



Utilizing Factor Analysis and Multiple Regression to Establish Evaluation Criteria for Maturity Models

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Abstract

This research aimed to establish evaluation criteria for maturity models by utilizing factor analysis and multiple regression. Their integration provided a systematic approach to defining operational performance tasks within each maturity level. The research results demonstrated how this approach was used to create tailored evaluation criteria in the maturity model for a digital marketing context, where providing customer care, delivering new experiences, and creating new processes with establishing partnerships were the critical evaluations for purchasing intentions. These factors were mapped in each evaluation criterion of the maturity level, providing a clear structure for improvement guidelines. The proposed method reduced the development time for the maturity model by minimizing the requirement for consulting experts or requiring conditions that had not yet fully established operational standards. This approach represented a novel idea for integrating empirical models derived from factor analysis and regression to establish evaluation criteria for maturity models. This idea facilitated the rapid and flexible creation of maturity models suitable for specific environments or contexts where standardized development criteria had yet to be fully defined.

Keywords: Factor Analysis, Multiple Regression, Intention to Purchase, Maturity Model



Introduction

In exploratory research, statistical techniques such as factor analysis and multiple regression have been widely applied to identify key factors influencing decision-making. Factor analysis simplifies complex data by grouping related variables into underlying components, while multiple regression predicts the impact of these factors on a dependent variable. These methods have been extensively used to examine purchasing intentions and behavioral patterns across various contexts (Alam et al., 2019; Jairak, 2016; Sin et al., 2012; Jairak et al., 2010).

Despite their effectiveness in analyzing influencing factors, these techniques have rarely been integrated into the development of maturity models, which serve as structured frameworks for assessing an organization's capability and development level over time.

A maturity model typically defines progressive stages, each representing increasing competence, efficiency, or sophistication within a particular domain. Organizations use these models to evaluate their current state, identify gaps, and set strategic goals for improvement. Traditionally, the assessment criteria for each stage are established based on expert opinions, industry standards, or best practices, which may not always be applicable in emerging or rapidly changing contexts (Rose, 2013).

This research proposes a novel approach by incorporating factor analysis and multiple regression to establish evaluation criteria for maturity models empirically. The evaluation criteria in this study consist of key operational performance tasks corresponding to different maturity levels. These criteria were selected based on their relevance to purchasing intentions in a digital marketing context, where factors such as providing customer care, delivering new experiences, and creating new processes with strategic partnerships play a crucial role in influencing consumer decisions (Jairak, 2024).

By leveraging statistical insights, this method enables a more systematic and data-driven identification of assessment criteria for each maturity level, reducing reliance on subjective judgment. One key challenge in defining these evaluation criteria is ensuring their applicability across different organizational contexts.

Traditional methods of maturity model development rely on industry benchmarks, which may not be well-suited for rapidly evolving sectors or emerging business environments. Additionally, expert-driven assessments can be time-consuming and



subjective, leading to variations in the interpretation of maturity levels (deBruin, 2007; Rose, 2013). By integrating factor analysis and multiple regression, this study provides an empirical foundation for establishing transparent, objective evaluation criteria. This facilitates the creation of adaptable models in new and evolving contexts. This approach ensures that organizations can assess and enhance their capabilities based on empirical evidence rather than relying solely on expert opinions or predefined industry standards.

Research Objectives

This study aimed to define evaluation criteria for assessing the performance of internal operations within a customized maturity model by analyzing the model results obtained from factor analysis and multiple regression techniques.

Literature Review and Conceptual Framework and Research Hypothesis

Factor Analysis and Multiple Regression in Predictive Analysis

Factor analysis and multiple regression are powerful statistical methods used in academic research to examine relationships between variables and predict outcomes. Factor analysis helps identify underlying structures within large datasets by grouping correlated variables into distinct factors, revealing shared characteristics or behaviors (Hair et al., 2010). This method is extensively applied in consumer behavior, marketing, and information systems to discover new influencing factors, such as determinants of purchase intention for energy-efficient household appliances or real estate (Alam et al., 2019; Wonggotwarin & Kim, 2017).

Multiple regression, on the other hand, is a predictive modeling technique that determines the impact of multiple independent variables on a dependent variable. Researchers often employ multiple regression following factor analysis to quantify the influence of extracted factors on behavioral outcomes, such as purchase intention (Al-Azzam & Al-Mizeed, 2021). For instance, Sin et al. (2012) utilized factor analysis to classify theoretical constructs before applying multiple regression to predict purchase behaviors.

While these techniques are commonly used in predictive analysis, their application in maturity models remains relatively underexplored. Maturity models are structured frameworks that assess organizational capabilities and progression over time, traditionally



based on expert judgment, industry benchmarks, or best practices (O'Regan, 2017; Rose, 2013). However, given the limitations of conventional validation methods in rapidly evolving business environments, integrating factor analysis and multiple regression offers a novel approach for empirically defining performance evaluation criteria within maturity models.

Maturity Models and the Integration of Factor Analysis and Multiple Regression

Maturity models provide structured frameworks for evaluating organizational development and performance across various domains. For instance, the Capability Maturity Model (CMM) has been widely adopted in industries to assess process maturity, project management capabilities, and technology adoption (O'Regan, 2017). However, as businesses encounter new operational challenges, researchers have sought to develop customized maturity models that reflect dynamic organizational needs and continuous improvement efforts (Kucinska-Landwójtowicz et al., 2024).

Performance evaluation within maturity models is traditionally based on qualitative assessments, including expert opinions and benchmarking against established industry standards (deBruin, 2007; Rose, 2013). However, these methods may not be suitable for emerging fields with standardized evaluation criteria still evolving. To address this gap, this study explores how factor analysis and multiple regression can be leveraged to empirically derive preliminary evaluation criteria for maturity models in new contexts. Using these statistical techniques, researchers can identify key operational performance factors corresponding to different maturity levels, offering a data-driven alternative to traditional assessment methods.

This integration aligns with previous studies that emphasize the need for empirical validation in maturity model development. For instance, Rose (2013) highlighted the importance of using data-driven approaches to enhance the objectivity and applicability of maturity models across diverse organizational settings. Similarly, recent research in digital marketing maturity models suggests that performance criteria should be informed by statistical analysis rather than relying solely on subjective expert judgment (Jairak, 2024). By incorporating factor analysis and multiple regression, this study introduces a new



methodology for developing evaluation criteria within maturity models, which can be applied in initial studies exploring maturity model development.

Research Methods

The researcher can present the research methods for this study as follows.

Step 1: Research Project Preparation

In this initial phase, the researcher investigates relevant literature to build an initial concept for utilizing factor analysis and multiple regression to clarify the evaluation criteria in maturity models. Additionally, this phase ensures that the study aligns with ethical guidelines, particularly concerning research involving human data collection. However, this study does not include direct data collection from human respondents, as it utilizes secondary data from prior empirical studies (With the certification number IRBCMRU 2024/451.24.09).

Step 2: Analysis and Synthesis of Related Research

This phase involves an in-depth examination of existing studies related to factor analysis and multiple regression, including the researcher's previous works and relevant external research. Factor analysis and multiple regression were selected for this study because they allow for empirically identifying key variables influencing the building of evaluation criteria for maturity models.

Instead of conducting new hypothesis testing, this study builds upon previous empirical models that have already demonstrated statistically significant relationships between independent and dependent variables. The researcher reviews past studies that applied multiple regression analysis to assess the impact of various factors, ensuring that only variables with confirmed statistical significance (p -values < 0.05) are considered for further analysis in Step 3.

Step 3: Expand on Analytical Results

Building upon prior empirical studies utilizing multiple regression, this phase introduces a new approach to refining evaluation criteria within maturity models. The researcher examines how previously validated statistical findings can be applied to define assessment criteria at different maturity levels. To ensure the robustness of this approach,



secondary data from earlier studies are reexamined to confirm the statistical significance and relevance of the identified factors. As established in prior research, the variables selected for defining assessment criteria have been empirically verified to influence organizational progression.

Research Results

Findings from the Previous Empirical Model

The literature review discusses various approaches to evaluating the quality of e-commerce websites (Cao et al., 2012; DeLone & McLean, 2003; Rababah et al., 2011). Nevertheless, DeLone & McLean's (2003) model is particularly noteworthy in website evaluation, as it assesses e-commerce websites from Information Quality, System Quality, and Service Quality. Some studies propose additional criteria for website evaluation (Bauer et al., 2006; Wolfinbarger & Gilly, 2003). For instance, Bauer et al. (2006) introduced the eTransQual assessment, focusing on websites serving European consumers. This assessment introduces five distinct factors for e-commerce website evaluation: Customer Service, Website Process, Reliability, Website Design, and Entertainment on websites.

Our previous study assessed website quality and its impact on purchase intention in Thailand by surveying a sample of Thai shoppers. We obtained responses from 2,151 participants through an online questionnaire. The findings indicated that online purchase factors deviate slightly from the DeLone & Mclean model. Specifically, the reclassification involves a shift from 1) Information Quality, 2) System Quality, and 3) Service Quality to 1) Quality of Information Security, 2) Quality of Functionality and Design, and 3) Quality of Service. When prioritized by significance, functionality and design quality emerged as the most influential factors affecting purchase intention, followed by information security and service quality (Jairak, 2016). Empirical evidence reveals that there have been changes in the composition of factors influencing purchase intention.

However, these changes do not significantly impact the original DeLone & McLean model. The quality of information, website security systems, and service quality continue to play crucial roles in fostering trust in the website and shaping purchasing decisions. The diagram in Figure 1 illustrates the elements that impact online purchases for e-commerce websites in Thailand.

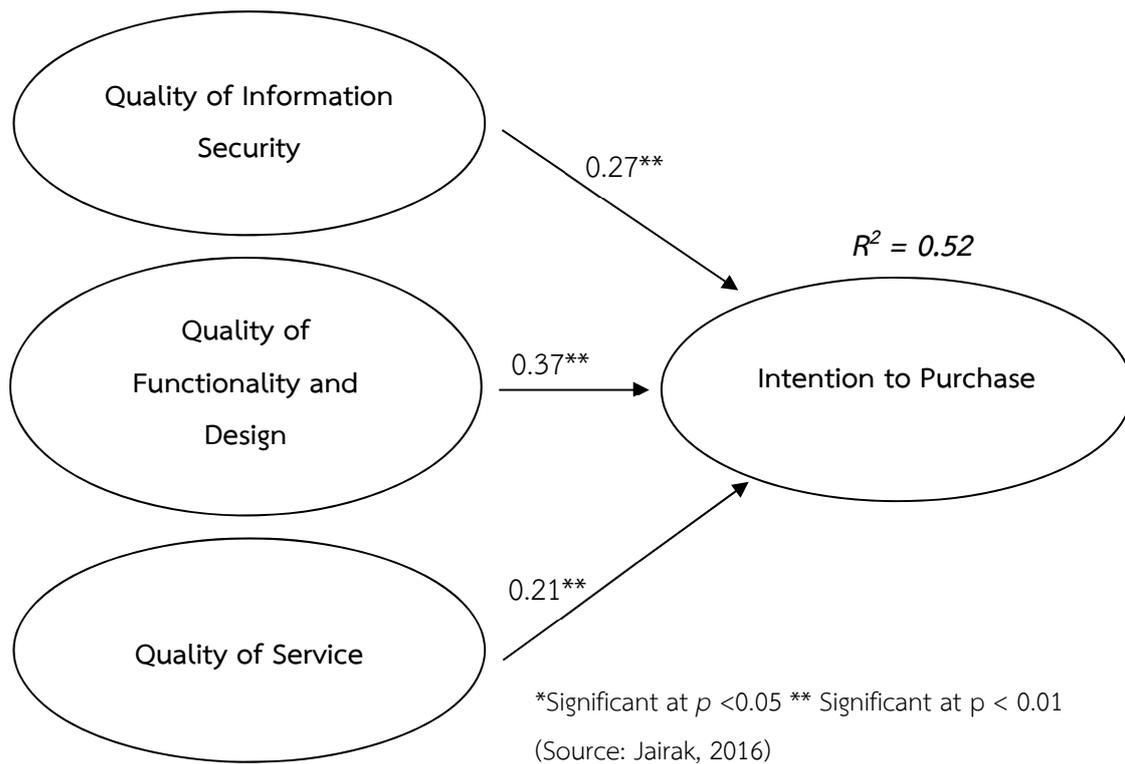


Figure 1: Empirical study illustrating the influence of factors on purchase intention among a sample of Thai shoppers in a website shopping scenario (Jairak, 2016).

The final results of the empirical research, derived from factor analysis and multiple regression analysis presented in Figure 1, demonstrate that the proposed model is consistent with the trust buying process through e-commerce websites. Building trust in e-commerce services starts with evaluating the website's trustworthiness during the information phase through the settlement phase; in the information phase, customers assess the quality of the information provided. Subsequently, it progresses to the agreement phase, where customers assess the system quality. They worry about proper web design, good functionality, security readiness, and prompt online ordering for products or services. Upon completing the purchase and receiving the products or services after post-payment, customers evaluate the quality of service supported by the online seller, representing the overall process within the settlement phase. The customer's evaluation of the e-commerce website's buying and selling process, as contextually discussed, is visually represented in Figure 2.

Information Phase	Agreement Phase	Settlement Phase
Quality of Service		
Quality of Functionality and Design		
Quality of Information Security		

Figure 2: The trust formation process leads to the intention to purchase e-commerce services. (Jairak & Praneetpolgrang, 2011).

The conceptual process for assessing customer trust in e-commerce websites, as depicted in Figure 2, can be leveraged to establish a model for managing website trust known as the Trust Capability Maturity Model (TCMM). This model evaluates the trustworthiness of e-commerce websites across five progressive levels: 1) Level 1: Online sellers lack a professional website suitable for long-term e-commerce activities. 2) Level 2: The website begins to establish fundamental trust. 3) Level 3: The website establishes a defined, reliable standard transaction process. 4) Level 4: Trustworthiness revolves around customer-centric services, and 5) Level 5: E-commerce website managers consistently provide excellent customer service (Jairak & Praneetpolgrang, 2011). Table 1 shows the summary details of the TCMM assessment.



Table 1: An overview of trust maturity levels in TCMM

Level	Focus	Performance Tasks
5: Optimization	Maintaining customer trust	<ul style="list-style-type: none"> ● Value creation ● Customer protection ● Global reach
4: Manage and control	Customer-centric	<ul style="list-style-type: none"> ● Control and monitor ● Purchasing decision support ● Customization progress ● Customer responsiveness
3: Standard	Setting standard for B2C e-commerce application	<ul style="list-style-type: none"> ● Web security and privacy ● Web reliability ● Account management ● Information flow and user interaction
2: Definition	Building initial trust	<ul style="list-style-type: none"> ● Valid profile ● Up-to-date information ● Proper web design ● Purchasing policy
1: Initial	Undefined trust	<ul style="list-style-type: none"> ● This level of operation has yet to establish trust.

Source: Jairak & Praneetpolgrang (2013)

The identification of performance tasks required at each level within the maturity model, as outlined in Table 1, typically involves using standard or best practices in each domain (Jairak & Praneetpolgrang, 2011). However, we have yet to come across any research that utilizes predictive models based on factor analysis and multiple regression to pinpoint performance tasks during each stage of development in the maturity model. The combination of the predictive model shown in Figure 1, the trust assessment based on website quality presented in Figure 2, and the operational details of each phase of the TCMM in Table 1 provide valuable insights for the researcher to identify the feasibility of connecting the predictive model derived from empirical research using factor analysis and multiple regression for describing performance tasks, enable the researcher to create

quality assessments aligned with the evaluation criteria at each level in the TCMM model, as described in Table 2 in the following section.

Establishing Evaluation Criteria in Maturity Level

As discussed in the previous section, the empirical findings derived from factor analysis and multiple regression offer a connecting idea for establishing evaluation criteria that precisely align with the maturity model's specific operational context.

Table 2: Connecting the predictive model derived from the empirical study to website assessment in TCMM

Level	Focus	Performance Tasks		
		Information Security	Functionality and Design	Service Quality
5: Optimization	Maintaining customer trust	●Customer protection	●Global reach	●Value creation
4: Manage and control	Customer-centric	●Control and monitor	●Customization progress ●Purchasing decision support	●Customer Responsiveness
3: Standard	Setting standard for B2C e-commerce application	●Web security and privacy	●Web reliability ●Information flow and user interaction	●Account management
2: Definition	Building initial trust	●Valid profile ●Up-to-date information	●Proper web design	●Purchasing policy
1: Initial	Undefined trust	●This level of operation has yet to establish trust.		

Source: Jairak & Praneetpolgrang (2013); Jairak (2016)

Table 2 visually illustrates the connection and integration of the predictive model utilizing data obtained from empirical research. The objective is to identify performance tasks within the quality components of the predictive model, as depicted in Figure 1. For



example, at level 2 of the TCMM, performance tasks related to the quality component of information security encompass a valid profile and up-to-date information used for assessing website quality. This discovery highlights the potential utilization of a predictive model, examined via factor analysis and multiple regression, in identifying evaluation criteria within the maturity model.

By employing a reverse process, we can leverage insights from factor analysis and multiple regression to evaluate the developmental stages within the maturity model. Consequently, this approach replaces the dependence on performance task identification from established standards or traditional best practices. This innovative methodology empowers researchers to craft novel maturity models in varied contexts by performing empirical studies to identify performance tasks at each level. Researchers can then use the question items for each factor within the model to create the initial idea for guidelines that describe performance tasks at each newly developed maturity model level. The following section will present details of expanding the maturity model in the new context.

Expanding the Maturity Model in the New Context

Integrating empirical research findings from factor analysis and multiple regression to design evaluation criteria in a maturity model can reflect a new perspective on applying a new maturity model in a novel operational environment or address the specific challenges organizations face. For instance, in digital marketing, organizations must respond to evolving customer behaviors driven by the increasing number of digital channels.

The current digital environment has transformed purchasing behaviors from traditional e-commerce, which relied heavily on websites, to digital marketing, which involves a variety of devices such as smartphones, tablets, and laptops. This shift presents new business challenges (Jairak, 2016; Jairak, 2024). The researcher's recent findings reveal that the key factors influencing purchase intention in digital marketing show a significant shift from traditional e-commerce models, as shown in Figure 1. Our recent study identifies three main factors influencing purchase intention in digital marketing, ranked by importance, which are as follows: 1) Delivering new experiences: This component involves creating value and delivering appealing and memorable experiences to customers. 2) Creating new processes with establishing partnerships: This component encompasses

developing innovative processes and collaborations that add value to products and services. 3) Providing customer care: This component refers to effective service and responsiveness to meet customer needs efficiently. Figure 3 illustrates the empirical model derived from our recent research findings. This approach expands the maturity model in the new context and presents the practical applications and outcomes in the final section of the research results.

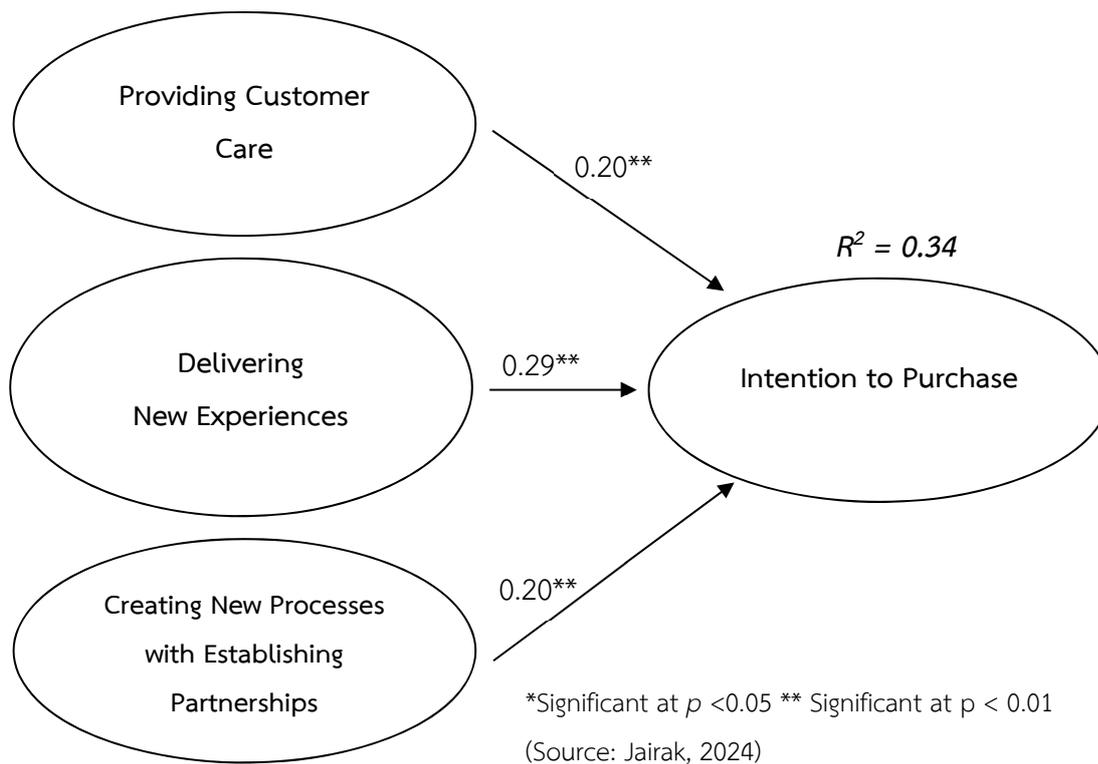


Figure 3: Empirical study illustrating the influence of factors on purchase intention among a sample of Thai shoppers in a digital marketing scenario (Jairak, 2024).

Practical Applications and Outcomes

The researcher used questions to represent operations within the empirical model derived from factor analysis and multiple regression, as depicted in Figure 3. These questions in each component were employed to identify the evaluation criteria for each performance task in the new maturity model, which aims to describe a new approach to online commerce conducted through multiple digital channels, referred to as digital marketing.



The question items for each component of the empirical model in Figure 3 were ranked based on the internal operation level. Compared to the previous maturity model levels presented in Table 2, this approach enabled the researcher to create a table that outlines operational capabilities across all levels in the newly developed maturity model, designed to support activities in digital marketing, as illustrated in Table 3.

Table 3: Connecting the predictive model derived from the empirical study to identify evaluation criteria in each maturity level for the new maturity model

Level	Focus	Performance Tasks		
		Providing Customer Care	Delivering New Experiences	Creating New Processes with Establishing Partnerships
5: Optimization	Sustaining Digital Marketing Ecosystems	<ul style="list-style-type: none"> ● Ensure consistent customer care 	<ul style="list-style-type: none"> ● Create engaging experiences to drive repeat purchases 	<ul style="list-style-type: none"> ● Develop innovative purchasing processes that deliver value and meet buyer needs
4: Manage and control	Enhancing Customer-Centric Experiences	<ul style="list-style-type: none"> ● Assign clear responsibility for customer care across channels 	<ul style="list-style-type: none"> ● Collect and utilize buyer data to create compelling value 	<ul style="list-style-type: none"> ● Collaborate with partners to design innovative data systems that impress customers
3: Standard	Implementing Consistent Digital Strategies	<ul style="list-style-type: none"> ● Effective customer lists and offer tailored discounts 	<ul style="list-style-type: none"> ● Present products that deliver value and align with buyer needs 	<ul style="list-style-type: none"> ● Develop new attractive products or services with partners
2: Definition	Establishing Basic Engagement	<ul style="list-style-type: none"> ● Implement clear customer care policies across channels. ● Engage with users interacting through likes, comments, and shares on social media. 	<ul style="list-style-type: none"> ● Promote brand initiatives effectively with accessible communication 	<ul style="list-style-type: none"> ● Introduce processes that add value for brand enthusiasts and supporters
1: Initial	Undefined Intention	<ul style="list-style-type: none"> ● There is no defined approach to creating purchase intention in digital marketing. 		

Source: Jairak & Praneetpolgrang (2013); Jairak (2024)

Table 3 illustrates the evaluation criteria for digital marketing maturity at different levels. Each level outlines specific focuses and performance tasks necessary for achieving maturity in customer care, delivering new experiences, and creating new processes with partnerships. At the Initial level (Level 1), there is no explicit intention to establish trust or create effective digital marketing strategies. The Definition level (Level 2) focuses on establishing foundational engagement. Brands introduce clear customer care policies, engage with users through social media interactions, and ensure that brand communications are accessible and relevant. They also introduce processes that add value for their supporters.

Brands consistently implement digital strategies at the Standard level (Level 3). Brands also effectively manage customer lists, provide personalized discounts, and partner with others to develop new, attractive products that meet consumer needs. For the Manage and Control level (Level 4), brands emphasize customer-centric experiences by assigning clear responsibilities for customer care, leveraging buyer data to deliver value, and collaborating with partners to create systems that enhance customer impressions.

Finally, the Optimization level (Level 5) focuses on sustaining robust digital marketing ecosystems. Brands ensure consistent and high-quality customer care, create engaging experiences that drive repeat purchases, and develop innovative purchasing processes to align with buyer needs. This progression in the proposed digital marketing maturity model demonstrates how brands evolve from undefined digital marketing practices to optimized systems that fully engage customers and create lasting value.

Research Discussion

The findings of this study highlight the potential of integrating factor analysis and multiple regression in maturity model development, offering a data-driven approach that moves beyond traditional reliance on expert opinions or industry benchmarks (deBruin, 2007; Rose, 2013). This integration aligns with the increasing emphasis in organizational research on leveraging empirical models to enhance the validity and applicability of maturity models in evolving business contexts (Kucinska-Landwójtowicz et al., 2024). By structuring evaluation criteria based on statistically significant factors influencing purchase



intention, the proposed methodology ensures that maturity model assessments are grounded in measurable operational performance rather than subjective assessments.

This research further extends the theoretical framework of maturity models by incorporating empirical evidence from the digital marketing domain (Jairak, 2024). Previous studies on maturity models, such as O'Regan (2017), primarily focused on capability progression in software engineering and business process management. However, our findings suggest that the core principles of maturity model development can be adapted to digital marketing contexts, where consumer engagement, process innovation, and service responsiveness are key determinants of organizational performance. This adaptation aligns with emerging research advocating for the domain-specific customization of maturity models to enhance their practical relevance (Kucinska-Landwójtowicz et al., 2024).

Moreover, the results support the theoretical underpinnings of consumer behavior models, particularly those related to trust and purchase intention in online environments (DeLone & McLean, 2003; Sin et al., 2012). The empirical evidence confirms that factors such as providing customer care, delivering new experiences, and creating new processes with strategic partnerships significantly impact purchase intention in digital marketing. These findings are consistent with prior studies emphasizing the role of consumer trust and perceived value in driving online purchasing decisions (Bauer et al., 2006; Wolfinbarger & Gilly, 2003).

Research Suggestions

This research proposes a technique combining factor analysis with multiple regression analysis to develop evaluation criteria for a maturity model. The findings indicate that this approach is well-organized when applied to new and specific contexts where traditional industry standards are yet to be established. By systematically deriving evaluation criteria from empirical data, this method reduces the uncertainty in early-stage maturity model development, ensuring that assessment criteria are aligned with actual performance determinants.

The results suggest that organizations seeking to develop customized maturity models should incorporate empirical modeling techniques to refine their evaluation



criteria. Specifically, businesses operating in dynamic sectors such as digital marketing can benefit from adopting data-driven assessment models that capture evolving consumer behaviors and operational effectiveness. This shift from expert-driven assessments to empirical validation provides a more adaptable and scalable approach to maturity model development.

Future research should focus on validating the proposed methodology by conducting comparative studies across different industries. This will help determine whether factor analysis and multiple regression can consistently identify relevant evaluation criteria in diverse business contexts. Additionally, integrating qualitative insights from industry experts in later stages can complement the empirical findings, ensuring that the maturity model remains practically applicable and widely accepted.

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