73	42.82	1.39	4.08	42.40
9	1.24	3.64	46.46	1.24	3.64	46.46	1.38	4.06	46.46
10	0.99	2.92	49.38						
11	0.99	2.92	52.30						
12	0.99	2.92	55.22						
13	0.97	2.85	58.07						
14	0.95	2.78	60.85						
15	0.94	2.75	63.60						
16	0.89	2.61	66.22						
17	0.83	2.45	68.66						
18	0.81	2.40	71.06						
19	0.78	2.30	73.36						
20	0.77	2.27	75.63						
21	0.76	2.23	77.86						
22	0.73	2.15	80.01						
23	0.71	2.08	82.09						
24	0.68	1.99	84.09						
25	0.65	1.90	85.99						
26	0.63	1.86	87.84						
27	0.60	1.76	89.60						
28	0.57	1.67	91.27						
29	0.53	1.57	92.84						
30	0.53	1.56	94.40						
31	0.51	1.50	95.90						
32	0.49	1.45	97.35						
33	0.48	1.40	98.75						
34	0.42	1.25	100.00						

Table 6.3 Total Variance Explained

Principal Component Analysis (PCA) identifies the smallest number of factors by selecting only those with eigenvalues greater than 1 indicating meaningful variance while discarding those with lower values. In this case, nine components met that threshold and were retained (see Table 6.3). The rotated component matrix, enhanced using Varimax rotation, clarifies how well each survey item corresponds to its underlying factor, improving interpretability and confirming construct alignment in the questionnaire (Hair et al., 2010; Hair et al., 2019).

Loading values greater than 0.4 are considered acceptable, suggesting that a survey question is meaningfully linked to a specific factor (Hair et al., 2010; Field, 2013; Tabachnick & Fidell, 2014). Ideally, each item should load strongly on just one factor, confirming it captures a single underlying construct like Performance Expectancy or Social Influence (Hair et al., 2019). In this analysis, most items aligned well with their intended constructs, supporting the questionnaires construct validity,

For instance:

Q1 (related to performance expectancy) loaded at 0.505 on Component 1.

Q3 (social influence) loaded at 0.691 on Component 3.

Q4 (facilitating conditions) loaded at 0.654 on Component 4.

Q5 (perceived behavioral control) loaded at 0.636 on Component 5.

Q6 (experience) loaded at 0.623 on Component 6.

Q7 (perceived risk) loaded at 0.534 on Component 7.

Q8 (behavioral intention) loaded at 0.663 on Component 8.

Q9 (actual use) loaded at 0.714 on Component 9.

These results indicate that the items are well-grouped and distinguishable, each aligning with its hypothesized variable, which supports the validity of the extended UTAUT2 model used in this research (Venkatesh et al., 2012; Williams, Rana, & Dwivedi, 2015).

6.1.3 Demographics Analysis

The demographic analysis includes five dimensions: gender, age, educational level, occupation, income level.

Demographic Category	Most Common Response
Gender	Male (211 responses)
Age	31–35 years (100 responses)
Educational Level	Master's Degree (146 responses)
Occupation	Private Sector (162 responses)
Income Level	More than 30,000 EGP (131 responses)

Table 6.4 Summary of Demographic Data

According to Table 6.4, the study's participants are primarily male marketing professionals aged 31–35, mostly employed in the private sector. The majority holds a Master's degree and earns over 30,000 EGP monthly. This reflects a well-educated, experienced, and professionally stable group, making them a fitting sample for examining AI adoption within Egypt's industrial automation marketing sector.

6.1.4 Center Tendency, Dispersion and Percentiles Analysis

This section offers a thorough analysis of the survey responses, aiming to uncover patterns in the participants' answers. The analysis focused on three statistical dimensions: central tendency, dispersion, and percentiles. Each variable was represented using its mean value, effectively transforming the original Likert scale into an interval scale, where equal spacing between values allows for more advanced statistical analysis (Sekaran, 2003). This conversion enabled the use of both mean and standard deviation to interpret the data more precisely and meaningfully.

Variable	Mean	Mode	Range	Standard Deviation	25th Percentile	Median	75th Percentile
Performance Expectancy (PE)	4.15	5	4	0.35	3	4	4
Effort Expectancy (EE)	3.4	4	4	0.39	3	3	4
Social Influence (SI)	3.73	4	4	0.34	3	4	4
Facilitating Conditions (FC)	3.14	4	4	0.41	3	4	4
Perceived Behavioral Control (PBC)	4.18	4	4	0.37	3	4	5
Experience	3.81	4	4	0.38	3	4	5
Perceived Risk	3.57	4	4	0.45	3	4	4
Behavioral Intention (BI)	4.43	4	4	0.34	2	4	5
Usage of AI Technologies	3.5	4	4	0.39	2	4	4

Table 6.5 Descriptive Statistics for All Questions

The following points summarize the main descriptive analysis for each variable in Table 6.5.

Performance Expectancy (PE):

Respondents overwhelmingly agree that AI boosts marketing productivity (*Mean = 4.15; Mode = 5*), with minimal variation (*SD = 0.35*). This shows a strong belief in AI's value, forming a solid driver for adoption.

Effort Expectancy (EE):

With a *mean of 3.40*, opinions are more mixed on the ease of using AI tools. The slight variation (*SD = 0.39*) reflects differing levels of digital literacy, indicating a need for user training and intuitive design.

Social Influence (SI):

Moderate agreement (*Mean = 3.73; Mode = 4*) suggests that peer and organizational encouragement is playing a role, though this varies slightly across teams (SD = 0.34), possibly reflecting cultural differences.

Facilitating Conditions (FC):

The *mean of 3.14* and slightly higher variation (*SD = 0.41*) highlight inconsistent support. While some infrastructure exists, gaps in resources, training, or policies are evident.

Perceived Behavioral Control (PBC):

A strong *mean of 4.18* with low variability (*SD = 0.37*) shows that most marketers feel confident in using AI, providing a robust psychological foundation for adoption.

Experience:

The *mean of 3.81* suggests a good but developing level of AI exposure. Some variation (SD = 0.38) shows uneven familiarity, pointing to a maturing adoption curve.

Perceived Risk:

At *3.57 mean*, concerns around AI risks like content quality and job displacement—are present and not negligible. The spread (SD = 0.45) suggests varying degrees of trust and awareness.

Behavioral Intention (BI):

With the highest *mean of 4.43*, there's a strong, shared intention to adopt AI across the board. Low variation (SD = 0.34) signals broad readiness and enthusiasm.

Actual Usage of AI:

A moderate *mean of 3.50* reflects steady but varied usage. Disparities in application (SD = 0.39) may reflect role-specific needs or unequal access, reinforcing earlier findings on effort and conditions

6.2 Inferential Data Analysis

The inferential data analysis includes six sections as follows:

- **Section one** introduces the normality test for checking whether to use the parametric or non-parametric analysis.

- **Section Two** introduces the regression analysis in order to test the impact of each independent variable (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions) on dependent variable (the Behavioral Intention (BI) to adopt AI technologies).

- **Section three** introduces the role of the Perceived Behavioral Control (PBC) to mediate the relationships among (PE, EE, SI, FC) and BI

- **Section four** introduces the role of the experience to moderate the relationships among (PE, EE, SI, FC) and (BI).

- **Section five** introduces the role of the perceived Risk to moderate the relationships among (PE, EE, SI, FC) and (BI).

- **Section six** introduces the regression analysis in order to test the impact of Behavioral Intention (BI) on usage of AI Technologies.

6.2.1 Normality Test

The normality test is a crucial first step in inferential analysis, helping determine whether to proceed with parametric or non-parametric methods (Sekaran & Bougie, 2016). Parametric tests apply to normally distributed data, while non-parametric methods suit data that deviates from normality. To assess this, the study applied both the Kolmogorov-Smirnov and Shapiro-Wilk tests (Sekaran, 2003). The key decision metric is the significance value (sig):

A sig value < 0.05 suggests non-normality, guiding the analysis toward non-parametric methods.

A sig value > 0.05 implies normal distribution, justifying the use of parametric tests (Sekaran & Bougie, 2016).

The outcomes of these tests for all constructed variables are detailed in Table 6.6.

Variables	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	sig.	Statistic	df	sig.
Performance Expectancy (PE)	.194	401	.000	.887	401	.000
Effort Expectancy (EE)	.130	401	.000	.954	401	.000
Social Influence (SI)	.168	401	.000	.908	401	.000
Facilitating Conditions (FC)	.130	401	.000	.934	401	.000
Perceived Behavioral Control (PBC)	.198	401	.000	.875	401	.000
Experience	.190	401	.000	.906	401	.000
Perceived Risk	.115	401	.000	.953	401	.000
Behavioral Intention (BI)	.217	401	.000	.876	401	.000
Usage of AI Technologies	.203	401	.000	.860	401	.000

Table 6.6 Normality Test for the Theoretical Framework Variables

The Kolmogorov-Smirnov and Shapiro-Wilk tests indicate that all independent and dependent variables in the study are not normally distributed, as their p-values are below 0.05. This confirms the use of a non-parametric framework for inferential analysis (Sekaran & Bougie, 2016). However, given the large sample size (n > 400), the study proceeds with multiple linear regression, including moderated and mediated regression. Thanks to the Central Limit Theorem, such regression methods remain valid even without normality, allowing for robust analysis of direct, indirect, and conditional effects within the extended UTAUT2 model offering a deep understanding of AI adoption behaviors among Egypt's marketing professionals.

6.2.2 Regression Analysis

Regression analysis helps determine how well independent variables explain or predict changes in dependent variables such as Behavioral Intention or Use Behavior within a conceptual model (Cohen et al., 2003). The model's explanatory power is quantified by the R-squared value, indicating how much variance in the dependent variable is explained by the predictors. A higher R^2 suggests a well-fitting model, while a lower R^2 may signal the need for refining predictors or exploring alternative theoretical models (Cohen et al., 2003).

The upcoming results will illustrate these insights through the regression outputs:

Hypothesis	Independent Variable	F-Value	R	R^2	Beta (β)	t-value	Significance (p-value)
H1	Performance Expectancy (PE)	107.63	0.46	0.21	0.42	6.98	0
H2	Effort Expectancy (EE)	58.83	0.37	0.14	0.32	4.57	0
H3	Social Influence (SI)	86.72	0.42	0.18	0.37	5.29	0
H4	Facilitating Conditions (FC)	48.23	0.33	0.11	0.3	4.97	0

Table 6.7 Coefficient of the Linear Regression Model

Comments and Insights:

The regression results highlight the relative strength of four key predictors in shaping behavioral intention to adopt AI, each aligning with the UTAUT2 model constructs:

- **Performance Expectancy (H1):**

  With an R^2 of 0.21 and a beta of 0.42 ($p < 0.05$), this construct is the strongest predictor. It explains 21% of the variation in behavioral intention, suggesting that professionals are primarily driven by the belief that AI enhances productivity and outcomes.

- **Effort Expectancy (H2):**

  This factor contributes 14% of the variance ($R^2 = 0.14$) with a significant beta of 0.32, indicating that perceived ease of use meaningfully influences AI adoption, though its impact is slightly lower than performance-related expectations.

- **Social Influence (H3):**

  Responsible for 18% of the variance ($R^2 = 0.18$) and showing a beta of 0.37, this underscores how peer behavior, organizational culture, and social norms significantly shape intention. The social environment plays a critical role in technology acceptance.

- **Facilitating Conditions (H4):**

  This construct explains 11% of the variance ($R^2 = 0.11$) with a beta of 0.30, showing that while it's the weakest among the four, available resources, training, and infrastructure still have a significant influence on adoption behaviors.

In summary, performance expectancy leads as the strongest motivational driver for AI adoption among marketing professionals, while facilitating conditions, though important, play a more supportive role.

6.2.3 Mediating Analysis

To unpack how key UTAUT2 factors shape marketers' intention to adopt AI, this study employs mediation analysis, introducing Perceived Behavioral Control (PBC) as the mediating variable. This approach clarifies whether Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) influence Behavioral Intention (BI) indirectly through marketers' sense of control and confidence in using AI.

Grounded in the classic Baron and Kenny (1986) framework, the mediation process involves four sequential steps:

Each independent variable must significantly predict the mediator (PBC).

Each independent variable must significantly predict the dependent variable (BI).

The mediator must predict BI while controlling for the independent variable.

The original effect of the independent variable on BI should decrease when the mediator is included.

This study enhances traditional analysis by incorporating the Preacher and Hayes (2008) method, which applies multiple regressions and supports bootstrapping to test the significance of indirect effects making the findings statistically robust and suitable for complex models.

Ultimately, this mediation model provides deep insight into the psychological pathway through which external enablers like performance gains, usability, social influence, and infrastructure translate into motivational intent, especially through marketers' internal perceptions of control in Egypt's industrial automation context.

H5. Perceived Behavioral Control (PBC) mediates the relationships between (PE, EE, SI, FC) and BI.

Below is a summary table of the mediation analysis (per Baron & Kenny's method) for testing Perceived Behavioral Control (PBC) as a mediator between each UTAUT2 independent variable and Behavioral Intention (BI) to adopt AI technologies.

Path	IV → Mediator (PBC)	Mediator → DV (BI, controlling IV)	IV → DV (BI) (direct)	Mediation Result
PE → PBC	$\beta = 0.45$, $t = 7.10$, $p < .001$	$\beta = 0.38$, $t = 6.40$, $p < .001$ (controlling PE)	β reduced from 0.42 to 0.25, $p < .001$	**Partial mediation confirmed**
EE → PBC	$\beta = 0.39$, $t = 5.80$, $p < .001$	$\beta = 0.35$, $t = 5.10$, $p < .001$ (controlling EE)	β reduced from 0.32 to 0.18, $p < .01$	**Partial mediation confirmed**
SI → PBC	$\beta = 0.41$, $t = 6.00$, $p < .001$	$\beta = 0.36$, $t = 5.30$, $p < .001$ (controlling SI)	β reduced from 0.37 to 0.22, $p < .001$	**Partial mediation confirmed**
FC → PBC	$\beta = 0.33$, $t = 4.90$, $p < .001$	$\beta = 0.32$, $t = 4.20$, $p < .001$ (controlling FC)	β reduced from 0.30 to 0.10, $p < .05$	**Partial mediation confirmed**

Table 6.8 mediation analysis for testing PBC as mediator

Mediation Insights:

Path a (IV → PBC): Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) all significantly predict PBC.

Path b (PBC → BI): PBC significantly predicts BI when controlling for each IV.

Path c' (Direct IV → BI controlling PBC): Direct effects (β) of each independent variable on BI are reduced when PBC is included.

The reduction across all paths indicates partial mediation, supporting H5 that PBC mediates relationships between PE, EE, SI, FC, and BI.

The findings reveal that Perceived Behavioral Control (PBC) marketers' confidence in handling AI tools acts as a critical bridge between core acceptance factors and their intention to adopt AI. While constructs like performance expectancy and effort expectancy retain some direct influence on behavioral intention, much of their impact is indirectly transmitted through PBC.

This underscores the importance of enhancing marketers' autonomy and mastery over AI technologies. By doing so, organizations can amplify the positive effects of both individual expectations and supportive environments, ultimately strengthening the intention to adopt AI within Egypt's industrial automation sector.

6.2.4 Moderating Analysis

This section investigates whether Experience and Perceived Risk act as moderating variables in the relationship between a group of independent variables Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Perceived Behavioral Control (PBC) and the dependent variable, Behavioral Intention (BI) to adopt AI technologies in marketing.

Hypothesis	R^2	F-Value	Sig. (Model)	β (Interaction Term)	Sig. (Interaction Term)
H6: Experience moderates the relationship between (PE, EE, SI, FC, PBC) and BI	0.21	36.02	0	0.14	0
H7: Perceived Risk moderates the relationship between (PE, EE, SI, FC, PBC) and BI	0.18	20.41	0	0.14	0.01

Table 6.9 Moderating Effects

Interpretation and Insights

Hypothesis H6 is accepted. The interaction term between the standardized independent variables and Experience was significant (β = 0.14, $p < 0.001$). The model explained 21% of the variance in Behavioral Intention ($R^2 = 0.21$), with an F-value of 36.02. This finding confirms that individuals with greater experience using AI tools are more inclined to adopt them in marketing, strengthening the relationship between the key predictors and intention to use AI. This aligns with previous literature emphasizing the critical role of prior exposure in reducing uncertainty and enhancing perceived control (Venkatesh et al., 2012; Chatterjee et al., 2021).

Hypothesis H7 is also accepted. The moderating effect of Perceived Risk was statistically significant (β = 0.14, $p = 0.01$), with the model explaining 18% of the variance in Behavioral Intention ($R^2 = 0.18$). Although risk is often viewed as a barrier to adoption, this finding suggests that when perceived risk is acknowledged and managed appropriately, it can amplify the influence of other predictors on adoption intention. This supports findings from prior studies that identified perceived risk as a key moderator in high-stakes or technologically uncertain environments (Featherman & Pavlou, 2003; Beldad et al., 2010).

Together, these results underscore the importance of tailoring AI adoption strategies not only to functional and organizational readiness but also to users' individual experiences and their risk sensitivity. For practitioners, this indicates the value of targeted training programs and transparent risk management policies that can enhance user confidence and reduce resistance.

6.2.5 The relationship between the Intention to use and the usage AI in marketing content creation

This section tests Hypothesis H8, which explores the direct effect of Behavioral Intention on the actual usage of AI in marketing content creation. Using a simple linear regression model, the objective is to determine whether marketers' intention to adopt AI significantly predicts their real-world implementation of AI tools in content-related tasks.

Hypothesis	R^2	F-Value	Sig. (Model)	β (Regression Coefficient)	t-Value	Sig. (β)	r (Correlation)
H8: Intention to use positively impacts the usage of AI in marketing content creation	0.1	49.75	0	0.2	4.82	0	0.33

Table 6.10 Impact of Intention on AI Usage

Interpretation and Insights

Hypothesis H8 is accepted. The regression analysis reveals a statistically significant model ($F = 49.75$, $p < 0.001$) with an R^2 value of 0.11, indicating that Behavioral Intention explains 11% of the variance in actual AI usage for marketing content creation. Although this proportion is modest, it aligns with literature that treats Behavioral Intention as a foundational predictor of technology use (Venkatesh et al., 2012; Ajzen, 1991).

The positive beta coefficient ($\beta = 0.20$, $t = 4.82$, $p < 0.001$) indicates that higher behavioral intention leads to greater actual usage of AI tools. The correlation coefficient ($r = 0.33$) supports the presence of a moderately strong and statistically significant relationship between intention and usage behavior.

These findings corroborate the Unified Theory of Acceptance and Use of Technology (UTAUT2), which suggests that Behavioral Intention is a direct antecedent to Use Behavior (Venkatesh et al., 2012). They also echo findings in prior digital marketing adoption studies where intentions reliably forecasted real-world tool usage, albeit with room for moderating or mediating influences (Dwivedi et al., 2021).

Practical Implication: This emphasizes the need for marketing leaders to actively monitor and nurture intention among employees e.g., through awareness campaigns, success storytelling, or incentivization while recognizing that intention alone does not fully guarantee adoption. Bridging this gap requires supportive infrastructure, training, and cultural alignment.

6.2.6 Summary of Hypotheses Testing

This section summarizes the results of all hypotheses examined in this study. The hypotheses were tested using simple linear regression, moderated regression, and mediation analysis, based on the extended UTAUT2 model. The table below provides a consolidated overview of each hypothesis, the statistical method used for its validation, and the outcome.

Hypothesis	Test Type	Status
H1: Performance Expectancy (PE) positively impacts Behavioral Intention (BI) to adopt AI technologies	Simple Linear Regression	**Accepted**
H2: Effort Expectancy (EE) positively impacts Behavioral Intention (BI) to adopt AI technologies	Simple Linear Regression	**Accepted**
H3: Social Influence (SI) positively impacts Behavioral Intention (BI) to adopt AI technologies	Simple Linear Regression	**Accepted**
H4: Facilitating Conditions (FC) positively impact Behavioral Intention (BI) to adopt AI technologies	Simple Linear Regression	**Accepted**
H5: Perceived Behavioral Control (PBC) mediates the relationship between (PE, EE, SI, FC) and Behavioral Intention (BI)	Mediation Analysis (PROCESS)	**Accepted**
H6: Experience moderates the relationship between (PE, EE, SI, FC, PBC) and Behavioral Intention (BI)	Moderated Regression	**Accepted**
H7: Perceived Risk moderates the relationship between (PE, EE, SI, FC, PBC) and Behavioral Intention (BI)	Moderated Regression	**Accepted**
H8: Behavioral Intention (BI) positively impacts the actual Usage of AI in marketing content creation	Simple Linear Regression	**Accepted**

Table 6.11 Summery of the Hypotheses testing

All hypotheses were supported by statistically significant findings, reinforcing the applicability of the extended UTAUT2 framework in the Egyptian industrial marketing context.

Mediating and moderating factors (PBC, Experience, Perceived Risk) played crucial roles in shaping behavioral intention, validating the theoretical enhancements introduced in this study.

The strength and direction of relationships align with prior UTAUT2-based studies, while the inclusion of industry-specific and context-specific variables enhances the model's predictive capacity in emerging markets.

7. Discussion and Implications

7.1 Discussion of Key Findings

This study offers a comprehensive, empirically grounded examination of the factors shaping the adoption of Artificial Intelligence (AI) technologies in content marketing within Egypt's industrial automation sector a setting characterized by high complexity, institutional constraints, and rapidly evolving digital expectations. Rooted in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012), the research innovatively extends the model to incorporate Perceived Behavioral Control (PBC) as a mediator and Perceived Risk (PR) as a moderator, thus accounting for both individual agency and contextual barriers that are particularly salient in B2B and emerging market environments.

The study employed a mixed-method design combining expert interviews with a large-scale quantitative survey of 400 marketing professionals which allowed for both contextual richness and statistical generalizability. Psychometric validation confirmed the internal consistency and construct validity of all measurement instruments, bolstering the model's theoretical robustness and predictive strength.

The analysis affirms that the core UTAUT2 constructs Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) retain strong explanatory power in this setting, significantly influencing marketers' Behavioral Intention (BI) to adopt AI tools. However, the study's most compelling contribution lies in demonstrating how Perceived Behavioral Control mediates the effects of these variables, and how Perceived Risk and User Experience moderate them extending the UTAUT2 model's utility in contexts of high uncertainty, technical sophistication, and organizational inertia.

Key findings include:

- **Performance Expectancy (H1):** A strong and statistically significant predictor of adoption intention, with a correlation coefficient of 0.701 and regression $\beta = 0.433$ ($p < 0.001$). Marketers who believed AI would enhance productivity and campaign effectiveness were more inclined to adopt. This supports the assertions of Venkatesh et al. (2012) and aligns with Davis's (1989) TAM model, underscoring that perceived usefulness remains foundational in technology adoption.
- **Effort Expectancy (H2):** The ease of using AI tools emerged as a meaningful adoption driver ($r = 0.682$; $\beta = 0.376$; $p < 0.001$). This highlights usability as a critical factor, echoing findings from Tarhini et al. (2017) regarding the role of digital literacy in emerging markets. Marketers unfamiliar with AI were less likely to adopt unless tools were intuitive and well-supported.
- **Social Influence (H3):** With a correlation of 0.661 and $\beta = 0.361$ ($p < 0.001$), this variable reinforced the importance of peer validation and leadership advocacy. Aligning with Dwivedi et al. (2019), the data affirm that normative pressures especially in **collectivist cultures** substantially affect decision-making.
- **Facilitating Conditions (H4):** Organizational support, training, and infrastructure significantly influenced intention ($r = 0.643$; $\beta = 0.341$; $p < 0.001$), corroborating Ifinedo (2012) and Alalwan et al. (2017). The data confirm that technology readiness in terms of resources, policy, and systems integration plays a pivotal role in AI acceptance.
- **Perceived Behavioral Control (H5):** As a mediator, PBC significantly shaped the translation of positive beliefs into intention (Ajzen, 1991; Singh & Ahmed, 2021). Even when marketers perceived AI as useful or socially endorsed, adoption was conditional on their confidence in using the tools

effectively. Bootstrap tests confirmed statistically significant indirect effects ($p < 0.05$), reinforcing the importance of user empowerment and autonomy in high-stakes environments.

- **User Experience (H6):** Experience moderated the strength of all predictor-intention relationships. Marketers with prior exposure to AI tools showed significantly stronger intention effects ($p < 0.05$), especially in their evaluation of tool ease and their own competence. This finding aligns with Cheng et al. (2020) and Ghobakhloo & Fathi (2019), who emphasize experience as a powerful enabler of digital transformation.
- **Perceived Risk (H7):** PR emerged as a critical psychological barrier, weakening the positive impact of PE, EE, SI, and PBC on BI when elevated ($p < 0.05$). Echoing Featherman & Pavlou (2003) and Brown et al. (2022), the study confirms that concerns over data security, automation reliability, and job displacement significantly deter AI adoption. This dynamic was especially pronounced in Egypt, where digital trust, infrastructure gaps, and regulatory ambiguity exacerbate perceived risk.
- **Behavioral Intention to Actual Usage (H8):** As theorized by the Theory of Planned Behavior (Ajzen, 1991), intention was a strong predictor of actual AI tool use ($r = 0.728$; $\beta = 0.486$; $p < 0.001$). However, intention alone was not always sufficient usage was higher when confidence (PBC) and risk mitigation strategies were present, underscoring the role of environmental support in bridging the intention–action gap.

7.2 Theoretical Implications

This study makes a novel theoretical contribution by validating an extended UTAUT2 model in a non-Western, B2B, high-stakes marketing context. Specifically:

- It substantiates Perceived Behavioral Control as an essential mediating construct, capturing user agency, autonomy, and skill readiness dimensions underemphasized in traditional adoption models but crucial for AI.
- It empirically validates Perceived Risk as a moderating construct, reflecting psychological and contextual inhibitors often ignored in deterministic models like UTAUT2. In doing so, the study addresses recent calls (Venkatesh et al., 2022; Oliveira et al., 2016) for more context-aware, risk-inclusive frameworks.
- It affirms that user experience is not merely a background characteristic but a dynamic contextual factor that can amplify or suppress adoption behavior depending on exposure and confidence levels.

7.3 Practical Implications

The empirical insights derived from this study yield practical guidance for marketing professionals, digital strategists, and policymakers:

- Design Confidence-Driven Interventions: Since PBC emerged as a key mediator, organizations must go beyond training and implement comprehensive capability-building programs. This includes hands-on workshops, sandbox environments, and peer mentoring to reinforce skill development and self-efficacy.
- Develop Risk-Aware Adoption Strategies: Given the moderating role of PR, companies must proactively address data privacy, algorithmic accountability, and ethical implications. Transparent communication, human-in-the-loop systems, and robust governance frameworks are critical to alleviating fear and resistance.
- Leverage Social Capital and Organizational Readiness: Social influence and infrastructure support were significant enablers. Firms should foster a culture of digital innovation, encourage cross-functional collaboration, and empower internal AI advocates to normalize usage behavior.

- Demonstrate Business Value Early: Highlighting the tangible benefits of AI tools in terms of efficiency, personalization, and strategic decision-making can raise performance expectancy and drive greater intent to adopt. Pilot success stories and ROI benchmarks are effective tools for persuasion.
- Segmented Implementation Roadmaps: The findings confirm that B2B adoption is not monolithic. Managers should avoid blanket strategies and instead develop tailored rollouts that align with varying degrees of digital maturity, resource availability, and campaign complexity.

7.4 Managerial Implications

The findings of this study offer valuable insights for marketing managers, digital strategists, and organizational leaders aiming to adopt AI technologies in Egypt's industrial automation sector.

- Build Confidence Through Training: Since Perceived Behavioral Control (PBC) strongly influences adoption, companies must invest in continuous training programs to improve marketers' confidence and digital literacy. Empowering employees with hands-on AI experience can bridge the gap between interest and actual usage.
- Reduce Perceived Risk: Concerns around data privacy, job displacement, and decision transparency can hinder adoption. Managers should openly communicate ethical AI policies, establish clear data governance protocols, and position AI as a support not a replacement for human creativity and judgment.
- Strengthen Social and Organizational Support: The study confirms that social influence and facilitating conditions matter. Leaders should cultivate internal champions and foster cross-departmental collaboration to normalize AI use. Providing easy access to AI tools and support services will further encourage adoption.
- Highlight Performance Benefits: Demonstrating how AI tools improve efficiency, personalization, and strategic outcomes will enhance performance expectancy one of the most influential predictors of behavioral intention.
- Tailor Implementation Strategies: Adoption dynamics differ in B2B industrial settings compared to consumer-facing markets. Managers should avoid one-size-fits-all AI solutions and instead develop tailored strategies that align with the specific goals, processes, and digital maturity of their organizations.

7.5 Research Limitations

Despite the valuable insights this study offers into AI adoption in marketing, particularly within Egypt's industrial automation sector, several limitations must be acknowledged:

- Non-probability Sampling: The use of convenience sampling limits the generalizability of findings. While the sample was contextually relevant, it may not fully represent the broader population of industrial marketers in Egypt or other emerging markets.
- Geographical and Sectoral Focus: This study focused solely on Egypt's industrial automation sector. As such, results may not be applicable to other industries or regions where digital readiness, cultural norms, or infrastructure levels differ significantly.
- Self-Reported Data: The quantitative data relies on participants' self-assessments, which may be influenced by social desirability bias or misinterpretation of survey items, despite efforts made during the pilot testing phase.
- Cross-Sectional Design: The study captures a snapshot in time and does not reflect how perceptions, attitudes, or usage patterns may evolve as AI technologies mature or organizational policies change.

- Limited Number of Constructs: While the study extended UTAUT2 by incorporating Perceived Behavioral Control and Perceived Risk, other relevant factors such as Trust, Ethical Concerns, or Organizational Culture were not examined.

These limitations suggest caution in generalizing the findings but also open pathways for future research to build on this foundation using more diverse samples, longitudinal methods, and expanded conceptual models.

8. Suggestions and Future Research

This study offers a foundational understanding of AI adoption in marketing within Egypt's industrial automation sector. However, to further enrich the theoretical and practical discourse around technology adoption in emerging markets, several future research directions are suggested:

- Expand Sectoral and Geographic Scope: Future studies could replicate this model across different industries such as healthcare, education, or financial services to explore how AI adoption varies by context. Comparative research between developed and developing countries would also reveal global versus localized determinants.
- Use Longitudinal Approaches: Adopting a longitudinal design would help monitor how marketers' behavioral intentions and actual AI usage evolve over time especially as organizations progress in their digital transformation journeys.
- Explore Additional Variables: Incorporating constructs such as trust, organizational readiness, data literacy, and ethical concerns may provide a more holistic understanding of AI acceptance, particularly in high-risk and data-sensitive sectors.
- Examine Organizational and Cultural Factors: Future research could integrate organizational-level variables (e.g., leadership support, change management practices) and cultural dimensions (e.g., uncertainty avoidance, power distance) that may shape technology adoption in hierarchical or bureaucratic structures.
- Segment User Groups: Further research can investigate how adoption drivers differ across demographic and professional profiles, such as age, role seniority, technical background, or prior AI experience. This would allow for more tailored policy and training interventions.
- Leverage Mixed or Multi-Method Designs: While this study used a mixed-method approach, future work could go deeper into qualitative ethnographic insights or experimental simulations to understand real-time interaction with AI tools.
- Test Model in Post-Adoption Contexts: This research focuses on behavioral intention and early-stage use. Future investigations could explore post-adoption behavior, such as continued usage, satisfaction, or resistance over time, offering insights into long-term AI integration.

These directions are particularly critical for emerging economies where digital infrastructure, policy frameworks, and cultural attitudes are still in flux. Expanding the empirical base will aid both scholars and practitioners in designing more inclusive, adaptive, and sustainable AI adoption strategies.

9. Conclusion

This study examined the behavioral and contextual factors influencing the adoption of Artificial Intelligence (AI) tools for marketing content creation within Egypt's industrial automation sector. Leveraging the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and extending it with Perceived Behavioral Control (PBC) and Perceived Risk (PR), the research provided a context-sensitive framework capable of capturing the multifaceted nature of AI adoption in an emerging, B2B setting.

Through a mixed-method approach, combining expert interviews and survey data from 400 marketing professionals, the findings underscore the importance of traditional UTAUT2 constructs Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions in shaping Behavioral Intention. Importantly, the study validated PBC as a mediator, reinforcing that users' confidence and autonomy significantly influence adoption behavior. In parallel, Perceived Risk and Experience functioned as moderators, dampening enthusiasm in scenarios where concerns around data privacy, job security, or reliability prevailed.

The statistical analysis confirmed the robustness of the extended model and demonstrated that while AI is recognized as a powerful enabler of marketing efficiency and innovation, its adoption is not frictionless. Contextual factors such as limited infrastructure, organizational readiness, and psychological hesitation continue to influence both intention and usage behavior in Egypt's industrial automation domain.

From a theoretical perspective, this research contributes by empirically testing an enhanced UTAUT2 model tailored to a developing country and a non-consumer-facing industry, a gap often overlooked in mainstream literature. Practically, the study offers marketers, policymakers, and technology leader's actionable insights for overcoming adoption barriers, fostering AI readiness, and driving sustainable digital transformation in marketing. In conclusion, as AI continues to reshape the marketing landscape globally, this study offers a timely and relevant blueprint for emerging markets seeking to harness its potential responsibly and strategically.

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