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# Digital Transformation of the Real Estate Rental Market in Saudi Arabia: User Acceptance of the Ejar Platform

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**Abstract:** This study examines user acceptance of the Ejar platform within the digital transformation framework in the real estate sector, which the government is working to bring about in light of Saudi Arabia's Vision 2030 program. Ejar fosters industrial modernization and regulation by facilitating formalized agreements, streamlined payment tracking, and dispute resolution mechanisms. An extended technology acceptance model (TAM) posits perceived ease of use (PEOU) and perceived usefulness (PU) as critical determinants of a user's behavioral intention (BI) to adopt a system. This research examined hypotheses concerning the influence of system quality (SQ), PEOU, PU, and their effect on user acceptance of Ejar. Empirical data were collected through a survey of Ejar users. Structural equation modeling (SEM) analysis revealed that PEOU and PU significantly influenced BI to utilize Ejar. Including SQ provided further insights, suggesting its potential influence on PEOU and PU. However, a particularly noteworthy finding emerged: no statistically significant correlation between PEOU and PU was observed. Despite this unexpected result, the findings suggest positive user attitudes toward Ejar, indicating its potential to foster increased user adoption and platform utilization. These findings contribute to understanding user acceptance in the context of government-driven digital platforms and digital transformation in the real estate rental sector.

**Keywords:** digital transformation, user acceptance, Ejar platform, technology acceptance model, real estate rental sector

## 1. Introduction

In 2016, Saudi Arabia launched the Vision 2030 economic plan. This plan aims to diversify the Kingdom of Saudi Arabia's economy and attract foreign and local investment to push it towards globalization (Moshashai et al., 2020). As part of Vision 2030, the Kingdom of Saudi Arabia is undergoing a digital transformation in government services to provide all services digitally and make them easily accessible. This transformation has been adopted by many government bodies, including the General Real Estate Authority, which launched the Ejar platform as part of efforts toward digital transformation in the real estate sector, contributing to enhancing transparency and governance of rental operations, in addition to protecting the rights of all relevant parties. The platform aims to regulate and modernize the rental sector, formalize rental agreements, track payments, and resolve disputes. The launch of the Ejar platform reflects the Saudi government's commitment to simplifying administrative processes, enhancing transparency, and protecting the rights of property owners and

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tenants. This platform allows property owners to register their properties, issue rental contracts electronically, and receive payments via electronic channels.

The working mechanism of the Ejar platform is to manage the rental process between the three parties involved: the broker, the lessor, and the lessee. The system is linked to the National Information Center, the Ministry of Commerce and Investment, the Ministry of Justice, and the Saudi Post (Alrahili & Aldahawi, 2020).

One of the essential criteria for the success of technology and digital transformation plans is the satisfaction and acceptance of beneficiaries. The importance of studying the behavior of users in regard to the Ejar platform is highlighted here, in order to understand the interaction between the platform and beneficiaries. It will also allow us to understand the factors that affect the extent of beneficiaries' acceptance of this platform, and thus the need for a study appears: acceptance or rejection of technology among beneficiaries of the Ejar platform.

This study investigated the factors influencing user acceptance of the Ejar rental system in Saudi Arabia. Specifically, it employs the technology acceptance model (TAM) as a theoretical framework to understand user perceptions and behaviors in regard to adoption the Ejar system.

## 2. LITERATURE REVIEW

As a starting point, we reviewed previous studies on the concept of digital transformation in general. Digital transformation refers to integrating digital technologies, strategies, and capabilities into various aspects of an organization or industry in order to fundamentally change how it operates and how it delivers value to its stakeholders (Rogers, 2016). It is not merely about adopting new technologies but involves a holistic reimagining and restructuring of culture, processes, and customer experiences to meet the evolving demands of the digital age. Digital transformation is not limited to any specific industry or sector. It has impacted many fields, including finance, healthcare, retail, manufacturing, and more (Langley & Leyshon, 2017). While the benefits of digital transformation can be substantial, it also comes with challenges, including the need for significant investment, overcoming resistance to change, and addressing potential ethical and regulatory issues related to data use. Successful digital transformation requires a clear vision, strong leadership, and a commitment to staying ahead in a rapidly changing digital landscape (Fields, 2022). Organizations that effectively navigate this transformation can enhance their competitiveness, customer satisfaction, and long-term sustainability (Barns, 2019).

Regarding digital transformation specifically in the real estate sector, previous studies have indicated that while the sector has not fully embraced digital technology or the digital economy as other sectors have done, there is immense potential for growth and innovation. This is a result of both the established processes and systems in the upstream and downstream real estate industries, as well as the disruption that digital technology has caused to conventional business practices, leaving the sector full of uncertainty (Baum, 2020). The adoption of various cutting-edge technologies in the industry is a topic of interest in several relevant research studies(Langley & Leyshon, 2017). Although the real estate business has long used digital technology, during the past ten years both the pace and scope of innovation have increased (Fields & Rogers, 2021). This intensity is linked to a wave of recent technology developments, such as cloud and mobile computing, as well as the rising importance of the platform business model, which has received substantial venture capital investment (Shaw, 2020). Beyond property listings, real estate technology companies are launching various digital platforms, such as construction management, home insurance, home sales, property valuation, and property management. These platforms are typically found as apps on smartphones and tablet computers, or as websites (Rogers, 2016).

Users' adoption and acceptance of technology are crucial to its success, ultimately leading to the success of digital transformation plans. Understanding user acceptance is essential for organizations to implement and promote technological solutions (Dube et al., 2020). Several models have been developed to study user acceptance of technology, including the extended expectation-confirmation model (EECM), the unified theory of acceptance and use of technology (UTAUT), and the technology acceptance model (TAM) (Singh & Somaiya, 2020). The EECM is a research framework focusing on the post-adoption stage of technology acceptance. Proposed by Bhattacharjee in 2001, it is an extension of the TAM that integrates expectation-confirmation theory. It suggests that users' post-adoption satisfaction and continued usage behavior are influenced not only by their initial expectations but also by confirmation of those expectations through actual system usage. In the context of the Ejar platform, EECM may shed light on how users' ongoing experiences and satisfaction with the platform affect long-term acceptance and usage (Kamal et al., 2020).

While the EECM, UTAUT, and TAM have similarities in studying user acceptance of technology, they also have distinct differences. After reviewing the literature on user acceptance of the Ejar rental system in Saudi Arabia, it became evident that the TAM, UTAUT, and EECM are all relevant frameworks for understanding user acceptance of technology. These models offer valuable insights into the factors influencing users' adoption and usage behaviors (Al-Mamary et al., 2023).

The TAM aims to demonstrate how users adopt and use new technologies in different contexts. These models are usually proposed at the organizational level, after thoroughly discussing the factors that must be assessed to ensure successful technology deployment in an organizational context. These factors may include the usefulness and ease of use of the technology, users' attitudes toward and beliefs about the technology, the culture and structure of the organization, and the level of support and training provided to users. By understanding and addressing these factors, institutions can increase the likelihood of technology adoption and successful implementation (Grover et al., 2019).

A study by Bhattarai and Maharjan (2020) confirmed that the TAM is based on the theory of reasoned action. This theory explains how behavior can be predicted based on attitudes, subjective norms, behavioral intentions, and perceived personal beliefs. The model is influenced by two factors: perceived ease of use (PEOU), which measures the extent to which the user expects the target system to be user-friendly, and perceived usefulness (PU), which measures the likelihood that using a particular system will improve its performance within a given context (Bhattarai & Maharjan, 2020).

Ullah et al.'s (2019) study, based on the concept of technology acceptance, presented a conceptual model for technology acceptance by stakeholders in the real estate sector (RESTAM) to meet their basic needs in the real estate industry, seeking to integrate disruptive technologies through Big9 technologies into the real estate industry to develop it from traditional properties to more innovative properties, which will lead to improvements in real estate services for various real estate stakeholders. The study indicated that using the TAM is the first step towards accepting these technologies, in addition to the possibility of expanding research to online real estate platforms, to determine the extent to which users accept them in preparation for the adoption and expansion of their use in the real estate industry (Ullah et al., 2019).

A study by Ullah and Sepasgozar (2019) indicated that although there are many technology acceptance models (TAMs) for websites, no active model is designed specifically for real estate websites. The practice and theory regarding TAMs for real estate sites must be aligned. Ullah and Sepasgozar intended to integrate the principles of the TAM into the system dynamic model, as the TAM is considered to be a widely recognized model that focuses on users' perceptions and attitudes toward technology adoption, and typically includes key constructs, such as perceived usefulness and perceived ease of use, which influence users' behavioral intention to use technology (Ullah & Sepasgozar, 2019).

Regarding the generalizability of the results of the TAM, a study conducted by Rafique et al. (2020) on verifying the acceptability of mobile library applications using the TAM stated that there are always limits to generalizing the results, as generalization is limited to the context of the study. The results cannot be generalized to other contexts. The results are not the same for other users, but nevertheless the proposed TAM can be extended to study technology acceptance in different groups and fields (Rafique et al., 2020).

A study by Ammenwerth (2019) indicated that Users are more likely to accept and use technology if they see it as valuable and easy to use. The unified theory of technology acceptance and use (UTAUT) relies on the TAM by incorporating additional factors that make it more difficult, such as social influence, facilitating conditions, and user experience, as this model provides a better and more in-depth understanding of technology acceptance and use. The study confirmed that the TAM and the UTAUT may not accurately predict technology acceptance and use and that this depends on the specific context. Social, organizational, and cultural factors may also affect technology acceptance (Ammenwerth, 2019).

Venkatesh et al.'s UTAUT, which was created in 2003, expands on the TAM by adding new dimensions, such as social impact, performance expectancy, effort expectancy, and facilitating conditions. It suggests that these factors and users' behavioral intentions directly influence their usage behavior (Zhao & Bacao, 2020). The UTAUT integrates several current models to pinpoint the critical elements that affect user acceptance: performance expectancy, effort expectancy, social impact, and facilitating conditions. Davis' 1989 TAM is a well-known framework for analyzing and forecasting users' technology adoption. It argues that people's attitudes and intentions regarding implementing a specific technology are greatly influenced by how beneficial and simple they perceive it to be. These factors determine a user's intention to use technology and their usage behavior (Al-Nuaimi & Al-Emran, 2021).

The technology acceptance model (TAM) emphasizes that users' acceptance of new technology is determined by perceived usefulness and ease of use. This model has been widely used, and its effectiveness in explaining and predicting user behavior towards technology has been demonstrated (Geasela et al., 2022). On the other hand, the UTAUT consolidates various factors, including performance expectancy, effort expectancy, social influence, and facilitating conditions, to provide a comprehensive understanding of user acceptance. Its holistic approach makes it a valuable tool for researchers and organizations seeking to understand and improve technology adoption (Abuhassna et al., 2023).

Meanwhile, the EECM emphasizes the post-adoption stage of technology acceptance, highlighting the importance of continuous usage and user engagement. This model is particularly relevant for understanding users' long-term behaviors and attitudes towards technology (Rafique et al., 2020).

As technology evolves, understanding user acceptance remains critical for designers, developers, and businesses that aim to introduce new technologies to the market. By considering the factors outlined in the TAM and its extensions, organizations can better anticipate user behaviors and tailor their strategies to enhance technology acceptance and usage (Rafique et al., 2020).

Recent studies have also focused on the role of trust, perceived risk, and personal innovativeness in technology adoption, shedding light on the complex interplay of individual characteristics and external influences (Nurqamarani et al., 2021). The emergence of mobile and ubiquitous computing has presented new challenges and opportunities in understanding user acceptance, as these technologies interact with users in various contexts and settings (Zhao & Bacao, 2020). While the TAM and its extensions provide a robust framework for understanding user acceptance, researchers have also emphasized the need to consider cultural and contextual differences in technology adoption. Cultural norms, values, and societal expectations can significantly impact users' attitudes and behaviors toward new technologies, highlighting the importance of a nuanced and culturally sensitive approach to studying technology acceptance (Momani, 2020).

As organizations navigate the rapidly changing landscape of technology, it is important to continue to explore and refine our understanding of user acceptance. By incorporating diverse factors and perspectives, more effective strategies can be developed to promote technology adoption and foster meaningful user engagement(Al-Mamary et al., 2023). Considering the specific context of investigating user acceptance of the Ejar rental system in Saudi Arabia, it is essential to delve deeper into the application of these models within this cultural and technological landscape.

## 3. RESEARCH MODEL AND HYPOTHESIS

Based on previous research and theoretical concepts, this study extended the TAM in the real estate rental domain by including one external variable: system quality (SQ). The dependent variable for this study was behavioral intention (BI), whereas SQ, perceived usefulness (PU), and perceived ease of use (PEOU) were independent variables. Figure 1 shows a graphical representation of the proposed hypothesis.

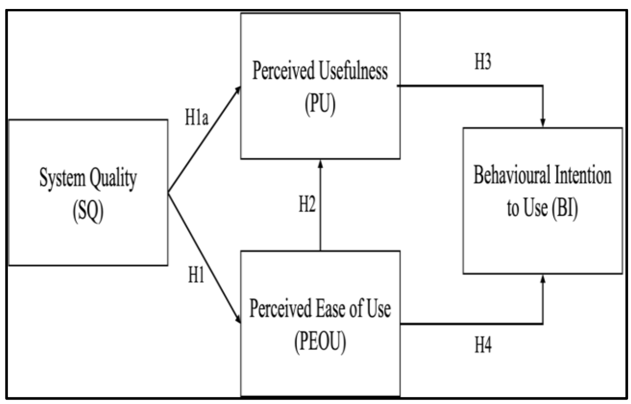


**Figure 1. Research Model**

### *3.1 Independent variable: System quality*

System quality is a crucial factor influencing user experience with information technology, encompassing aspects like ease of use, accessibility, and reliability (Ullah et al., 2021). This study integrates SQ as an independent variable within the TAM framework to explore its influence on perceived ease of use (PEOU) and perceived usefulness (PU) of the Ejar platform. Understanding this relationship is vital for assessing the impact of SQ on both PEOU and PU, ultimately influencing user behavioral intentions towards Ejar. Therefore, this research posits the following hypothesis:

**H1.** System quality of the Ejar rental platform has a positive effect on perceived ease of use.

**H1a.** System quality of the Ejar rental platform has a positive effect on perceived usefulness.

### *3.2 Independent variable: Perceived ease of use (PEOU)*

The technology acceptance model (TAM) posits that perceived ease of use (PEOU) is a key factor influencing user behavior toward information systems (Davis, 1989). PEOU means the degree to which a user perceives a system to be effortless in terms of mental and physical demands during interaction. In simpler terms, it reflects the user’s experience of using the system without encountering significant difficulty. Existing research consistently highlights the positive influence of PEOU on user adoption and utilization of technologies (Ullah et al., 2019). For instance, Ullah and Sepasgozar (2019) found a correlation between PEOU and perceived usefulness in the context of real estate systems.

Similarly, studies have explored the positive impact of PEOU on user intention to utilize mobile library services (Ullah & Sepasgozar, 2019). Building upon this research, this study investigates the influence of PEOU on user behavior towards the Ejar platform. Therefore, this research posits the following hypothesis:

**H2.** Perceived ease of use has a positive influence on the perceived usefulness of the Ejar rental platform.

**H3.** Perceived ease of use of the Ejar rental platform has a direct and positive influence on users' intention to use the platform.

### *3.3 Independent variable: Perceived usefulness (PU)*

Within the TAM (Davis, 1989), perceived usefulness (PU) reflects the degree to which users believe a system enhances their work or goals. In the context of Ejar, PU signifies users' perception of its value for the real estate rental sector (e.g., in the development of streamlined agreements). Prior research suggests a positive link between PU and user adoption (Venkatesh et al., 2012). This study investigates the influence of PU on user behavior towards Ejar. Thus, it is theorized that:

**H4.** Perceived usefulness of the Ejar rental platform has a positive influence on users' intention to use the platform.

### *3.4 Dependent variable: Behavioral intention to use (BI)*

Within the TAM framework, user behavior is often measured through behavioral intention to use (BI) (Venkatesh et al., 2012). BI reflects a user's propensity to adopt and utilize a particular system (Mathieson et al., 2001). Research suggests a strong correlation between BI and actual user behavior (Ajzen & Fishbein, 2000). Studies have shown that PEOU and PU have a more direct influence on BI compared to usage behavior or attitude (Venkatesh et al., 2012). Therefore, this study adopts BI as the dependent variable to assess the impact of PEOU and PU on user adoption of the Ejar platform.

## 4. RESEARCH METHODOLOGY

### *4.1 Questionnaire development*

A structured survey was developed to gather data from Ejar users regarding the factors influencing platform adoption (based on the proposed model). The survey leveraged established measures from prior literature (see Table 1) to assess key constructs, such as perceived ease of use, perceived usefulness, and system quality. It includes demographic questions (age, gender, qualification, nationality, and user type) and a construct measurement section using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). All questions were adapted from the literature to specifically target the Ejar platform context, resulting in 19 questions measuring both independent and dependent variables.

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**Table 1. Measurement Items**

| Variable | Statements | Reference |
|---|---|---|
| **Perceived Usefulness** | | |
| PU1 | The Ejar platform offers features that would save me time and effort in the rental process. | (Ullah & Sepasgozar, 2019) |
| PU2 | Using the Ejar platform would be a valuable way to manage my rental property and facilitate the rental process. | (Ullah & Sepasgozar, 2019) |
| PU3 | I believe the Ejar platform would lead to a more efficient and transparent rental experience. | (Ullah & Sepasgozar, 2019) |
| PU4 | Using the Ejar platform helps preserve my rights by documenting the contract electronically. | (Ullah & Sepasgozar, 2019) |
| PU5 | Overall, I find the Ejar platform to be a useful tool for the real estate rental market. | (Ullah & Sepasgozar, 2019) |
| **Perceived Ease of Use** | | |
| PEOU1 | I find the Ejar platform to be easy to navigate. | (Ullah et al., 2019) |
| PEOU2 | I can easily find the information I need on the Ejar platform. | (Ullah et al., 2019) |
| PEOU3 | Learning to use the Ejar platform does not require a lot of effort and technical knowledge. | (Ullah et al., 2019) |
| PEOU4 | I am confident in my ability to use all the features of the Ejar platform. | (Ullah et al., 2019) |
| PEOU5 | Overall, I find the Ejar platform easy to use. | (Ullah et al., 2019) |
| **System Quality** | | |
| SQ1 | The Ejar platform is generally fast and responsive. | (Ullah et al., 2021) |
| SQ2 | I rarely experience technical difficulties when using the Ejar platform. | (Ullah et al., 2021) |
| SQ3 | The layout and system design of the Ejar platform are friendly. | (Ullah et al., 2021) |
| SQ4 | The Ejar platform is accessible 24 hours a day, seven days a week. | (Ullah et al., 2021) |
| SQ5 | Overall, I am satisfied with the technical quality of the Ejar platform. | (Ullah et al., 2021) |
| **Behavioral Intention** | | |
| BI1 | I plan to use the Ejar platform for my future rental transactions. | (Davis, 1989) |
| BI2 | I am likely to recommend the Ejar platform to others for their rental needs. | (Davis, 1989) |
| BI3 | I believe the Ejar platform will become a widely used tool in the Saudi Arabian rental market. | (Davis, 1989) |
| BI4 | I expect to use the Ejar platform on a regular basis to manage my rental needs. | (Davis, 1989) |

### *4.2 Pilot study*

To ensure the survey's effectiveness, a pilot test was conducted with ten Ejar users, reflecting the target population. Their feedback on clarity, completeness, length, and scale appropriateness led to refinement. Unclear questions were rephrased, a nationality question was added based on a

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suggestion, and the wording was improved for specific questions identified as difficult to understand. This pilot test ensured that the final survey was well-designed and gathered the necessary data.

*4.3 Data collection*

A web-based survey instrument was employed to collect data from Ejar platform users in the Kingdom of Saudi Arabia, encompassing both citizens and residents (primary users of e-government services tend to be citizens (Tremblay-Cantin et al., 2023)). Participation was voluntary, and a random sample of 500 individuals received the survey link. To enhance participation, a follow-up email reminder was sent after three days. Following data cleaning to remove invalid or partial responses and to identify and exclude biased responders, 156 valid responses were obtained, resulting in a 31.2% response rate. Table 2 presents the demographic profiles of the respondents.

The findings presented in Table 2 indicate a higher representation of male participants (67.3%) than female participants (32.7%) in the study sample. The results demonstrated a varied age distribution, with nearly half of the participants falling within the age bracket of 30 to 39 (50.6%). Additionally, 21.2% were aged between 40 and 49, 14.7% were younger than 30, and 13.5% were 50 or above. The results revealed a predominance of Saudi nationals among the study participants, accounting for 89.1% of the sample, while non-Saudi nationals constituted 10.9%.

In terms of educational attainment, a majority of participants (63.5%) held bachelor's degrees, followed by 16.0% who held postgraduate degrees. Additionally, 10.3% of the participants had completed high school, 7.1% held diplomas, and 3.2% had education levels below high school. Finally, the study participants were categorized into distinct user types, revealing that 60.3% were tenants, 26.3% were property owners, and 13.5% were real estate brokers.

**Table 2. Demographic Data**

| | | **n** | **%** |
|---|---|---|---|
| **Gender** | Male | 105 | 67.3% |
| | Female | 51 | 32.7% |
| **Age** | Younger than 30 | 23 | 14.7% |
| | 30 – 39 | 79 | 50.6% |
| | 40 – 49 | 33 | 21.2% |
| | Above 50 | 21 | 13.5% |
| **Nationality** | Saudi | 139 | 89.1% |
| | Non-Saudi | 17 | 10.9% |
| **Education Level** | Below High School | 5 | 3.2% |
| | High School | 16 | 10.3% |
| | Diploma | 11 | 7.1% |
| | Bachelor's | 99 | 63.5% |

| | | n | % |
|---|---|---|---|
| | Postgraduate | 25 | 16.0% |
| **User Type** | Tenant | 94 | 60.3% |
| | Owner | 41 | 26.3% |
| | Broker | 21 | 13.5% |

## 5. DATA ANALYSIS

The analysis of moment structures 24.0 software package was utilized to conduct the statistical analysis of the measurement and structural models, and a portion of the data examination. The SPSS software (version 25.0) was employed for additional data examination and descriptive statistics.

### *5.1 Data examination*

According to Hair et al. (2018), data examination demands time but is an indispensable preliminary phase in statistical analysis that is frequently neglected by researchers. It is essential to verify whether the data aligns with the prerequisites of the chosen multivariate analysis technique. This involves uncovering missing values, analyzing outliers, and assessing normality assumptions, which are crucial for most multivariate methods (Hair et al., 2018).

### *5.2 Missing values*

Missing values refer to data points that were not provided or recorded by respondents for various reasons. To assess the presence of missing values, frequency tables were generated for each measurement item in this study, which revealed no instances of missing data across any measurement item. This can be attributed to the design of the online survey, which mandates that participants respond to all survey questions.

### *5.3 Outliers analysis*

Outliers are data points within a variable that deviate significantly from the rest and are either exceptionally large or small (Hair et al., 2018). These observations stand out because of their high or low scores compared with the others. In this study, standardized Z-scores were employed to detect potential outliers for each individual measurement item (univariate outliers), whereas the Mahalanobis distance was used to identify potential outliers across all measurement items (multivariate outliers). According to Hair et al. (2018), a standardized Z-score below -3 or exceeding 3 is indicative of outliers. The analysis of standardized Z-scores for the responses of 156 participants across 19 measurement items revealed scores ranging from 1.223 to -2.692. Consequently, none of the responses from the 156 participants surpassed the threshold of ±3, indicating the absence of univariate outliers (Hair et al., 2018).

The data were further examined for potential multivariate outliers using Mahalanobis distance (D2). According to Hair et al. (2018), the D2 measure, divided by the number of variables involved (D2/*df*), is approximately distributed as a t-value. Thus, observations with a (D2/*df*) value exceeding 2.58 can be designated as possible multivariate outliers. The results in Appendix 2 show that the largest Mahalanobis distance (D2) was 46.441 (corresponding to participant no. 125). By dividing the largest value for D2 by the number of variables involved in the calculations (19-measurement item), the maximum value for D2/*df* is 2.444, which is far below the cut-off value of 2.58. Therefore, it can be concluded that the examination of D2 values for all cases did not indicate signs of multivariate outliers in the data (Hair et al., 2018).

### *5.4 Normality analysis*

Normality, a critical assumption in multivariate analysis (Hair et al., 2018), pertains to the notion that data distribution within each variable and all possible linear combinations of variables follow a normal distribution. In this study, we assessed normality using skewness and kurtosis measures for each measurement item to characterize the shape of the data distribution and verify the normality assumption. According to Hair et al. (2018), data are typically considered normal when skewness falls within the range of -1 to +1 and kurtosis within -3 to +3.

Upon examining the skewness and kurtosis values of the 38 measurement items, we found skewness ranging from -0.967 to -0.229 and kurtosis from -0.871 to 0.516. Consequently, it is evident that both the skewness and kurtosis values for all the measurement items fall within the normal distribution range, as recommended. Thus, we can conclude that the collected data conform to the assumption of normality.

## 6. RESULTS AND DISCUSSION

### *6.1 Measurement model*

After conducting the data examination, the proposed measurement model was validated utilizing confirmatory factor analysis. Confirmatory factor analysis is a statistical method aimed at assessing the degree to which the indicators accurately measure the latent (unobserved) constructs they represent and whether these constructs are distinct from each other (Collier, 2020).

We employed analysis of moment structures 24.0, structural equation modeling software, to conduct confirmatory factor analysis. The four measurement constructs were derived from the study survey: system quality, perceived usefulness, perceived ease of use, and behavioral intention to use (Figure 2). In line with Hair et al. (2018), the measurement model was validated by evaluating several critical criteria, including goodness of fit, potential refinement of the measurement model if necessary, construct validity, and reliability.

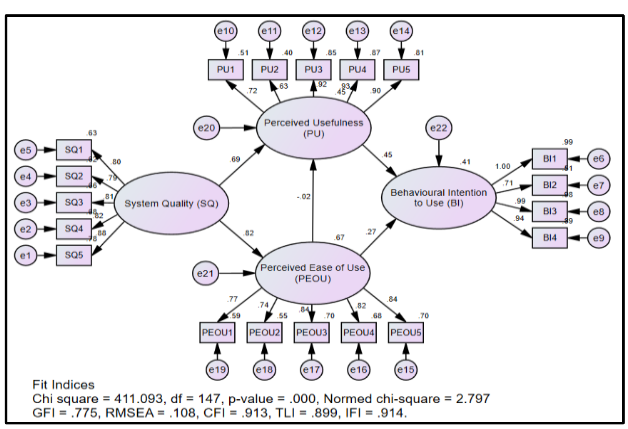


**Figure 2. Initial Measurement Model**

#### *6.1.1 Goodness of fit*

After estimating the measurement model, researchers typically assess its adequacy by considering one or more of the overall goodness-of-fit indices. In this study, various fit indices were used to evaluate the goodness of fit of the measurement model. Table 3 presents a comparison of these indices with their respective recommended thresholds, as specified in Thakkar (2020).

It is evident from the results that the model demonstrated a poor fit, as three fit indices failed to meet the recommended values. Specifically, the goodness-of-fit index value was 0.775 (< 0.8), Tucker–Lewis index value was 0.899 (<0.9), and the root mean square error of approximation value was 0.108 (> 0.1), indicating a notable issue with the fit of the measurement model that requires attention.

**Table 3. Measurement Model Fit Assessment**

| Fit Index | Value | Recommended Value |
|---|---|---|
| Normed chi-square ($\chi^2/df$) | 2.797 | < 3 |
| Goodness-of-fit index | 0.775 | > 0.8 |
| Root mean square error | 0.108 | 0.08 to 0.1 (good fit) |
| Comparative fit index | 0.913 | ≥ 0.90 |
| Tucker–Lewis index | 0.899 | ≥ 0.90 |
| Incremental fit index | 0.914 | ≥ 0.90 |

*6.1.2 Purification of the measurement model*

The analysis revealed that the measurement model exhibited a poor fit to the data, as evidenced by the three fit indices failing to meet desirable thresholds. Consequently, it is imperative to diagnose and refine the measurement model to enhance its fit before proceeding with further assessments of its reliability and validity. Any adjustments to the measurement model were executed cautiously, focusing on observing improvements in goodness-of-fit indices following each modification until the fit indices of the confirmatory factor analysis model reach acceptable levels (Collier, 2020). In line with the approach advocated by Hair et al. (2018), two main criteria were utilized to diagnose and refine the measurement model: indicator loadings and modification indices.

6.1.2.1 Indicators loadings

The first step is to check the model indicator loadings, with a rule of thumb suggesting that standardized indicator loadings should be 0.7 or higher. Loadings of this size or greater confirm that the indicators are highly related to their associated constructs, whereas low loadings suggest that a variable is a candidate for removal from the model (Hair et al., 2018). Table 4 presents the indicator loadings and related constructs. The results in Table 4 show that only one indicator had loadings less than 0.7 (PU2); consequently, it was removed from the model.

**Table 4. Indicator Loadings and Their Related Constructs**

| Construct | Indicator | Loading |
|---|---|---|
| System quality (SQ) | SQ1 | 0.796 |
| | SQ2 | 0.790 |
| | SQ3 | 0.813 |
| | SQ4 | 0.824 |
| | SQ5 | 0.884 |
| Perceived usefulness (PU) | PU1 | 0.715 |
| | **PU2** | **0.633** |
| | PU3 | 0.923 |
| | PU4 | 0.930 |
| | PU5 | 0.902 |
| Perceived ease of use (PEOU) | PEOU1 | 0.769 |
| | PEOU2 | 0.744 |
| | PEOU3 | 0.835 |
| | PEOU4 | 0.824 |
| | PEOU5 | 0.837 |
| Behavioral intention to use (BI) | BI1 | 0.997 |
| | BI2 | 0.711 |
| | BI3 | 0.988 |
| | BI4 | 0.942 |

6.1.2.2 Modification indices

Modification indices play a crucial role in suggesting potential model adjustments to enhance the data fit. These indices, which are available in the analysis of moment structures output, are computed for every unestimated relationship within a model. Following the threshold suggested by Hair et al. (2018), where modification indices greater than 4 indicate potential improvements, the model was refined by introducing covariances between several error terms within the same construct (see Figure 3).

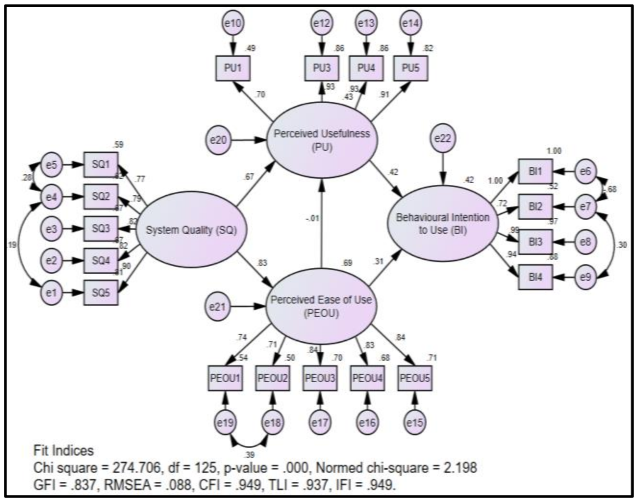

**Figure 3. Modified Measurement Model**

Finally, the purification of the measurement model showed a significant improvement in the values of the fit indices of the modified measurement model. Table 5 presents a comparison of the values of the goodness-of-fit indices for the initial and modified measurement models against their recommended values.

Overall, the modified measurement model maintains the same four constructs assessed by 18 indicators (with one indicator removed from the initial model). The goodness of fit results indicated notable enhancements, including improvements in the normed chi-square, comparative fit index, and incremental fit index. The significant increase in the goodness-of-fit index is particularly noteworthy, from 0.775 in the initial model to 0.837 in the modified model. Additionally, the root mean square error decreased to 0.088, falling below the threshold of 0.1, indicating a favorable model fit. Furthermore, there was a substantial improvement in the Tucker–Lewis from 0.937 in the initial model to 0.899 in the modified model.

**Table 5. Measurement Model Fit Assessment**

| Fit Index | Initial Model | Modified Model | Recommended Value |
|---|---|---|---|
| Normed chi-square ($\chi^2/df$) | 2.797 | 2.198 | < 3 |
| Goodness-of-Fit index | 0.775 | 0.837 | > 0.8 |
| Root mean square error | 0.108 | 0.088 | 0.08 to 0.1 (good fit) |
| Comparative fit index | 0.913 | 0.949 | ≥ 0.90 |
| Tucker–Lewis index | 0.899 | 0.937 | ≥ 0.90 |

| Fit Index | Initial Model | Modified Model | Recommended Value |
|---|---|---|---|
| Incremental fit index | 0.914 | 0.949 | ≥ 0.90 |

*6.1.3 Construct Reliability*

Construct reliability assessment allows evaluation of the extent to which a set of variables is consistent with what it intends to measure (Hair et al., 2018). Construct reliability was assessed utilizing Cronbach's alpha and composite reliability. The results in Table 6 show that Cronbach's alpha for the constructs ranged from 0.902 to 0.953, whereas composite reliabilities ranged from 0.900 to 0.954. Both Cronbach's alpha and composite reliabilities for each construct in the model were above the 0.70 benchmark (Hair et al., 2018). Hence, construct reliability was established for the modified measurement model.

**Table 6. Indicator Loading, Composite Reliability, Cronbach's Alpha, and Ave of the Modified Measurement Model**

| Construct | Indicator | Loading | Composite Reliability | AVE | Cronbach's Alpha |
|---|---|---|---|---|---|
| System quality (SQ) | SQ1 | 0.796 | 0.912 | 0.676 | 0.910 |
| | SQ2 | 0.790 | | | |
| | SQ3 | 0.813 | | | |
| | SQ4 | 0.824 | | | |
| | SQ5 | 0.884 | | | |
| Perceived usefulness (PU) | PU1 | 0.700 | 0.925 | 0.758 | 0.922 |
| | PU3 | 0.927 | | | |
| | PU4 | 0.929 | | | |
| | PU5 | 0.906 | | | |
| Perceived ease of use (PEOU) | PEOU1 | 0.769 | 0.900 | 0.644 | 0.902 |
| | PEOU2 | 0.743 | | | |
| | PEOU3 | 0.835 | | | |
| | PEOU4 | 0.824 | | | |
| | PEOU5 | 0.837 | | | |
| Behavioral intention to use (BI) | BI1 | 0.997 | 0.954 | 0.841 | 0.953 |
| | BI2 | 0.711 | | | |
| | BI3 | 0.988 | | | |
| | BI4 | 0.942 | | | |

*6.1.4 Construct validity*

According to Hair et al. (2018), construct validity is the extent to which sets of measured items accurately reflect the theoretical latent constructs they are designed to measure. Thus, construct validity deals with measurement accuracy. Following Hair et al. (2018), convergent and discriminant validity were investigated to evaluate the constructs' validity.

**Convergent validity** means the extent to which indicators of the same construct converge (Hair et al., 2018). Convergent validity was assessed using factor loadings and the average percentage of variance extracted (AVE). The results in Table 6 show that the factor loadings of all indicators were high, ranging from 0.700 to 0.997. In addition, the AVE value for all constructs was above the suggested cut-off of 0.5 (Hair et al., 2018). Therefore, it can be concluded that the model exhibited satisfactory convergent validity.

**Discriminant validity** measures how much a concept is different from other concepts. A concept with high discriminant validity means that it is unique and represents something that other concepts do not. This is an essential indicator of a construct's accuracy and ability to capture a specific phenomenon (Hair et al., 2018). The study assessed discriminant validity using the Fornell and Larcker criterion (Fornell & Larcker, 1981). According to this criterion, discriminant validity is determined when the square root of AVE for a construct is greater than its correlation with the other constructs in the model. Table 7 shows the results of Fornell and Larcker's criterion, where the values in the diagonal (bold) are the square root of AVE for each construct, and the other values represent the correlations between the constructs in each respective row and column. We may easily notice that the diagonal values (square root of AVE) exceed all other values (correlations) in each row and column; hence, discriminant validity is established.

**Table 7. Fornell–Larcker Discriminant Validity Results**

| | **SQ** | **PU** | **PEOU** | **BI** |
|---|---|---|---|---|
| **SQ** | **0.822** | | | |
| **PU** | 0.625 | **0.871** | | |
| **PEOU** | 0.726 | 0.522 | **0.803** | |
| **BI** | 0.647 | 0.618 | 0.514 | **0.917** |

*6.2 Structural model*

We tested the proposed model, which depended on the structural model in Figure 4. The model consisted of four latent variables: perceived usefulness, perceived ease of use, system quality, and behavioral intention to use, which were identified using 18 indicators. To test the research hypothesis, we tested the direct effect relationships in the model by examining path estimates and t-values.

The examination showed that four out of the five paths were statistically significant at a p-value of $< 0.05$. The values of $R^2$ (variance explained) indicated that the model explained approximately 68.9% of the variance in perceived ease of use ($R^2 = 0.689$, $p < 0.05$), 43.5% of the variance in perceived usefulness ($R^2 = 0.435$, $p < 0.05$), and 41.8% of the variance in behavioral intention to use ($R^2 = 0.43$, $p < 0.05$). The results of the direct effect relationships are presented in Table 8 and in Figure 4 (standardized estimate and p-value are shown only for significant paths).

The results in Table 8 examine the hypothesis of a direct effect relationship in the structural model by presenting an unstandardized path estimate and its standard error along with the standardized path estimates and its corresponding t-value and significance level (p-value). The results examine four main hypotheses in the study; the first hypothesis (H1 and H1a) tests the direct effect of system quality on perceived ease of use and perceived usefulness. The second hypothesis (H2) tested the direct effect of perceived ease of use on perceived usefulness. The third (H3) and fourth (H4) hypotheses tested the direct effect of perceived ease of use and perceived usefulness on behavioral intention to use. Next, we discuss the results of the path analysis in relation to the research hypothesis.

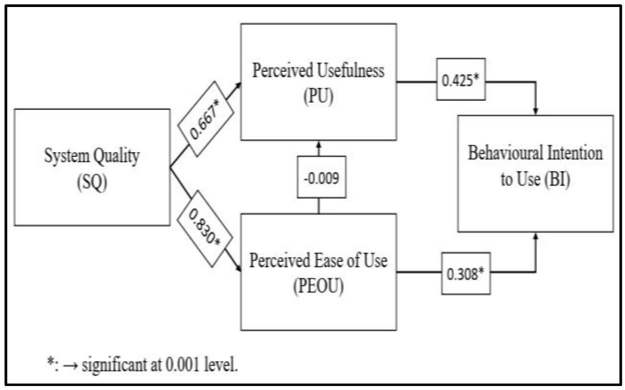


**Figure 4. Hypotheses Results of the Structural Model**

**H1: System quality of the Ejar platform has a positive effect on perceived ease of use.**

The results showed a significant relationship between system quality and perceived ease of use. The standardized estimate was 0.830, and the t-value was 8.263, with a p-value of less than 0.001, indicating a significant effect of system quality on perceived ease of use. This result indicates that the impact of the Ejar rental platform's system quality on its perceived ease of use varies significantly from zero at the 0.001 level. Hence, H1 is supported. In addition, the positive value of the standardized estimate (β=0.830) indicates a positive effect, which means that when system quality increases by one standard deviation, perceived ease of use will increase by 0.830 standard deviations.

**H1a: System quality of the Ejar platform has a positive effect on perceived usefulness.**

The results show a significant relationship between system quality and perceived usefulness. The standardized estimate was 0.667, and the t-value was 4.108, with a p-value of less than 0.001, indicating a significant effect of system quality on perceived usefulness. This result indicates that the effect of the Ejar rental platform's system quality on its perceived usefulness is significantly different from zero at the 0.001 level. Hence, hypothesis H1a is supported. In addition, the positive value of the standardized estimate (β=0.667) indicates a positive effect, which means that when system quality increases by one standard deviation, then perceived usefulness will increase with 0,667 standard deviation.

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**Table 8. Examining Results of Hypothesized Direct Effects**

| Path | Unstandardized Estimates | | Standardized Estimates | t-value | p-value | Hypothesis Results |
|---|---|---|---|---|---|---|
| | Estimate | S.E. | Beta (β) | | | |
| SQ → PEOU | 0.743 | 0.090 | 0.830* | 8.263 | < 0.001 | H1 **Supported** |
| SQ → PU | 0.537 | 0.131 | 0.667* | 4.108 | < 0.001 | H1a **Supported** |
| PEOU → PU | -0.008 | 0.133 | -0.009 | -0.062 | 0.950 | H2 **Rejected** |
| PEOU → BI | 0.410 | 0.111 | 0.308* | 3.681 | < 0.001 | H3 **Supported** |
| PU → BI | 0.629 | 0.128 | 0.425* | 4.919 | < 0.001 | H4 **Supported** |

**H2: Perceived ease of use has a positive influence on the perceived usefulness of the Ejar platform.**

The results displayed no significant relationship between perceived ease of use and perceived usefulness. The standardized estimate was -0.009 (too close to zero), the t-value was -0.062, and the p-value was 0.950 (>0.05), indicating no significant effect of perceived ease of use on perceived usefulness. Thus, hypothesis H2 are rejected.

**H3: Perceived ease of use of the Ejar platform has a direct and positive influence on users' intention to use the platform.**

The results showed a significant relationship between perceived ease of use and behavioral intention to use. The standardized estimate was 0.308, and the t-value was 3.681, with a p-value of less than 0.001, indicating a significant effect of perceived ease of use on behavioral intention to use. This result indicates that the effect of perceived ease of use of the Ejar rental platform on users' behavioral intention to use is significantly different from zero at the 0.001 level. Hence, hypothesis H3 is supported. In addition, the positive value of the standardized estimate (β=0.308) indicates a positive effect, which means that when perceived ease of use increases by one standard deviation, behavioral intention to use increases by 0.308 standard deviation.

**H4: Perceived usefulness of the Ejar platform has a positive influence on users' intention to use the platform.**

The results showed a significant relationship between perceived usefulness and behavioral intention to use. The standardized estimate was 0.425, with a t-value of 4.919 and a p-value of less than 0.001, indicating a significant effect of perceived usefulness on behavioral intention to use. This result indicated that the impact of the perceived usefulness of the Ejar rental platform on users' behavioral intention to use is significantly different from zero at the 0.001 significance level. Hence, hypothesis H4 is supported. In addition, the positive value of the standardized estimate (β=0.425) indicates a positive effect, which means that when perceived usefulness increases by one standard deviation, behavioral intention to use increases by 0.425 standard deviations.

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## 7. CONCLUSIONS

This study investigated user acceptance of the Ejar platform, a Saudi Arabian government initiative transforming the real estate rental sector through digitalization. By leveraging the technology acceptance model (TAM) as a theoretical lens, this study explored factors influencing user adoption and utilization of Ejar. These findings largely support the hypothesized relationships, demonstrating that perceived ease of use (PEOU) and perceived usefulness (PU) significantly impact users' behavioral intention (BI) to adopt and utilize Ejar. This suggests positive user attitudes towards Ejar, potentially leading to increased user adoption and platform use. However, an unexpected result emerged: The hypothesized influence of system quality (SQ) on PEOU and PU was not statistically significant. This implies that SQ improvements might enhance user perceptions of ease of use and usefulness. Furthermore, this study underscores the critical role of user satisfaction and acceptance in the success of technological interventions and digital transformation initiatives. Understanding user behavior and the factors influencing Ejar acceptance is crucial for effective platform implementation and widespread adoption. Future research avenues include expanding user group studies and incorporating additional technology acceptance models for a more comprehensive understanding of user behavior and acceptance determinants. This knowledge may be leveraged to continuously improve the Ejar user experience and drive successful digital transformation in the real estate rental sector.

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