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Research Paper

Intention to Use the Good Doctor Health App in Lower-Middle Class

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ABSTRACT

This study examines the factors influencing the intention to use the Good Doctor health application, focusing on perceptions of utility and convenience, health knowledge, and the moderating role of income level. Data were collected through questionnaires distributed to the general public, including users and non-users of the Good Doctor app. A total of 250 respondents were initially surveyed, with 166 meeting the required criteria. The purposive sampling method was employed. Structural Equation Modeling (SEM) with path analysis was used for hypothesis testing. The findings indicate that perceptions of utility, convenience, and health knowledge significantly positively affect the intention to use the app. Additionally, higher income levels further enhance the likelihood of using health applications.

1. INTRODUCTION

The use of health applications in society with intermediate to lower economic levels needs further study. Based on data, the intermediate to lower population in Indonesia amounts to 27.2 million of the total Indonesian population of 270 million, or less than 10% of the total population. Most work informally in the intermediate to lower category, accounting for 56.5%. The data also shows that internet users in Indonesia total 198.9 million, or around 73.7% of the population (suara.com, 2020). This means that part of Indonesia's intermediate to lower-income population already uses Internet services. However, many in the intermediate to lower-income category have not yet utilized online health applications to access health information services effectively. This condition impacts the health level, which remains low in this demographic.

The health condition of society in Indonesia is still concerning, especially among the intermediate to lower class during the COVID-19 pandemic. Poor people are the most affected because they ignore current conditions. This happens due to the lack of knowledge possessed by the community, with poor people being among those reluctant to adhere to health protocols and unwilling to seek treatment from doctors. The intermediate to lower class needs to expand their knowledge about maintaining health during the pandemic to improve their immune systems and avoid the COVID-19 virus (liputan6.com, 2020). The role of health applications becomes essential in providing information and improving health among the intermediate to lower class. Therefore, studying the intention to use health applications in this demographic is necessary.

This study uses the Technology Acceptance Model (TAM) as the basic model. Researchers have widely used TAM as a valid model to test the acceptance of an information system (Alsharo et al., 2018). TAM testing in various studies has mostly been applied to study objects with respondents from higher-income circles who have the skills and abilities to use system applications (Tubaishat, 2017; Tao et al., 2018; Deng et al., 2018). However, this study differs by focusing on the intermediate to lower-income population. This study focuses on the intermediate to lower class (poor) who already use smartphones but have not yet utilized them optimally to access health information. Thus, this research expands the TAM model by studying the intermediate to lower-income population, making it an interesting research area.

Technology Acceptance Model, as a basic model for testing technology acceptance, needs expansion in the form of additional variables. This study introduces the health knowledge variable, which can influence Perception of usefulness and intention to use as an extension of the TAM model (Tao et al., 2018). Health knowledge indicates an individual's understanding of their health condition. Health knowledge is essential for all community groups and plays a role in responding to changes in health developments. Previous studies also explained that good health knowledge enables individuals to perceive the benefits of a health application system, which can influence their intention to use health applications (Beldad and Hegner, 2017). This explanation suggests that sufficient health

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knowledge encourages individuals to use health applications to maintain their health. Various opinions indicate that health knowledge influences individuals' intention to use health applications.

The use of health applications has now become a trend among global communities. Health applications are chosen for their effectiveness and convenience, allowing users to maintain their health by consulting doctors periodically without needing direct visits (Saare et al., 2019; Brătucu et al., 2020). However, health applications are still relatively unfamiliar for the intermediate to lower-income population due to the low health knowledge required. Health applications should be easy to operate so that everyone can use them. This explanation highlights the importance of convenience in using health applications and its effect on the intention to use them.

Differences in income levels play a role in forming societal strata, which influence the extent of smartphone utilization. Smartphone utilization varies among groups, with the intermediate to lower-income group tending to use smartphones primarily for communication. However, in the intermediate to upper-income groups, smartphones are used for various important purposes, such as health applications. Higher individual income influences health knowledge, which impacts the intention to use health applications (Bucci et al., 2019; Papazoglou & Galariotis, 2020). Based on this explanation, it can be interpreted that higher income positively impacts health knowledge, increasing the intention to use health applications.

This study tests the intention to use health applications in the intermediate to lower-income population. A lack of knowledge makes it difficult for this demographic to adapt to the digital era, necessitating increased knowledge. Intention to use health applications is influenced by usability (Yee et al., 2019) and convenience perception (Alsharo et al., 2018) and is based on the level of knowledge individuals possess. The Indonesian population in the poor category, with below-average income, affects their use of health applications. Therefore, this study proposes the title: "Formation of Intention to Use the Good Doctor Health Application in the Intermediate to Lower Class in Central Java."

The use of smartphones has become a necessity for every individual, from lower-income to upper-income circles. However, smartphone usage among the intermediate to lower class is less than optimal, especially for smartphone-based health services. This lack of optimization is due to this demographic's relatively low health knowledge, which makes health applications unfamiliar. The Technology Acceptance Model (TAM), as a basic model, still has weaknesses, such as inconsistent results regarding Perception of usefulness and convenience perception's influence on the intention to use. This study investigates the influence of income level and health knowledge on the intention to use smartphone-based health applications among the intermediate to lower-income population, considering the effect of convenience and usability perception from health applications. The problem formulation is: "How can the intention to use the smartphone-based Good Doctor health application among the intermediate to lower-income population be increased by considering the influence of convenience, usability perception, and health knowledge?"

Based on the problem formulation above, the research objectives to be achieved in this study are: testing the influence of Perception of usefulness on the intention to use the Good Doctor health application; testing the influence of convenience perception on the intention to use the Good Doctor health application; testing the influence of health knowledge on the intention to use the Good Doctor health application; testing the influence of health knowledge on Perception of usefulness and its impact on the intention to use the Good Doctor health application; testing whether income level strengthens the influence of Perception of usefulness on the intention to use the Good Doctor health application; testing whether income level strengthens the influence of convenience perception on the intention to use the Good Doctor health application; testing whether income level strengthens the influence of health knowledge on the intention to use the Good Doctor health application; and testing whether income level strengthens the influence of health knowledge on utility perception.

This study is expected to provide theoretical explanations for the intention to use health applications and serve as a reference for further studies on the intention to use online health applications, with income level as a moderating factor and ease of use, usefulness, and health knowledge as theoretical variables.

2. LITERATURE REVIEW

2.1. Intention to Use

Referring to the theory of cybernetics, the intention is behavior that leads to objectives (Adam and Mele, 2013). The concept of objectives indicates that an individual will make decisions and take action if they know what can be achieved, pushing the individual to behave (Ajzen, 1985). Another study conducted by Searle (1979) stated that intention is an individual's tendency to behave in making decisions influenced by the existence of trust. Based on this explanation, it can be concluded that intention is the desire of an individual to engage in behavior based on personal will and evaluation of specific behavior.

Intention undergoes development caused by changes in research objects. The identified intention has three developmental definitions: intention to use (Agrebi & Jallais, 2015), intention to adopt (Karahoca et al., 2017), and intention to behave (Kahlor et al., 2019). Intention to use can be interpreted as a condition that allows individuals to engage in behavior by deciding whether to use an application (Agrebi & Jallais, 2015). The intention to adopt is the desire of individuals to enhance the use of information systems through existing innovations (Karahoca et al., 2017). Intention to behave involves decision-making influenced by subjective norms and attitudes, with attitudes shaped by individual beliefs (Ajzen & Fishbein, 1980). This study uses the Good Doctor online health application as its object, and intention behavior in this study refers to the intention to use the Good Doctor application, defined as an individual's prediction actually to use it.

Apart from the debate surrounding the definition of intention, measuring tools for intention remains a discussion topic due to differences in research objects. A study by Singh and Sinha (2020) proposed four tools to measure intention to use online health applications: intention to increase the use of health applications, intention to use health applications, plans to use health applications, and intentions to try to use health applications consistently. Previous studies by Alharbi and Drew (2014) proposed two tools to measure intention to use: plans to use and intention to use applications, supported by personal assumptions. Heerink et al. (2008) offered a differing opinion and proposed four tools to measure intention to use: intention to use applications, belief in using applications, plans to use applications, and gradual usage of applications. Based on the various explanations, this study adopts a modified measurement tool tailored to the research object.

The study of intention formation still encompasses diverse formative variables. The variables forming an intention to use in this study are the perception of usefulness (Alsharo et al., 2018), convenience perception (Yee et al., 2019), and the level of health knowledge (Saare et al., 2019; Brătucu et al., 2020), with income level as a moderating variable (Bucci Alberto et al., 2019; Papazoglou & Galariotis, 2020). This is based on previous studies, which identified these variables as strong factors influencing the intention to use health applications among the lower-income population. The explanation of each formative variable for intention behavior is detailed as follows.

2.2. Perception of usefulness

According to Davis (1989), the foundational concept of perception of usefulness is the extent to which individuals believe using a specific information system can improve their work performance. Another concept, presented by Khayati and Zouaoui (2013), defines usefulness perception as being shaped by perceived benefits in performance believed by the individual when using an information system. The perception of utility in health applications is defined as an individual's belief in the ability to integrate health applications into their daily activities (Park & Chen, 2007). Based on this explanation, Perception of usefulness can be concluded as a belief in using a specific system that provides benefits and enhances individual performance in their work.

The debate about measurement tools for perceiving usefulness in various studies remains important. A study by Harrigan et al. (2021) proposed three tools for measuring utility using online applications: improved performance, increased productivity, and enhanced effectiveness. A study by Hung and Jen (2012) proposed three tools for measuring the perception of usefulness in using health applications: health applications fulfilling individual health needs, helping to increase effectiveness, and being useful for managing and organizing individual health. Another study by Alsabawy et al. (2016) proposed four tools for measuring utility in online learning systems: faster completion, improved performance, increased productivity, and easier learning. Based on these explanations, differences in the number of tools used for measurement are due to the diversity of research objects and objectives. Thus, this study modifies the measurement tools for Perception of usefulness to align with the research object used.

Previous studies have shown a positive relationship between perceived usefulness and the intention to use. A study by Suki and Suki (2011) indicated that Perception of usefulness positively influences the intention to use, explaining that the greater the perceived benefits of online applications, the more comfortable individuals feel using and accessing these services, increasing their intention to use them. A study by Kim and Lee (2014) stated that when individuals perceive an application as valuable and useful based on prior experience, it significantly impacts their intention to use it. Perception of usefulness also positively affects the increased use of online applications that can be utilized simultaneously with other tasks (Paul et al., 2012). The relationship between utility and the intention to use is also observed among Jordanian citizens who use government applications for gathering information and conducting transactions (Almahamid et al., 2010). Government applications that provide accurate and high-quality information influence the increasing intention to continue using them (Almahamid et al., 2010). These opinions demonstrate that a high Perception of usefulness can form the foundation for individuals to enhance their behavioral intention to use health applications.

Hypothesis 1: The higher the perceived usefulness, the greater the intention to use online health applications.

2.3. Perception of ease

As stated by Davis (1989), the foundational concept of convenience perception is the belief that using a system can minimize effort and optimize time efficiency. Saadé and Bahli (2005) defined convenience perception as behaviour requiring minimal time and energy to operate. A study by Abdullah et al. (2016) defined convenience perception as an individual's belief that ordering online is not difficult and requires minimal effort. Bhattacherjee and Hikmet (2007) defined convenience perception as an individual's belief in using a system that is beneficial for their job without consuming much time. Convenience perception in home information systems for hospitals is also defined as the expectation that the existing system is easy for individuals to operate (Ammenwerth, 2019). Based on this explanation, since this study uses health applications as its object, the definition of convenience perception in health applications refers to the belief that using a system is not difficult, does not consume much time, and requires minimal effort.

In addition to the concept of convenience perception, the similarity in measurement tools atoss various studies also becomes an important discussion. Various studies propose similar tools for measuring convenience perception, such as learning the health application being very easy, the application making it easier to fulfil individual desires, and individuals becoming skilled in using the health application (Wu et al., 2003; Calisir and Calisir, 2004; Guo et al., 2012). Although the measurement tools are similar, prior studies have used different research objects. For instance, Wu et al. (2003) examined factors influencing the acceptance of mobile computing in the healthcare industry. In their study, Calisir and Calisir (2004) used information systems and proposed similar tools for measuring convenience perception. Guo et al. (2012) focused on preventive online health services for the elderly and suggested similar measurement tools. Based on these explanations, while there is a similarity in measurement tools, differences in research objects necessitate modifications. Therefore, this study adapts the measurement tools for convenience perception to align with the research object.

Convenience perception has a positive relationship with the intention to use. A study by Leong et al. (2020) stated that convenience perception positively influences the intention to use easy and time-efficient online payment applications. The use of online fitness applications is perceived as helpful for individuals in saving time while maintaining their health (Grazía-Fernández et al., 2020). A simple-to-use system encourages individuals to desire systems that help them effectively and efficiently manage their insurance (Gharakhani and Pourhashemi, 2020). A study by Yee et al. (2019) revealed that convenience perception positively impacts patients' intentions to use mobile health applications, enabling users to control their health management effectively. These opinions show that convenience perception forms the basis for individuals' decisions to use a system.

Hypothesis 2: The higher the perception of ease, the greater the intention to use online health applications.

2.4. Health Knowledge

The perceived level of knowledge is defined as the individuals' understanding of the information obtained (Park et al., 1988). Health knowledge is a systematic process to identify, capture, and transfer information and knowledge that individuals can use to improve their health (Nicolini et al., 2008). Health knowledge has two conceptual definitions: subjective health knowledge and objective health knowledge (Hoque et al., 2018). Subjective health knowledge refers to an individual's perception of information about a product. In contrast, objective health knowledge refers to an individual's understanding of the accuracy of information they possess about a product. In their study, Bălan et al. (2021) wrote that health knowledge owned by individuals in providing information about COVID-19 in society influences public decisions to receive COVID-19 vaccination. Based on several studies, the level of health knowledge can be defined as the information owned by individuals about health, with the expectation that individuals can enhance their health with the information they possess.

Apart from the concept of health knowledge level, tools for measurement in various studies are still a significant debate. A survey by Hoque et al. (2018) explains three measurement tools: knowledge deeply owned by the individual, having more knowledge than others, and being considered an expert in a field. Another study conducted by Neblett et al. (2020) proposed five tools for measuring knowledge levels: the individual does not know the topic accurately, the individual knows very little about the topic, the individual knows the topic, but only vaguely, the individual knows a little about the topic being discussed, and the individual knows all the discussion topics. Another study by Wang et al. (2021) proposed three tools for measuring understanding of genetic testing: the individual does not know about genetic testing, the individual knows about genetic testing but only partially, and the individual has overall knowledge about genetic testing. Based on these studies, differences in measurement tools are due to the diversity of research objects conducted.

Previous studies have shown a positive connection between the level of health knowledge and the intention to use. A study conducted by Su et al. (2013) wrote that the level of knowledge possessed by an individual has a positive connection to the intention to use educational health websites. These websites provide patients and their family members with health information for online consultations. This is expected to increase individual knowledge, thus influencing their intention to use educational health websites. Nurses' knowledge level has a significant positive relationship with the intention to use medical tools in hospitals (Eskandari et al., 2017). This is due to nurses' experience level and ability to operate medical tools, which influences their intention to use them. Sheba et al. (2021) stated that the level of knowledge has a positive connection to the intention to use digital dental technology for predoctoral students. This condition arises because digital dental technology is easy to operate, and its efficiency influences the intention of students to use it. Based on these explanations, the level of health knowledge can be interpreted as the basis for an individual's decision-making to use a system.

Hypothesis 3: The higher the level of health knowledge, the greater the increase in intention to use online health applications.

Various studies show a significant relationship between the level of knowledge and utility perception. A survey by Teo (2011) stated that the level of knowledge strongly influences the perception of usefulness in helping individuals become more productive. The results of other studies also show a strong relationship between the level of knowledge and perception of usefulness (Singh et al., 2018). The level of knowledge individuals possess helps them improve their health quality, which provides benefits through using health applications on websites. A study by El-Emran et al. (2020) stated that the level of knowledge has a positive connection to a perception of usefulness in using information systems, which assists individuals in their daily lives. Based on the above arguments and evidence, the hypothesis proposed is as follows:

Hypothesis 4: The higher the level of health knowledge, the greater the increase in the perception of the usefulness of online health applications.

2.5 Income Level

Income level is defined as the maximum amount that an individual can consume in one period (Hicks, 1939). Brooks (2018), in his study, defines income level as the amount required by an individual to fulfil life needs, such as paying taxes, measuring production, measuring household resources, measuring individual welfare, and covering health maintenance costs. Hasan (2018) defines income level as the opportunity for an individual to save or consume within a certain time frame in the form of salary, wages, rent, and other profits obtained. Therefore, it can be concluded that income level is the maximum amount that an individual can consume to fulfil their life needs within a certain time frame in the form of salary, wages, rent, and other benefits obtained.

The Central Bureau of Statistics explains that income level is differentiated into four groups: the very high-income group, with an average income exceeding IDR3,500,000 per month; the high-income group, with an average income between IDR2,500,000 and IDR3,500,000 per month; the middle-income group, with an average income between IDR1,500,000 and IDR2,500,000 per month; and the low-income group, with an average income below IDR1,500,000 per month (Rakasiwi and Kautsar, 2021). The World Bank classifies countries based on National Gross Income (NGI) per capita into four categories: low-income level, with an average income of $1,035 US per year; lower-middle-income level, with an average income between $1,035 US and $4,045 US per year; upper-middle-income level, with an average income between $4,045 US and $12,535 US per year; and high-income level, with an average income above $12,535 US per year (money.kompas.com, 2020). Thus, the classification of income levels in society is high, upper-middle, lower-middle, and low.

Previous studies find the role of income level in strengthening the connection between perceived utility and perceived ease of use to intention to use. Income level influences an individual's intention to use applications for buying clothes online (Chi et al., 2018). Communities with high-income levels have more experience in internet usage and, therefore, are more likely to prefer online shopping. A study by Park et al. (2021) states that income level can strengthen the connection between perceived utility and intention to use. Similar results show that an individual's income level plays a role in acquiring more information to use a system that makes their tasks easier compared to individuals with low-income levels. The income level that an individual has influenced their intention to use an information system (Shin et al., 2018; Park et al., 2021). Individuals with high-income levels tend to have good knowledge to complete their tasks. A study by Jaradat et al. (2018) states that higher income levels among individuals increase their confidence because their skills facilitate system usage, affecting their intention to use the information system. Based on the evidence above, the following hypotheses are proposed:

Hypothesis 5: Higher income levels can strengthen the relationship between perceived utility and intention to use.

Hypothesis 6: Higher income levels can strengthen the relationship between perceived ease of use and intention to use.

Various studies show a significant relationship between income and health knowledge regarding the intention to use. A high-income level allows individuals to possess sufficient knowledge of information systems, influencing their use of these systems (Chi et al., 2018). High-income individuals are more likely to adopt new technologies, which can be determined by their knowledge level or information (Chawla and Joshi, 2018). Nduneseokwu et al. (2017) state that an individual's income level influences their knowledge of applications, giving them confidence to use such applications. Based on the above argument, the following hypothesis is proposed:

Hypothesis 7: Higher income levels can strengthen the relationship between health knowledge level and intention to use.

Previous studies on income level and health knowledge level regarding perceived usefulness reveal a significant relationship. High-income individuals have adequate knowledge about online payment services, making such services easier to use and more useful than individuals without sufficient knowledge (Lwoga and Lwoga, 2017). There is a connection between social status, including income level, and individuals' knowledge about perceived usefulness. Individuals with high income levels tend to have a high level of knowledge, which influences their perception of the usefulness of an information system (Lael-Monfared et al., 2019). Knowledge level positively correlates with perceived usefulness, moderated by income level. This relationship ensures that individuals effectively use information systems (Hamidi and Chavoshi, 2018). Based on the evidence above, the following hypothesis is proposed:

Hypothesis 8: Higher income levels can strengthen the relationship between health knowledge level and perceived usefulness.

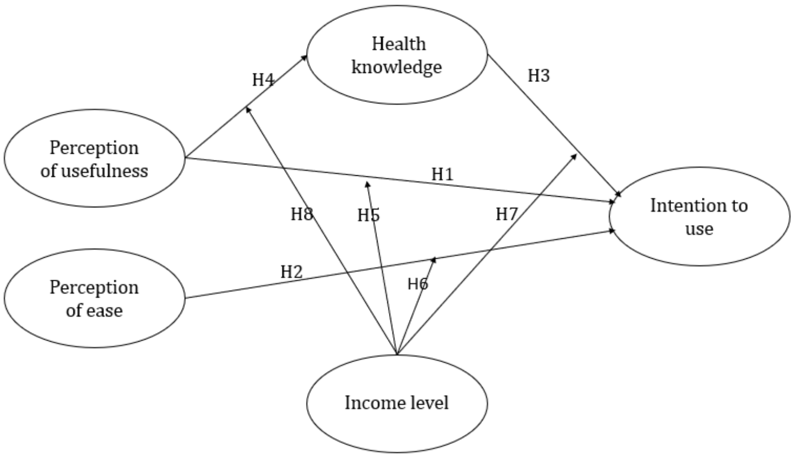

Figure 1. Conceptual Framework

3. METHODS

This is a causal study conducted to test the cause and effect of each variable studied (Sekaran, 2003). It tests variables that become the reason for the intention to use the Good Doctor application. The survey method was chosen to gather information, with the draft prepared and submitted to respondents and data collection conducted to obtain natural data. Reviewed from the time dimension, this study uses toss-sectional data, meaning the data collection process is carried out during a specific period (Sekaran, 2003).

The variables in this study are measured using operational definitions based on indicator variables and appropriate measurement scales. *Intention to use* is defined as the likelihood of an individual engaging in a behavior and deciding whether or not to use an application (Agrebi & Jallais, 2015). This variable is measured using a 5-point Likert scale with the following indicators: (1) intention to use health applications, (2) plans to use health applications, (3) willingness to consistently try using health applications, (4) confidence in using health applications, and (5) gradual adoption of health applications (Heerink et al., 2008; Alharbi & Drew, 2014; Singh & Sinha, 2019). *Perception of usefulness* is defined as the belief that using a particular system offers benefits and improves efficiency in completing tasks (Davis, 1989; Khayati & Zouaoui, 2013; Park & Chen, 2007). This variable is also measured using a 5-point Likert scale, with the following indicators: (1) health applications meet personal health needs, (2) health applications improve effectiveness, (3) health applications help manage and organize personal health, (4) health applications enhance performance, and (5) health applications boost productivity (Hung & Jen, 2010; Alsabawy et al., 2016; Harrigan et al., 2021). *Perception of ease* refers to an individual's belief that using a system is simple, time-efficient, and requires minimal effort (Davis, 1989; Saadé & Bahli, 2005; Abdullah et al., 2016; Bhattacherjee & Hikmet, 2007; Ammenwerth, 2019). This variable is measured using a 5-point Likert scale with indicators such as: (1) ease of learning the application, (2) the application makes it easier to fulfill personal needs, and (3) individuals become proficient in using the application (Wu et al., 2003; Calisir & Calisir, 2004; Guo et al., 2012). *Health knowledge level* is defined as the information individuals have about health, which helps them improve their well-being (Park et al., 1988; Nicolini et al., 2008; Hoque et al., 2018; Bălan et al., 2021). This variable is measured using a 5-point Likert scale, with indicators such as: (1) in-depth health knowledge, (2) possessing more health knowledge than others, and (3) being considered an expert in health (Hoque et al., 2018; Neblett et al., 2020; Wang et al., 2021). *Income level* as a moderating variable is defined as the maximum amount that an individual can consume to fulfil their needs over a certain period in the form of salary, wages, rent, and other benefits obtained (Hicks, 1939; Brooks, 2018; Hasan, 2018). Income level is measured with a categorical scale divided into three levels: (1) income level IDR500,000 – IDR1,000,001, (2) income level IDR1,000,001 – IDR1,500,000, (3) income level IDR1,500,000.

3.1. Testing Instrument Study

3.1.1 AVE Validity Test

Discriminant validity occurs if two different instruments measure two different constructs and produce scores that are not correlated. It can be evaluated by comparing the AVE (average variance extracted) with the squared correlation between constructs in pairs. Fornell and Larcker (1981) recommend a discriminant validity test, namely that the AVE should exceed the squared correlation between paired constructs.

3.1.2 EFA Validity Test

Exploratory Factor Analysis (EFA) (Table 1) determines whether a construct can be explained by its indicators. Suppose the indicators can form a construct or variable. In that case, it is shown by a high loading factor value (>0.3), meaning the measurement is already by the data, and Kaiser-Meyer-Olkin (KMO) values > 0.5 (Ghozali, 2005). The instrument's validity is determined based on the loading factor values. The details contained in each factor must have a loading greater than 0.3 (Nurosis, 1986).

Table 1. Validity test results AVE and EFA

Indicator	Loading Factor	AVE value (>0.5)	EFA Value	Information
N1	0.962	0.823	0.966	Valid
N2	0.896			Valid
N3	0.832			Valid
N4	0.756			Valid
GP1	0.764	0.760	0.936	Valid
GP2	0.857			Valid
GP3	0.844			Valid
GP4	0.850			Valid
GP5	0.821			Valid
MP1	0.946	0.783	0.950	Valid
MP2	0.719			Valid
MP3	0.767			Valid
PS1	0.882	0.867	0.981	Valid
PS2	0.915			Valid
PS3	0.931			Valid

3.1.3. Reliability Test

Reliability is the indicator of the reliability or trustworthiness of research results (Hair et al., 2010). The internal consistency coefficient can be obtained from the normal product-moment correlation or the Spearman-Brown correlation coefficient, which corrects the product-moment correlation coefficient (table 2).

Table 2 Reliability Test Results

Indicator	Alpha Coefficient	Information
Intention to Use (NM)	0.915	Reliable
Perception of usefulness	0.924	Reliable
Convenience Perception	0.898	Reliable
Health Knowledge Level	0.934	Reliable

3.2. Population, Sample, and Sampling Techniques

The population is the overall number of objects or subjects with certain characteristics and qualities determined by the researcher for study (Wiratna, 2018). The target population in this study is the lower-middle-class public. The sample is part of the population possessing certain characteristics used for research (Wiratna, 2018). The research sample is the lower-middle-class public with internet access and never used the Good Doctor application. The selection of the lower-middle-class public with internet access is based on the consideration that respondents can still carefully and objectively fill out the research questionnaire. This sampling technique is conducted using a non-probability sampling design. Non-probability sampling is a technique where each member of the population does not have an equal chance of being selected as a sample (Noor, 2011). The use of non-probability sampling in this research is due to the unknown actual population size. Each population member's probability is unknown (Kuncoro, 2003). Given the characteristics of the existing population and the study's objectives, the purposive sampling method reinforces the determination of respondents as the sample in this study. In this study, respondents know about health applications but have never used them. This research uses structural equality as the data analysis technique. A questionnaire is considered valid if it has a factor weight of 0.4 for a sample size consistent with the factor weight provided in the table.

3.3. Data Source

A data source is the subject from whom the data is obtained (Wiratna, 2018). In this research, data was obtained from answers to distributed questionnaires. This study uses primary data, which is obtained through field surveys using an original data collection method (Kuncoro, 2003). The primary data in this study is obtained from respondents, namely the lower-middle-class public who have never used the Good Doctor health application, through distributed questionnaires. This research uses a rating scale model for the questionnaire, where respondents directly select the range of available answers according to their interests. The scale used for measuring respondents' interest is a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

3.4. Data Analysis Techniques

This study's analysis and hypothesis testing use the Structural Equation Model (SEM) method. SEM is a statistical technique that tests and estimates causal connections by integrating factor analysis and path analysis. Technically, hypothesis testing is conducted using the Amos program version 16 to understand the quality of connections in the proposed structural model.

3.5. Testing Hypotheses

In this study, hypothesis testing is conducted using Structural Equation Modeling (SEM), which integrates both factor analysis and equation modeling (Sarwono, 2010). Two data analysis techniques are employed: (1) Confirmatory Factor Analysis (CFA), used to identify the most dominant factors within a set of variables, and (2) Regression Weight, which examines the strength of the relationships between variables. Factor analysis in this study aims to simplify complex problems by identifying patterns and reducing data for easier interpretation. It explores the interrelationships among the variables, revealing deeper structures within the observed data. There are two types of factor analysis: exploratory factor analysis and confirmatory factor analysis (Sarwono, 2010). This research utilizes CFA to confirm and empirically test models derived from specific theoretical frameworks. The primary question in CFA is how well the empirical data fits the proposed model. SEM is chosen for its efficiency in combining measurement and structural models, offering advantages over traditional multivariate techniques. Hypothesis testing in this study uses SEM with structural equation models and path analysis. Causality or the relationships between variables in the model are tested using the maximum likelihood (ML) estimation method, which generates a critical ratio (T) value equivalent to the t-value in regression analysis. Additionally, this study investigates the moderating role of income levels in influencing the formation of usage intentions. Moderation testing uses SEM, which can handle multi-level and complex hypotheses. This process effectively combines regression and factor analysis to examine these relationships.

4. RESULTS

4.1 Sample Description

Based on the data collected through questionnaires distributed over a one-month period, the responses were categorized by gender, age, education level, occupation, familiarity with the Good Doctor app, and frequency of use. The characteristics of the sample are summarized in Table 3. The results reveal that the largest group of respondents (80.4%, or 201 individuals) is in the 21–30 age range. The second-largest group, aged 31–40 years, consists of 33 respondents (13.2%). The third-largest group is those under 20 years old, accounting for 13 respondents (5.2%). The 41–50 age group follows with 2 respondents (0.8%), and the group over 51 has just 1 respondent (0.4%). This distribution shows that most responses came from the 21–30 age group, likely influenced by the researcher's entrepreneurial environment. Table 3 also highlights educational backgrounds, with the largest group (72%, or 180 people) having completed high school/vocational school or equivalent. The next most common education levels, junior high school, and other qualifications represent 13.6% (34 respondents). The smallest group, with only 2 respondents (0.8%), has an elementary school education. Regarding occupation, Table 3 reveals that the largest number of respondents (36.4%, or 91 people) are entrepreneurs. The second-largest group comprises temporary employees (18.8%, or 47 respondents), followed by a third category labeled "other occupations" (16.8%, or 42 respondents). Other occupations include housewives (10%, or 25 people), daily laborers (7.2%, or 18 people), traders (5.2%, or 13 people), household assistants (4%, or 10 people), and craftsmen (1.6%, or 4 people). This data suggests that most responses were collected from individuals in an entrepreneurial environment. Table 3 further reinforces this distribution, confirming that the sample predominantly represents people involved in entrepreneurial activities.

The sample characteristics based on monthly income are as follows: According to data use in this research, the largest group of respondents (52%, or 130 people) earn IDR 1,000,001–1,500,000 per month. The second-largest group (26.4%, or 66 people) earn between IDR 500,001–1,000,000. The third group, earning above IDR

1,500,000, comprises 28 respondents (11.2%). The smallest group (10.4%, or 26 people) earn IDR 500,000 or less. Regarding the frequency of Good Doctor app usage (Table 4.10), 79.6% (199 respondents) have never used the app. Sixteen respondents (6.4%) have used it once, 21 (8.4%) have used it twice, and 14 respondents (5.6%) have used it more than three times.

Table 3. Sample Demographic profile

Characteristics	Profile	Frequency	Percentage
Gender	Man	114	45.6%
	Woman	136	54.4
Age (years old)	<20 years	13	5.2%
	21 years - 30 years	201	80.4%
	31 years - 40 years	33	13.2%
	41 years - 50 years	2	0.8%
	>51 years	1	0.4%
Education level	Primary school	2	0.8%
	Junior High School	34	13.6%
	Senior High School	180	72%
	Above senior high school	34	13.6%
Total		250	100%

4.2 Goodness of Fit Test

The goodness of fit test is conducted to assess whether the research model aligns with the data based on the following criteria; results of the data analysis in this study are presented as follows:

Table 1. Goodness of Fit Test Results

Fit Index	Output Value	Results	Information
CMIN	Expected Small	84,867	
GFI	≥ 0.90	0, 950	Very good
RMSEA	≤ 0.80	0, 040	Very good
AGFI	≥ 0.90	0, 873	Marginal
TLI	≥ 0.90	0.9 88	Very good
NFI	≥ 0.90	0.9 77	Very good
CFI	≥ 0.90	0.9 95	Very good
CMIN/DF	≤ 2.00	1,267	Very good
RMR	≤ 0.03	3,210	Marginal

Table 4 shows seven criteria for Goodness of Fit, most of which are very good. This indicates that the model is an excellent fit. Based on these results, this research model perfectly fits the data.

4.3. Assumption Test of Data Normality

Testing data normality in SEM analysis is conducted using Maximum Likelihood Estimation (MLE), which assumes that the data are normally distributed, univariate or multivariate. The normality test uses the critical ratio (t) criteria for skewness and kurtosis. Data are normally distributed if the t value lies within the range $-2.58 < t < \pm 2.58$ at a 1% significance level (0.01). The results of the data analysis can be seen in the attachment. The data normality test using t criteria shows values within ± 2.58 at a 1% significance level (0.01). The multivariate t value is within the range $-2.58 < t < \pm 2.58$, with a value of 2.065. From these results, it can be concluded that the normality test criteria in this research are fulfilled.

4.4. Hypothesis Testing

Hypothesis testing is conducted to assess causal relationships between variables in the research model by examining probability (P) values. The variable relationship is considered significant or supported if the P value is less than 0.05. The results of the significance tests for relationships between variables are shown in the following table:

Table 5. Hypothesis Test Results

Hypothesis	β	t	p	Results
health knowledge →Intention to use	1,092	2,625	0.013	H1 Supported
Perception of ease → Intention to use	0.443	2,701	0.005	H2 Supported
Perception of ease → Intention to use	1,548	2,546	0.026	H3 Supported
Perception of ease → health knowledge	0.147	2,410	0.031	H4 Supported
health knowledge*Income → Intention to use	0.073	2,607	0.012	H5 Supported
health knowledge*Income →Intention to use	0.006	3,352	0.003	H6 Supported
Perception of ease*Income → Intention to use	0.124	3,024	0.004	H7 Supported
Perception of ease*Income → health knowledge	0.016	2,667	0.009	H8 Supported

Based on the hypothesis test results, the following conclusions can be drawn: *Perception of Usefulness on Intention to Use:* The estimated value is 1.092, with a t-value of 2.626 and a probability value of P = 0.013 (P < 0.05). This indicates that Perception of Usefulness positively influences the Intention to Use the Good Doctor application, supporting Hypothesis 1. *Convenience Perception on Intention to Use:* The estimate is 0.443, with a t-value of 2.701 and a probability value of P = 0.005 (P < 0.05). This shows that Convenience Perception positively influences the Intention to Use, supporting Hypothesis 2. *Health Knowledge on Intention to Use:* The estimate is 1.548, with a t-value of 2.546 and a probability value of P = 0.026 (P < 0.05). This suggests that Health Knowledge positively influences the Intention to Use, supporting Hypothesis 3. Health Knowledge on Perception of Usefulness: The estimate is 0.147, with a t-value of 2.410 and a probability value of P = 0.031 (P < 0.05). This indicates that Health Knowledge positively influences the perception of Usefulness, supporting Hypothesis 4. *Perception of Usefulness on Intention to Use at Different Income Levels:* The estimate is 0.073, with a t-value of 2.607 and a probability value of P = 0.012 (P < 0.05). This demonstrates that Perception of Usefulness positively influences the Intention to Use across various income levels, supporting Hypothesis 5*. Convenience Perception on Intention to Use at Different Income Levels:* The estimate is 0.006, with a t-value of 3.352 and a probability value of P = 0.003 (P < 0.05). This indicates that Convenience Perception positively influences the Intention to Use across income levels, supporting Hypothesis 6. *Health Knowledge on Intention to Use at Different Income Levels:* The estimate is 0.124, with a t-value of 3.024 and a probability value of P = 0.004 (P < 0.05). This shows that health knowledge positively influences the intention to use it at different income levels, supporting Hypothesis 7. *Health Knowledge on Perception of Usefulness at Different Income Levels:* The estimate is 0.016, with a t-value of 2.667 and a probability value of P = 0.009 (P < 0.05). This indicates that Health Knowledge positively influences the perception of usefulness at different income levels, supporting Hypothesis 8. In conclusion, all hypotheses tested are supported, indicating positive relationships between the variables across different income levels.

5. DISCUSSION

This study shows that Perception of usefulness positively influences the intention to use the Good Doctor health application. This is shown through hypothesis test results with a probability (p) value smaller than 0.05, an estimated 1.092, and a t value of 2.625. Based on these results, it can be concluded that Hypothesis 1 is supported, which can be explained as Perception of usefulness influencing the intention to use health applications. Various previous studies have found that Perception of usefulness significantly influences the intention to use health applications. Health applications are chosen because of their effectiveness in operation, and their use can maintain health through periodic consultations with doctors without face-to-face meetings (Saare et al., 2019; Brătucu et al., 2020). The study by Tahar et al. (2020) states that usability perception positively affects the intention to use health applications because it reflects how users feel technology aids individual productivity. Another study by Van et al. (2021) explains that the perceived usefulness obtained by individuals using applications can enhance work quality. This is supported by studies conducted by Basuki et al. (2022), which show that individuals use health applications because they are perceived to enhance productivity and simplify work. This study indicates that the Good Doctor health application benefits users based on the explanations provided. The perceived usefulness of the Good Doctor health application lies in its provision of digital health services, which can be accessed in various situations. These study results can also be interpreted to mean that the Good Doctor health application helps individuals effectively provide health services while continuing to work and engage in other activities, especially among the middle-to-lower socioeconomic classes.

This study demonstrates that convenience perception positively influences the intention to use the Good Doctor health application, supported by a probability value (p) less than 0.05, an estimated value of 0.443, and a t-value of 2.701. These results confirm that individuals are more likely to use health applications when they perceive them as convenient. Yee et al. (2019) found that convenience perception facilitates users' decisions to use mobile health applications, enhancing health management. Tahar et al. (2020) suggest that a user-friendly system increases the intention to use it, and Van et al. (2021) highlight that users favor applications that minimize effort and save time. Basuki et al. (2022) also support this, noting that ease of use is a key factor in selecting health applications. The Good Doctor application allows individuals to consult healthcare professionals remotely, offering convenience, especially for individuals in middle-to-lower socioeconomic groups.

Additionally, this study reveals that health knowledge positively influences the intention to use the Good Doctor health application, as evidenced by a probability value (p) less than 0.05, an estimated value of 1.548, and a t-value of 2.546. Higher health knowledge leads to a greater intention to use health applications, supporting findings from Rangraz et al. (2020) and Wang et al. (2021). They emphasize that individuals with higher health knowledge are more inclined to use health applications. Sheba et al. (2021) and Klaver et al. (2021) also support this, suggesting that higher knowledge improves the ease of using health technologies. In this study, respondents with at least a high school education demonstrated a stronger intention to use the Good Doctor application, particularly those from middle-to-lower socioeconomic backgrounds. The study further shows that health knowledge positively influences utility perception, with a probability value (p) less than 0.05, an estimated value of 0.147, and a t-value of 2.410. This aligns with Singh et al. (2018), who found that more excellent health knowledge enhances the perceived usefulness of health applications. Deng et al. (2020) and Holtz et al. (2020) also emphasize that health knowledge can increase user engagement and decision-making in health management. This suggests that individuals with higher health knowledge are more likely to recognize the value of using health applications.

Furthermore, the study finds that income level positively influences utility and convenience perception, supporting Hypotheses 5 and 6. Income level was found to increase the perceived usefulness of health applications, as indicated by a probability value (p) less than 0.05, an estimated value of 0.073, and a t-value of 2.607 for utility perception, and an estimated value of 0.006 with a t-value of 3.352 for convenience perception. Research by Chi et al. (2018) and Park et al. (2021) suggests that higher income levels correlate with a stronger intention to use digital applications, as individuals with higher incomes are more familiar with technology. Similarly, Fernandez et al. (2020) and Wang and Qi (2021) emphasize that higher income enhances convenience perception, making applications like Good Doctor more accessible and attractive. This study's findings show that respondents with incomes between IDR 1,000,001 and IDR 1,500,000, representing a sufficient standard of living, tend to view the Good Doctor application as more convenient and useful. Finally, income level positively influences health knowledge, with a probability value (p) less than 0.05, an estimated value of 0.124, and a t-value of 3.024. Higher-income allows individuals to access better education and health resources, enhancing their health knowledge and intention to use health applications. Chi et al. (2018), Chawla and Joshi (2018), and Jaradat et al. (2018) argue that income level strengthens health knowledge, making individuals more likely to use health technologies. Schrauben et al. (2021) found that individuals with higher income and education levels are more likely to use digital health applications, which aligns with the findings of this study.

In conclusion, this study confirms that health knowledge, income level, and convenience perception significantly influence the intention to use the Good Doctor health application. Respondents with higher health knowledge, income, and convenience perception are more likely to use such applications, so service providers can leverage these insights to improve user engagement, particularly among middle-to-lower socioeconomic groups.

6. CONCLUSION

This study was conducted to test the determinants of intention to use the Good Doctor health application among lower-middle-class communities. The intention to use the Good Doctor health application is influenced by utility perception, convenience perception, health knowledge level, and the moderating role of income level. The results of the data analysis in this study support all the tested hypotheses. It can be interpreted that the intention to use the Good Doctor health application among lower-middle-class communities is high due to its ability to save time and energy, thereby enhancing productivity in daily life. Individuals' high level of health knowledge helps them manage their health with the assistance of information systems like the Good Doctor health application, reducing the need to visit health clinics for professional medical consultations. The use of health applications in this study is also supported by the income level of individuals, where higher income levels increase the intention to use health applications.

7. LIMITATIONS AND RECOMMENDATIONS

This study has some limitations that need to be acknowledged. First, it focused solely on the Good Doctor health application, which is relatively new, having launched in 2020 on Google Play and the App Store. As a result, some respondents were unfamiliar with the application. Additionally, the study specifically targeted the lower-middle-class community, making finding participants who met the sample criteria challenging. The offline data collection process also proved time-consuming, as many in the lower-middle-class community are familiar with health applications but do not use them widely. Future studies could consider the following recommendations to address these limitations: Broader Research Object: Choose a more widely recognized health application or platform to simplify participant recruitment across different demographics. Improved Data Collection: While offline data collection can be effective, researchers should assist respondents in filling out questionnaires to ensure more accurate data retrieval. Expanded Demographics: Future research should include a more diverse sample that spans all socioeconomic classes, from lower to upper classes, to enhance the generalizability of the findings.

Based on the findings of this study, the following practical recommendations are made for the service provider of the Good Doctor application: Perception of Usefulness: Service providers are encouraged to enhance the "Consult a Doctor" feature to allow users to more effectively monitor their health and promote the adoption of a healthy lifestyle through the app. Convenience Perception: Service providers should improve the user experience by simplifying the process of updating personal information, such as changing phone numbers or email addresses, without deleting and reinstalling the application. Health Knowledge Level: Service providers should consider expanding the information system by introducing a dedicated health goals page. This page would provide users with valuable health-related knowledge and deeper insights into health improvement strategies. These recommendations aim to improve user satisfaction and increase the overall utility of the Good Doctor application.

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