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ANKARA YILDIRIM BEYAZIT UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES

THE DIFFERENCES IN BEHAVIORAL FINANCE BIASES BASED ON COLLEGE STUDENTS' COGNITIVE REFLECTION: EXAMPLE OF ANKARA

MASTER'S THESIS

Nurbanu KURTULMUŞ

FINANCE AND BANKING PROGRAM

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Thesis Advisor
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CONFIRMATION PAGE

The thesis study "The Differences in Behavioral Finance Biases Based on College Students' Cognitive Reflection: Example of Ankara," prepared by Nurbanu KURTULMUŞ is approved anonymously/by majority votes by the jury as master's thesis in Ankara Yıldırım Beyazıt University Social Sciences Institute Department of Finance and Banking.

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I certify that this thesis fulfills all the requirements to be deemed a master thesis at Ankara Yıldırım Beyazıt University, Graduate School of Social Sciences, Department of Finance and Banking.

Director of the Institute of Social Science

DECLARATION

As a result, I declare that all information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct. I also say that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work; otherwise, I accept all legal responsibility.

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Nurbanu KURTULMUŞ

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ABSTRACT

The Differences in Behavioral Finance Biases Based on College Students' Cognitive Reflection: Example of Ankara

This study aimed to examine whether there were differences between the cognitive reflection levels of university students and behavioral biases such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. In addition, it also aimed to examine if cognitive reflection levels and behavioral biases of university students differed according to their demographic characteristics. This descriptive and cross-sectional quantitative research was conducted in a relational screening model for this purpose. The study sample consisted of 388 participants selected through a simple random sampling method among students at universities in Ankara province. The research collected primary data using an online questionnaire that included questions about cognitive reflection and behavioral biases such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. SPSS v26 software was utilized for data analysis in the study. Chi-square test, t-test, and ANOVA analysis were employed for testing the research hypotheses. As a result of the investigation, it was determined that intuitive participants with low cognitive reflection tended to exhibit more base ratio neglect bias and exponential growth bias compared to analytical participants. On the other hand, it was determined that overconfidence bias and mental accounting bias did not differ significantly according to the cognitive reflection levels of the participants. In addition, it was observed that cognitive reflection and behavioral biases did not differ significantly according to the demographic characteristics of the participants.

Keywords: Cognitive Reflection, Overconfidence, Mental Accounting, Behavioral Finance, Base-Rate Neglect, Exponential Growth Bias

ÖZET

Üniversite Öğrencilerinin Bilişsel Yansımalarına Dayalı Davranışsal Finans Yanlılıklarındaki Farklılıklar: Ankara Örneği

Bu çalışmada üniversite öğrencilerinin temel oran ihmali, aşırı güven, zihinsel muhasebe ve üssel büyüme gibi davranışsal yanlılıklarında bilişsel yansıma düzeylerine göre farklılık olup olmadığının incelenmesi amaçlanmıştır. Ayrıca üniversite öğrencilerinin bilişsel yansıma düzeylerinin ve davranışsal yanlılıklarının demografik özelliklerine göre farklılık gösterip göstermediğinin incelenmesi de amaçlanmıştır. Bu amaç doğrultusunda tanımlayıcı ve kesitsel nitelikteki bu nicel araştırma, ilişkisel tarama modelinde gerçekleştirilmiştir. Araştırmanın örneklemini Ankara ilindeki üniversitelerde öğrenim gören öğrenciler arasından basit tesadüfi örnekleme yöntemiyle seçilen 388 katılımcı oluşturmuştur. Araştırmada, bilişsel yansıma ile temel oran ihmali, aşırı güven, zihinsel muhasebe ve üssel büyüme yanlılığı gibi davranışsal yanlılıklarla ilgili sorular içeren çevrimiçi bir anket kullanılarak birincil veri toplanmıştır. Elde edilen verilerin analizinde SPSS v26 yazılımı kullanılmıştır. Araştırma hipotezlerinin test edilmesinde ki-kare testi, t-testi ve ANOVA analizi gerçekleştirilmiştir. Analizler sonucunda bilişsel yansıması düşük sezgisel katılımcıların analitik katılımcılara göre daha fazla temel oran ihmali yanlılığı ve üssel büyüme yanlılığı sergileme eğiliminde oldukları belirlenmiştir. Öte yandan aşırı güven yanlılığı ve zihinsel muhasebe yanlılığının katılımcıların bilişsel yansıma düzeylerine göre anlamlı bir farklılık göstermediği tespit edilmiştir. Ayrıca bilişsel yansıma ve davranışsal yanlılıkların katılımcıların demografik özelliklerine göre anlamlı düzeyde farklılaşmadığı görülmüştür.

Anahtar Kelimeler: Bilişsel Yansıma, Aşırı Güven, Zihinsel Muhasebe, Davranışsal Finans, Temel Oran İhmali, Üssel Büyüme Yanılgısı

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LIST OF ABBREVIATIONS

CHE : Council of Higher Education (Yükseköğretim Kurulu)

CRT : Cognitive Reflection Test

Df : Degrees of Freedom

sd : Standard Deviation

USA : United States of America

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1. INTRODUCTION

The concept of individual rationality, which allows for the scientific examination of individuals in the context of fields such as business or economics, holds a prominent position in social sciences. However, more research must be done on the concept of rationality itself. This assumption represents a concept dictated by disciplines like business and economics, which have extensively interacted with statistics and econometrics since the 1900s. From this perspective, individuals are expected to be rational, considering their economic benefits and interests, and exhibit rational behavior regarding spending, investment, and savings. However, recent studies in the field of behavioral economics (or finance/marketing) indicate that certain behavioral biases, triggered by heuristics, which are shortcuts originating from individuals' brain structures and can be generalized to almost all individuals, significantly violate this fundamental assumption (Polat & Duman, 2020).

Research conducted in behavioral finance, which examines how psychology influences the financial decisions of individuals, markets, and organizations, has investigated a wide range of biases, many of which have their origins in the field of psychology (Coval & Shumway, 2005). These biases in finance include base-rate neglect, overconfidence, mental accounting, and exponential growth bias (Leeper, 2015). Base-rate neglect refers to the tendency of individuals to disregard or give insufficient weight to the base rate information in favor of more descriptive information, failing to consider both sets of information adequately (Hoppe & Kusterer, 2011). Overconfidence occurs when individuals believe their knowledge to be more accurate than it is (Gervais et al., 2011). Mental accounting involves the process of coding, categorizing, and evaluating events when making decisions (Thaler, 1999). Lastly, exponential growth bias describes the tendency of consumers to simplify functions with exponential terms by linearizing them during their evaluation (Stango & Zinman, 2009). These behavioral biases have been found to impact the field of finance in various ways, such as influencing asset prices, increasing trading activity among individuals, diminishing trading performance, driving detrimental acquisitions that harm shareholder wealth, shaping

spending decisions based on previous patterns, underestimating the long-term costs of delaying retirement savings, and more (Leeper, 2015).

Researchers have also examined individuals' capacity to resist the impulse to provide an immediate response, commonly known as cognitive reflection (Frederick, 2005). Researchers have employed a three-question cognitive reflection test (CRT) tool to measure cognitive reflection. Previous studies have indicated that the susceptibility to certain behavioral biases, like overconfidence, varies depending on an individual's level of cognitive reflection (Frederick, 2005; Hoppe & Kusterer, 2011; Oechssler et al., 2009). Recently, Toplak et al. (2011) developed an updated version of the cognitive reflection instrument, addressing concerns about the internal consistency of the previous test. However, only some behavioral biases have been thoroughly investigated to determine whether there are differences in susceptibility based on an individual's level of cognitive reflection, as measured by the CRT. Additionally, the previously studied biases have yet to utilize the updated version of the CRT, which now consists of seven questions.

On the other hand, this study will be carried out on university students, as it is observed as an inadequate field of study in Ankara in the light of Frederick's research. The research is conducted in this field because most behavioral finance studies involve individual investors with a certain income. This research will examine the relationship between behavioral finance biases and university students' cognitive reflection levels. University students are the architects of the future economies of countries. At this point, students with great importance should be evaluated regarding behavioral finance and cognitive reflection. Today, students studying at the university are Generation Z. There are few studies on Generation Z worldwide (Yıldırımer et al., 2011). To evaluate the financial structure of countries, more studies should be done on this generation, which is of great importance for the future.

In this context, the problem that forms the basis of the research is to determine whether there is a difference between the cognitive reflection levels of university students and their behavioral biases, such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. Sub-problems of the research explore whether there are differences between gender, age, ethnicity, field of study, class status, and region.

This study aims to determine whether there are differences between the cognitive reflection levels of university students and behavioral biases, such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias, to find answers to research problems. In addition, it also aimed to examine if cognitive reflection levels and behavioral biases of university students differ according to their demographic characteristics such as gender, age, ethnicity, field of study, class status, and region.

2. LITERATURE REVIEW

2.1. Traditional Finance

Traditional finance is built on the assumption that individuals are rational in their decisions and do not possess psychological biases in their predictions (Nofsinger, 2014). The concept of the rational individual in traditional finance represents an unrealistic entity that is fully informed, capable of accurately predicting the future, devoid of any memory limitations, unaffected by emotions in the decision-making process, immune to repeating the same mistakes, capable of anticipating change and possessing complete control over their decisions (Demir, 2013).

Traditional finance, which emerged in the early 19th century, gained momentum in the latter half of the 20th century (Kıyılar & Akkaya, 2020). During this period, traditional finance focused on developing theories and models that individuals could utilize to optimize the expected return and risk associated with their investments (Nofsinger, 2014).

2.1.1. Traditional Finance Theories and Models

The currently accepted theories in the field of finance are commonly referred to as standard or traditional finance theories (Ricciardi & Simon, 2000). These theories are based on the fundamental assumptions that all participants operating in the economy and financial markets are rational, have access to all relevant information, and can process it perfectly (Tekin, 2016).

According to traditional finance theories based on these assumptions, individuals are presumed to consider and calculate all possibilities and utilities under uncertainty during decision-making. In these theories, individuals' psychology is wholly disregarded, and it is assumed that they will always make rational decisions akin to a robot (Güngör & Demirel, 2018).

Expected utility theory is considered one of the fundamental pillars of traditional finance. Prior to the development of prospect theory, it was widely employed to explain individuals' decision-making behavior under risk conditions. The origins of expected utility theory can be traced back to Daniel Bernoulli, who laid its groundwork in 1738, and it was further refined and expanded upon by John Von Neumann and Oscar

Morgenstern in 1944 (Sefil & Çilingiroğlu, 2011). This theory played a significant role in understanding how individuals assess and evaluate uncertain situations, providing insights into their financial preferences and choices.

Based on maximizing expected utility, the Expected utility theory has been developed to aid decision-making and rational choices under risk and uncertainty (Şenkesen, 2009). According to this theory, individuals make decisions by relying on probabilistic calculations and choose the option that maximizes their utility or overall satisfaction (Tekin, 2016).

The foundation of traditional finance is closely related to modern portfolio theory and the efficient market hypothesis (Ricciardi & Simon, 2000). Traditional portfolio theory argues that a rational investor can reduce portfolio risk through diversification. According to the theory, since the expected returns of each financial asset in the portfolio will have different directions, the risk of a diversified portfolio will also decrease. On the other hand, modern portfolio theory is a theory proposed by Markowitz that addresses the inability to reduce risk to the desired level (Güngör & Demirel, 2018). It acknowledges the limitations of diversification in eliminating risk and provides a framework for optimizing portfolio selection based on risk-return trade-offs.

Markowitz (1959), states that diversification generally reduces risk but does not eliminate it. The most significant aspect of Markowitz's theory is to demonstrate that the risk that matters to an investor is not the risk of an individual security. The theory highlights that what matters in reducing portfolio risk is the impact security will have on the overall portfolio and its interaction with all other securities in the investor's portfolio (Rubinstein, 2002). It emphasizes the importance of considering the effects of the securities' interactions and changes within the portfolio rather than solely focusing on the risk of individual securities.

One of the significant theories within traditional finance is the Efficient Market Hypothesis. An efficient market is characterized as a market where prices always fully reflect all available information. The Efficient Market Hypothesis argues that in an efficient market, investors can always have access to all information regarding security prices (Fama, 1970). The theory assumes the presence of a large number of buyers and sellers who have no influence on the market, rapid and low-cost access to information

about securities, immediate price reactions to new information, low transaction costs, and well-developed institutional structures in the markets (Altunöz & Altunöz, 2018).

In the development of traditional finance, pricing models such as the capital asset pricing model, arbitrage pricing model, and option pricing model have also played a significant role. These models provide investors with insights into securities' valuation, returns, and risks. However, it has been observed that individuals are more influenced by psychology and emotions when making investment decisions rather than the financial theories and models mentioned above (Nofsinger, 2014).

The abstract nature of traditional finance theories, which exclude behavioral elements shaped by psychology and emotions, has led to a new approach called behavioral finance. This approach places human psychology at the center, aiming to explain market fluctuations and crises that traditional finance theories fail to account for. (Sefil & Çilingiroğlu, 2011).

2.2. Behavioral Finance

2.2.1. Definition of Behavioral Finance

Traditional finance theories have assumed investors to be rational individuals who can solve complex problems, even under the influence of emotions, to maximize their utility. These theories depict a rational individual, referred to as "homoeconomicus," who utilizes the Expected Utility Theory to make investment choices, selects an appropriate portfolio, avoids repeating the same mistakes, and updates their expectations in line with the information arriving in the market, as assumed by the Efficient Market Hypothesis (Sefil & Çilingiroğlu, 2011).

However, many economists have realized that these assumptions must align with real-life events. The inadequacy of traditional finance theories in explaining market anomalies that emerged after the 1970s has paved the way for the emergence of behavioral finance. Behavioral finance relies on cognitive psychology and recognizes the limitations of arbitrage. Furthermore, it assumes that individuals are prone to repeating the same mistakes and susceptible to psychological factors' influence. While there are critics who oppose these assumptions, there are also proponents who accept them.

Traditional finance assumes investors seek to maximize utility by considering risk and expected returns based on the Expected Utility Theory. However, behavioral finance suggests that investors, when making investment decisions, consider risk, expected returns, and other variables as they seek to satisfy their preferences rather than solely maximize their expected utility. This is because the evaluation of all variables is not perfect, and in such circumstances, satisfaction rather than utility maximization becomes the best achievable outcome.

For example, investors who choose to invest in environmentally friendly "green funds" that promote harmony with nature or individuals who avoid investing in companies involved in tobacco and alcohol production are driven by the goal of satisfaction rather than utility maximization. By nature, humans are inclined to seek pleasure and avoid pain. Consequently, their behaviors are driven by the pursuit of pleasure. It is at this point that individuals can deviate from rationality.

Traditional finance and behavioral finance differ in terms of their methodologies. In traditional finance, the primary approach involves developing a model, making testable predictions, and subjecting those predictions to empirical testing. On the other hand, in behavioral finance, observations of actual behaviors precede the development of models. As a result, traditional finance focuses on prescribing how investors should behave, while behavioral finance focuses on describing how investors behave.

The fundamental assumptions of behavioral finance (Ritter, 2003) are as follows:

- Individuals are considered "normal" rather than "rational."
- They consider more variables than risk and expected returns in their investment decisions.
- Their goal is satisfaction rather than utility maximization.
- It focuses on how people behave rather than how they should behave.

Behavioral finance demonstrates that individuals cannot always behave rationally, thus challenging the validity of the Efficient Markets Hypothesis and the Expected Utility Hypothesis. According to the Efficient Markets Hypothesis, current prices reflect all readily available information in the market without cost or effort. However, due to perceptual differences, there will be different price expectations even if everyone has access to the same information. This leads to certain anomalies in the market (Tufan, 2008).

Anomaly refers to irregular and irrational events in the markets. Behavioral finance explains anomalies that are not taken into account by traditional finance. Behavioral finance emerged by considering that many market anomalies could be attributed to human psychology or by incorporating psychological elements into the decision-making process (Cornicello, 2003).

In 1979, psychologists Kahneman and Tversky laid the foundations of Prospect Theory in contrast to Expected Utility Theory in traditional finance. They developed this theory by studying soldiers about to join the Israeli army at Hebrew University in Jerusalem. Kahneman's work in behavioral finance gained recognition in the scientific community, and was awarded the Nobel Prize in 2002. As a result, the number of studies in this field has increased over time, encouraging many academics to conduct research in this area (Sefil & Çilingiroğlu, 2011).

At this stage of the study, different definitions of behavioral finance in the literature are given:

Let us assume that investors are rational, according to Tufan (2008). In the decision-making stage, there will be predictions and risks due to the future and uncertainty. Since investors have different economic perceptions, their preferences will vary, leading to differences in the indices and ratios that guide investor decisions. It will be impossible to explain trends solely based on economic parameters; behavioral factors also influence these changes. Economic factors and behavioral factors are interrelated and mutually influence each other.

According to Russel (2000), behavioral finance involves identifying how investors behave irrationally and making systematic errors when predicting the expected returns on their financial assets. *Behavioral finance* is an interdisciplinary field that seeks to explain the causes of anomalies in financial markets.

According to Prast (2004), behavioral finance is a science that investigates the influence of psychology on financial markets and investor decisions.

Barberis and Thaler (2002) define *behavioral finance* as a proposition that explains how real individuals make decisions and create differences, which traditional finance theories ignore.

Lastly, Traditional Finance Theories need to be revised to explain the reasons behind the deviations of stock prices from their fundamental values, market fluctuations, and anomalies observed in financial markets. Markets do not operate as modeled in Traditional Finance Theories, and prices do not form as predicted by those theories. The failure of the Efficient

Market Hypothesis to hold in markets, along with the presence of market fluctuations, anomalies, and the absence of a system where individuals make rational decisions, has paved the way for the consideration of human psychology and behavior in financial and economic analyses, leading to the emergence of behavioral finance (Cajueiro & Tabak, 2009).

If we were to describe behavioral finance in essence, it could be explained through two concepts: investor biases (psychological factors) and the arbitrage boundary resulting from investor irrationality. Investors need to possess a flawless system that maximizes gains and minimizes losses. Psychological biases, personal characteristics, emotions, and tendencies influence investors' decisions and systematically lead to errors. Investors tend to choose behaviors that satisfy themselves rather than relying on mathematical models when making decisions.

2.2.2. Behavioral Finance Biases

2.2.2.1. Base-Rate Neglect Bias

Base Rate Neglect or Base Rate Fallacy occurs when an individual underestimates or neglects the base rates during information evaluation (Tversky & Kahneman, 1974). The individual's disregard for the probabilities associated with the outcomes is expressed instead of evaluating them based on the representativeness heuristic.

Tversky and Kahneman attributed the base rate neglect to the representativeness heuristic, which is the tendency of individuals to evaluate probabilities based on how closely something resembles a reference rather than using the actual probabilities associated with it (Hayta, 2014). Essentially, individuals assess the likelihood of object A being a reflection of a characteristic related to object B.

Researchers have observed that when individuals are asked to determine the probabilities associated with a specific outcome and are provided with new or additional information about that situation, they often need to incorporate the previous probabilities associated with that situation. However, if no specific information had been given, individuals would rely more on the previous probabilities related to the situation.

For instance, in a scenario where a random individual is selected from a sample of 100 people consisting of 30 engineers and 70 lawyers, participants have been found to disregard the initially known ratio of 30% engineers to 70% lawyers when presented with characteristic features such as "having no interest in politics and spending a significant

amount of leisure time on mathematical puzzles." Instead, they interpret the given information, which could be neutral, as a base rate and provide responses accordingly.

Therefore, it is evident that individuals exhibiting the base rate neglect do not make inferences based on the Bayes' Rule, as proposed by Expected Utility Theory (Tversky & Kahneman, 1974; Birnbaum, 1983).

Uncertainty, an indispensable aspect of individuals' lives, leads individuals to rely on intuitive judgments due to insufficient formal models to calculate the probabilities of all events. However, intuitions regarding probabilities often deviate significantly from the principles of probability theory (Barbey & Sloman, 2007).

Under normal circumstances, individuals do not place and analyze everyday events in complex tables of probabilities; they do not evaluate compound probabilities by combining primary attributes. Instead, they often rely on limited heuristics such as representativeness and availability (Kahneman & Tversky, 1983).

When individuals are asked to evaluate an event's probability, they mainly consider the base rate probability information and specific evidence related to the current issue (Tversky & Kahneman, 1981). In such a situation, if an individual falls into the representativeness heuristic and neglects the base rate probability, the base rate fallacy occurs (Hoppe & Kusterer, 2011).

Kahneman and Tversky (1972) revealed a surprising aspect of human judgment in their study: When participants were provided with information about the prevalence of specific characteristics in a population and brief personality sketches, their predictions were predominantly based on clinical descriptions.

Even when participants believed clinical descriptions had little predictive value and substantial monetary incentives were provided for accurate predictions, this finding was confirmed even when the base-rate percentages were highly extreme.

Nisbett and Borgida (1975) demonstrated in a different domain that individuals tend to rely on clinical descriptions to understand the causes of past behavior and predict future actions while neglecting base-rate information (Nisbett & Borgida, 1975).

To explain the base rate fallacy, an example given by Russel and Norvig (1995) describes a situation where there is a test with a 99% accuracy rate in diagnosing a specific disease. It is assumed that the doctor informs the patient of good and bad news regarding their condition, emphasizing that the test has a 99% accuracy rate. If the patient has the disease, the test will show a positive result with a 99% probability. Conversely, if the patient does not have the disease, the test will show a negative result with a 99% probability.

In the given scenario, we are asked to consider the test coming out positive as bad news and the probability of the disease occurring as 1/10,000 as good news (Russell & Norvig, 1995).

Given this information, we are asked about the likelihood of being sick. In such a situation, pessimism will likely arise in individuals, and the intuitive judgment of System 1 will have a significantly high estimation regarding the probability of having the disease.

However, when the situation is calculated with the help of System 2, it will be observed that the individual's probability of carrying the disease is significantly lower than System 1's pessimistic estimate (Axelsson, 2000).

$$P(S\backslash R) = \frac{\frac{1}{10.000} \times 0{,}99}{\frac{1}{10.000} \times 0{,}99 + (1 - \frac{1}{10.000}) \times 0{,}01} = 0{,}0098 \cong \%1$$

One recurring finding in research on decision-making is that decision-makers sometimes make the normatively optimal decision. A commonly observed pattern in this regard is as follows:

"Steve is a timid and introverted individual. Although he is always willing to help others when asked, he has little interest in people and the world. Additionally, Steve can be described as gentle and naïve in nature, and he values precision and pays attention to details."

In light of this information, the probability of Steve being a farmer, salesperson, pilot, or librarian is questioned. According to the representativeness heuristic, individuals in such an example base their decisions on the extent to which Steve represents or resembles the stereotypes associated with each profession.

Using this intuitive method, the individual evaluates the probability of an uncertain event based on the similarity between the essential characteristics and the main population, reflecting the distinctive features of the mental process created in their mind (Davidson & Hirtle, 1990).

However, there is an inconsistency between the essential characteristics presented in such a question and the probabilities of occurrence of the corresponding answers in the main population. In that case, individuals will fall into a fallacy by neglecting the base rates. A classic example designed by Kahneman to demonstrate how individuals deviate from base rates is as follows (Kahneman, 2011):

"Tom W is a graduate student at your local university. Please rank the following nine graduate specialization areas according to the probability of Tom W currently studying in one of these departments.

Business Administration

Computer Science

Engineering

Humanities

Law

Medicine

Library

Science

Physics

Social Sciences"

The given question only provides distribution information, in other words, information about the base rates. Therefore, the answers given to this form of the question will be based on the average values of the mentioned specialization areas. However, Kahneman designed an experiment that disrupts the base rates by adding additional information to the question:

Below is a personality description of Tom W written by a psychologist based on psychological tests of uncertain validity during his senior year of high school:

Tom W is brilliant but needs more genuine creativity. He thrives on order and clarity, needing well-structured systems where every detail falls into its rightful place. Although his writing occasionally sparkles with stale wordplay and bursts of imagination from science fiction, it is mainly dull and mechanical. A strong need for competence drives him. He harbors little understanding or sympathy towards others and dislikes interacting with people. Despite being self-centered, he possesses a profound sense of morality.

In his research, Kahneman demonstrates that when individuals are provided with cues embedded in the given description, indicating that Tom W resembles a specific group stereotype (representativeness heuristic), they tend to neglect the base rate in their responses. This situation leads individuals to prefer determining similarity, which is an easier path, rather than assessing probability.

To reinforce the difference between base rate probabilities and similarity (representativeness heuristic), Kahneman provides another striking example:

Which of the following predictions do you perceive as a more accurate estimation regarding a woman who reads The New York Times in the New York subway?

a) The woman possesses a doctoral degree.

b) The woman is not a university graduate.

Based on the representativeness heuristic, System 1 would associate the woman with a group of individuals who have obtained a doctoral degree. However, when System 2 comes into play by considering the distribution information, it becomes evident that the basic proportions among individuals traveling on the subway reflect the opposite scenario, where there are more non-college graduates than individuals with a doctoral degree. One of the most famous examples, further elaborated by Kahneman and Tversky, to illustrate this concept in a more complex manner is as follows (Kahneman, 2011):

Linda is 31 years old, single, ambitious, and highly intelligent. She has received education in the field of philosophy. During her student years, she showed a keen interest in discrimination and social justice issues, actively participating in anti-nuclear demonstrations. In this case:

a) Linda is an elementary school teacher.

b) Linda works at a bookstore and takes yoga classes.

c) Linda is actively involved in the feminist movement.

d) Linda works as a psychiatric social worker.

e) Linda is a member of a women's voting association.

f) Linda works as a teller at a bank.

g) Linda is an insurance salesperson.

h) Linda works as a bank teller and is actively involved in the feminist movement.

When basic probabilities are disregarded, the likelihood of Linda belonging to a feminist group and taking yoga classes becomes more prominent, while the probability of her being an insurance salesperson or a bank teller is pushed further back. On the other hand, the pattern known as the conjunction fallacy, which vividly demonstrates the fundamental probability fallacy, arises when the majority of participants from different groups perceive the probability of Linda being a bank teller as lower than the probability of her being a feminist bank teller, which is a subset of that group. One of the modeling examples conducted by Hsee (1998) on the conjunction fallacy that leads to the fundamental probability fallacy is as follows (Hsee, 1998):

	A Team (40 pieces)	B Team (24 pieces)
Dinner Plates	8 intact pieces	8 intact pieces
Bowls	8 intact pieces	8 intact pieces
Dessert Plates	8 intact pieces	8 intact pieces
Cups	8 piece, 2 of them broken	
Saucers	8 piece, 7 of them broken	

In the experiment, participants were subjected to two different types of tests: In the first test, both teams were presented together for sale, while in the other test, only one of the teams was presented for sale. The rational outcome favored Team A, which had parts with additional economic value when both teams were presented: Participants were willing to pay $32.09 for Team A and $29.70 for Team B. In the subsequent test, only one of the teams was presented for sale, and the inconsistency, referred to as "less is better" by Hsee, occurred as participants were willing to pay $23.25 for Team A and $32.69 for Team B.

Decisions made by individuals partially reflect the subjective degree of belief of the decision-maker regarding uncertain events (Barbey & Sloman, 2007). The most critical decisions are based on beliefs about the probabilities of uncertain events, such as the outcome of a choice, the guilt of a suspect, or the future value of a currency, and are expressed through subjective statements like "I think...", "There is a chance that...", "It is unlikely..." and similar expressions.

Beliefs about these uncertain events are sometimes expressed numerically as ratios or subjective probabilities. At this point, what becomes essential is the factors that determine these beliefs and how individuals evaluate the value of an uncertain event or an uncertain quantity (Tversky & Kahneman, 1975).

In particular, when the visibility is poor, such as when the visual distance is weak, objects' contours (outer boundaries) may become blurred, leading to inaccurate estimations of distances (Tversky & Kahneman, 1975). Similarly, when making predictions involving uncertain quantities, such as the value of the Dow Jones index on a specific day, future sales of a product, or the outcome of an election, individuals can utilize two types of information: singular information and distributional information.

Singular information (case data) consists of evidence related to the specific situation under investigation. On the other hand, distributional information (base-rate data) is composed of knowledge about the distribution of outcomes in similar situations. For instance, when predicting the lifespan of a patient, singular information would include factors such as age, health condition, and past medical history. In contrast, distributional information would be derived from relevant population statistics.

Singular information defines specific characteristics that distinguish the problem from others, while distributional information characterizes the observed outcomes in general situations of the same class. Many prediction problems are unique because they involve small amounts of available relational distributional information, if any. Experts should rely on singular information when making predictions, such as estimating nuclear energy demand on a specific date or predicting when a cure for leukemia will be found. However, the issue is that evidence shows individuals need to be sufficiently sensitive to distributional data, even when it is available.

On the other hand, in the context of planning, there are many examples where the distribution of outcomes based on past experiences is disregarded. Planning fallacy results from the tendency to overlook distributional data, and the internal approach to evaluating these plans likely generates an underestimation bias. A construction project can be completed on time only if there are no delays in material delivery, strikes, or unforeseen weather conditions.

Each of these disruptions is improbable, but the possibility that at least one of them may occur can be significant (Kahneman & Tversky, 1977). However, this combinatorial thinking needs to be adequately represented in individuals' intuitions (Bar-Hillel, 1973).

Studies on the base rate fallacy suggest that, as assumed, individuals often violate the use of Bayes' theorem in their reasoning. An example illustrating this issue involves judges, whose decisions carry significant importance.

Research by Hammerton (1973) and Kahneman and Tversky (1972) is based on the finding that when judges are asked to solve a statistical problem, their typical response differs from the Bayesian solution. Bar-Hillel (1980), Lyon and Slovic (1976), Fischhoff, Slovic, and Lichtenstein (1977), and many other researchers have investigated this topic in various ways. The classic example used by Kahneman and Tversky (1972), which has become well-known, is the taxi problem, described as follows:

A hit-and-run traffic accident occurred one night in a city where two taxi companies (blue and green) operate. The following information is provided regarding the situation:

- *85% of the taxis in the city are Green, while 15% are Blue.*
- *A witness shared that the vehicle involved in the accident was Blue.*

The court has tested the ability of individuals to identify taxis under appropriate viewing conditions. When presented with a sample taxi that is half blue and half green, the witness made accurate identifications in 80% of the cases. Taking this information into account, when questioned about the probability of the taxi involved in the accident being blue instead of green, the typical response is 9%, while the normative solution is 41% (Birnbaum, 1983).

2.2.2.2. Overconfidence Bias

Individuals can be inherently overconfident. Overconfident individuals exaggerate their knowledge and abilities, believing they can control outcomes and underestimating risks (Nofsinger, 2014).

Overconfidence refers to individuals' unwarranted belief in their intuitive thinking, decision-making, and cognitive abilities (Pompian, 2006). Many psychology and behavioral finance researchers who study overconfidence have demonstrated that individuals tend to overstate their skills and predictions regarding success (Ricciardi & Simon, 2000).

For example, Svenson (1981) asked a group of university student drivers to evaluate their driving abilities compared to other drivers. Most drivers perceived themselves as better and more skilled than the average driver. In a similar study, Cooper, Woo, and Dunkelberg (1988) asked 2,994 entrepreneurs who had recently started their businesses about their chances of success in the business world. These entrepreneurs perceived their business success chances as 81%, while they perceived the success chances of other new businesses like theirs as only 33%.

Numerous studies in the field of behavioral finance have shown that overconfident individuals tend to take more risks and engage in more trading activities when making investments, resulting in lower returns (Nofsinger, 2014).

For instance, Barber and Odean (2001) examined the phenomenon of excessive trading among overconfident investors, considering gender differences among investors. The study covered 1991-1997 and analyzed a sample of 35,000 investors, consisting of 29,659 males and 8,005 females.

The study is based on two hypotheses: first, that men engage in more trading than women, and second, that because of excessive trading, men perform worse than women. According to the analysis, men trade 45% more than women. Additionally, the study found that single men engage in trading 67% more than single women. The transaction costs resulting from excessive trading reduce men's net returns by 2.65% annually, while they decrease the net returns of women by 1.72%.

In summary, men trade more than women, resulting in lower returns. Furthermore, these differences are more pronounced among single men and single women.

The tendency of overconfidence leads individuals to exhibit faulty behaviors in their financial decision-making. These faulty behaviors can be summarized as follows (Pompian, 2006):

- Overconfident individuals tend to exaggerate their abilities in evaluating investments. This can lead them to ignore negative information about their investments.
- Overconfident individuals may engage in excessive trading because they believe they possess exclusive information that others do not have. Excessive trading behavior, in turn, leads to low returns over time.
- Overconfident individuals may underestimate downward risks in their portfolios. This results in unexpectedly low portfolio performance.
- Overconfident individuals tend to need more diversification in their portfolios. This exposes them to higher levels of risk than they can tolerate.

Individuals commonly tend to be overconfident in their daily lives and financial transactions. When making decisions, individuals must trust their knowledge, skills, abilities, and predictions. However, unrealistic overconfidence can lead to adverse outcomes. Therefore, making decisions based on conscious research is healthier, considering a realistic assessment of our information, skills, and abilities.

Investing is challenging as it requires gathering information, analyzing the collected data, and making decisions based on the analysis. Overconfident investors perceive their abilities to be higher than they are and misinterpret the accuracy of information (Nofsinger, 2014). *Excessive confidence* can be defined as "unwarranted beliefs about a person's intuitive thinking, decision-making, and cognitive abilities." Overconfident individuals

believe that their information is superior to that of other investors and that they act much more innovatively than other investors (Cornicello, 2003).

Excessive confidence has two aspects: "miscalibration" and the "above-average effect." Miscalibration refers to individuals providing estimates within very narrow intervals regarding probability distributions. For example, participants were asked questions such as "What is the average weight of an adult blue whale?" "How many bones are there in the human body?" "What is the length of the Amazon River?" Despite not knowing the subjects, they were asked to provide a range that they believed included the highest and lowest possible values. The participants were instructed to provide a range that would ensure 90% confidence that the correct answer fell within that range without making the range too broad or too narrow.

Most participants answered five or more questions incorrectly, even when they did not know the subjects, indicating their excessive confidence. Despite their knowledge, many finance professors also answered at least five questions incorrectly. The above-average effect refers to individuals having unusually positive impressions about themselves. A study conducted on university students used the question, "Are you a good driver? When comparing yourself to other drivers you encounter on the road, do you consider yourself an average, above-average, or below-average driver?" 82% of the students evaluated their driving skills as above average (Svenson, 1981). 82% of the participants displayed overconfidence.

Overconfidence in their abilities and knowledge makes investors feel good about themselves, leading them to invest even in areas where they should not (Veeraraghavan, 2010).

Overconfidence bias also affects the decisions of investors in financial markets. Overconfident investors in the markets engage in more trading compared to rational investors. This is because overconfident investors have more trust in their own information and evaluation abilities. They also perceive the risks in their investment transactions to be lower than those of other investors. This leads to excessive trading, risk-taking, and losses (Barber & Odean, 2001).

Barber and Odean (2001) stated that excessive trading harms one's wealth, indicating that overconfident investors reduce their returns by engaging in excessive trading. They also found that men tend to display more overconfidence bias than women, resulting in lower investment earnings. The study highlighted that unmarried men engage in more trading, negatively impacting their profits.

Stango and Zinman (2008) attempted to determine the existence of overconfidence based on gender differences in social groups through their study. They examined ten student groups to test the hypothesis that individuals behave overconfidently within social groups. The findings of this study supported the literature, indicating that when examined individually, "male investors exhibit more overconfidence compared to female investors." Although women are less prone to overconfidence than men, they tend to exhibit more overconfidence within social groups than men.

Gonzalez and Svenson (2014) researched investors of a German brokerage firm to test whether there is a positive relationship between overconfidence and trading volume. In order to determine the levels of overconfidence among participants, Gonzalez and Svenson asked questions such as "What percentage of brokerage firm customers is better at identifying stocks with above-average returns compared to you?" Glaser and Weber could assess participants' levels of ability by accessing their past performance data and trading records.

No relationship was found between participants' responses and their past performance. However, the evaluation revealed that overconfident investors engage in more trading, indicating higher trading volumes (Stango & Zinman, 2008). There is a positive relationship between overconfidence and trading volume. The tendency of overconfidence leads investors to have higher trading volume. Since they buy and sell assets more quickly, they pay more commissions, resulting in lower overall income due to high commission fees.

Overconfidence also increases investors' tendency to take risks. Traditional finance assumes that rational investors minimize their level of risk while attempting to maximize their returns. However, the tendency of overconfidence leads investors to misinterpret the risk levels in their investments, exposing them to more risk. There are two reasons why overconfident investors have high risk: first, their desire to invest in stocks associated with high risk, such as shares of new and small businesses, and second, their reluctance to diversify their portfolios, preferring to manage their portfolios with low diversification (Nofsinger, 2014).

In conclusion, overconfidence is individuals' excessive trust in their abilities and knowledge compared to other investors. This sense of confidence leads to excessive trading in the market, resulting in increased transaction costs and decreased returns.

Additionally, overconfident investors perceive their own risk to be lower than that of other investors and exhibit reluctance in risk diversification and portfolio allocation.

2.2.2.3. Mental Accounting Bias

Mental accounting plays a role in individuals' lives, similar to the accounting system used by businesses. Accounting refers to recording, summarizing, analyzing, verifying, and reporting financial transactions carried out by businesses. Similarly, individuals use a mental accounting system to track where their money goes and to control their expenses. In this context, mental accounting represents individuals' cognitive tendency to organize, evaluate, and monitor their financial activities. (Thaler, 1999).

When making decisions related to their financial activities, individuals often rely on mental accounting. While mental accounting can sometimes be a helpful tool, it generally leads to poor decisions. This is because mental accounting causes individuals to allocate their money to different categories or accounts (Ariely & Kreisler, 2020).

Individuals mentally separate their money based on their needs, such as food, rent, electricity, and entertainment (Veeraraghavan, 2010). For example, individuals are willing to pay more for a meal at a restaurant than at home because they mentally distinguish between eating at home and eating at a restaurant. However, individuals can save money if they choose the more expensive meal at home and the more straightforward meal they typically have at the restaurant. This situation arises from individuals creating a mental separation by establishing separate budgets for food and entertainment (Ritter, 2003).

One example of poor decision-making from mental accounting is related to credit card and cash payments. When individuals use credit cards, they spend more money, purchase more expensive items, and leave more extensive tips than cash payments (Ariely & Kreisler, 2020).

This situation stems from individuals mentally evaluating credit card and cash payments differently. Another effect of mental accounting on individuals' economic activities is that it leads them to perceive regular income and unexpectedly obtained income differently. This hinders individuals from saving from their regular salaries while causing them to direct unexpectedly obtained income such as bonuses or tax refunds towards savings or investments.

This is because individuals keep unexpectedly obtained gains in their mental wealth account while considering their regular salaries as part of their mental consumption account.

Individuals need help to save from the mental account allocated for consumption. Mental accounting also influences investment decisions by causing individuals to use separate mental accounts for their investments (Nofsinger, 2014). Mental accounting leads to misperceptions of investment risks, resulting in higher risk-taking, lower diversification, and lower returns (Döm, 2003).

However, mental accounting can also serve as a control mechanism and benefit individuals. For example, an individual can create a separate mental account for retirement investments and another for purchasing a home. This differentiation allows for a more straightforward measurement of progress toward each goal (Baker & Nofsinger, 2002).

Considering the cognitive limitations of individuals, mental accounting can be a helpful practice. However, individuals should refrain from allowing the categorization of money to control their financial decisions. It is important to remember that all the money spent, saved, or invested belongs to the individual. Therefore, individuals should remember that money is fungible and a unified whole rather than being confined to specific categories. Categorization violates the fungibility of money and deprives it of its fundamental utility (Ariely & Kreisler, 2020).

Mental accounting, or cognitive accounting, is a term used to describe the individual evaluation and perception of investments from different perspectives. Individuals allocate a portion of their income for necessary needs and another for discretionary or optional purposes, which is an example of this type of accounting (Nofsinger, 2014). It focuses on how individuals assess their financial decision-making and the outcomes (Banks & Oldfield, 2007).

Individuals tend to organize their lives based on mental states (Banks & Oldfield, 2007). In other words, investors making decisions as if their identity did not exist leads to incorrect and unnecessary risk-taking and misusing the process. However, this behavior can sometimes have the opposite effect and result in significant gains in a short period (Thaler, 1999). Additionally, individuals judge their portfolio values based on stable increases or economic factors, which can decrease their portfolio values (Nofsinger, 2014).

Thaler (1999) explained mental accounting as cognitive operations synchronizing and synthesizing individuals' financial activities. He reinforces three elements of this behavioral pattern:

- It involves forming and interpreting decision scope, encompassing the development and analysis. The accounting system includes preconceived and necessary syntheses of past events.

- It pertains to distribution according to accounts.
- It encompasses the frequency of synthesis (Ariely & Kreisler, 2020).

Pompian (2006) lists how investors or individuals can make incorrect decisions through mental accounting as follows:

● Investors or individuals fall into the error of unique individual categorizations or compositions in their investments. Separating these categorizations and giving appropriate importance to their relationships is crucial for investors or individuals, as they need to pay attention to these connections to ensure their performance.

● Investors or individuals tend to differentiate returns obtained from existing income and capital analysis irrationally.

● The party burdened by the transaction can cause different analyses of stocks for investors or individuals.

● Stocks that have been beneficial in the past can change over time, leading to difficulties in selling.

Mental accounting also plays a role in individuals' perception of investment risk. Individuals or investors tend to account for each type of investment separately mentally. Consequently, it is common practice to evaluate each type individually (Stango & Zinman, 2008).

2.2.2.4. Exponential Growth Bias

Established economic models assume that individuals make decisions regarding their spending, saving, investment, or borrowing based on the relative costs and benefits of these preferences and actions (DellaVigna, 2009). However, a growing body of research has focused on the often-overlooked fourth factor of consumers' perception of the relative prices associated with borrowing and saving.

In other words, it is understood that individuals misperceive these prices, and these misperceptions often lead individuals to underestimate the costs of short-term borrowing compared to the benefits of long-term investment or saving. These patterns of misperception can be explained by the exponential growth bias, which represents the linearization of functions at a cognitive micro-level (Stango & Zinman, 2008).

A wide range of phenomena in daily life also exhibit exponential qualities. The set of nonlinear functions inherently includes accelerated functions, either positive or negative, such as in heating or cooling processes, biological growth, expansion of area due to diameter expansion, subjective perception of physical densities, or situations involving combined probabilities, where geometric growth rather than arithmetic growth is observed.

However, research findings indicate that individuals need help understanding these nonlinear phenomena and making incorrect predictions (De Bock et al., 2002).

In the financial literature, arithmetic or linear growth represents simple interest, while geometric or exponential growth represents compound interest. For example, let us assume that a particular space has a temperature of 10 degrees Celsius at 06:00. It increases by 2 degrees or 20% every hour until evening (18:00). An hourly increase or decrease of 2 degrees represents an arithmetic situation similar to simple interest. In contrast, a rate of 20% represents a geometric situation similar to compound interest.

Technically, the exponential growth bias results from individuals' process of linearizing functions involving exponential terms. In other words, the exponential growth bias refers to the underestimation of future value, which is much lower than it should be, due to the neglect of compound interest for a variable with a constant growth rate.

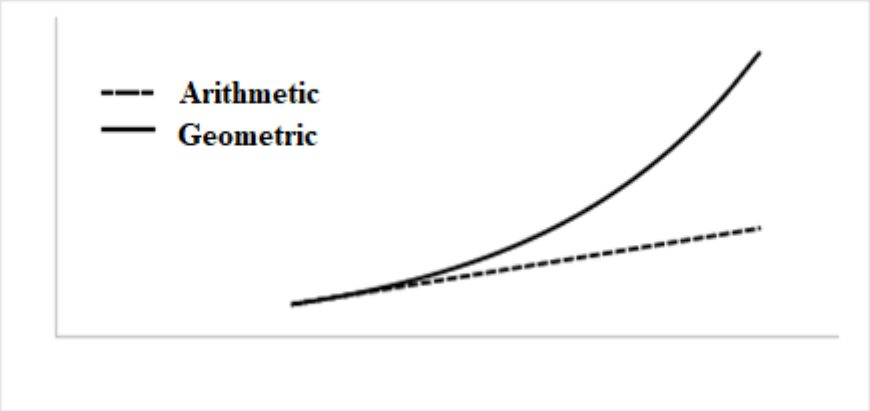

Figure 2.1. Difference between Arithmetic and Geometric Growth

The exponential growth bias can occur when individuals underestimate the incremental additions to their existing debt or the incremental additions to their investment or savings. This bias is empirically significant because it leads individuals to borrow more and invest or save less, as they tend to overlook the compounding returns.

The story of the presence of a chessboard in algebra and finance literature represents an exciting tale of how a geometric increase is arithmetically calculated, falling into the trap of exponential growth bias (Terzioğlu, 1974):

> *For example, the chess story is narrated as follows: Brahman Sissa, who spent his free time playing backgammon, invented a war game to educate and entertain the ruler Balhait. This game was based on the Indian army at that time, consisting of four classes: elephants, horse riders, war chariots, and foot soldiers. Brahman Sissa combined the Sanskrit word "çatur," meaning "four," with the word "anga," meaning "part," to create the name of the war game, "çaturanga."*
>
> *He taught the rules of the game to the ruler Balhait. The pieces resembled the current chess pieces to some extent. The ruler became so fond of this new game that he stopped playing other games. He wanted to reward Brahman, the inventor of this beautiful game, and said, "Ask for anything you desire from me." Despite Sissa stating twice that he had no other desire than the ruler's well-being, upon the insistence of the ruler, he said, "Well then, give me grains of wheat.*
>
> *However, for the first square of the chessboard, give me 1 grain of wheat; for the second square, give me 2 grains; for the third square, give me 4 grains; and so on, doubling the amount each time until the 64th square, where you will give me all the grains of wheat corresponding to the entire chessboard!" The ruler immediately ordered the fulfillment of this seemingly simple request. They brought a plate of wheat grains.*
>
> *However, when it came to the 13th square, and they realized that they would need 4096 grains of wheat, they came to their senses. They sat down and calculated that more than all the wheat in India would be needed to fulfill Brahman's request.*

The standard financial method that summarizes the growth rates to convert present value (P) to future value (F) or vice versa is calculated through the geometric mean that

compounds over a specific period (n) based on an interest rate (i) of increase. This formulation, known as compound interest, is as follows:

$$\mathbf{F = P\ (1+}\boldsymbol{i}\mathbf{)}^{\boldsymbol{n}}$$

An example was observed using a sample of individuals knowledgeable about the exponential discounting formula in economic and financial decision-making. It was observed that individuals could not evaluate the compound interest reduction formula provided by the exponential function and overvalued the simple interest reduction formula. In an experiment comparing linear, exponential, quadratic, and cubic functions, it was found that individuals made the most negligible error with quadratic functions (Benzion, Shachmurove & Yagil, 2003).

When individuals are faced with a situation involving compound interest, it is known that most of them naturally anchor to simple interest and fall into the exponential growth bias while calculating the outcomes of compounding. Moreover, this tendency positively correlates with the increase in the period or interest rate (Stango & Zinman, 2008). In a gain situation, the cumulative percentages related to the amount increase; in a loss situation, they decrease. This creates an asymmetric graph of exponential growth and decay.

For example, in a scenario where the discount rates increase and decrease by 5%, 10%, 15%, and 20%, respectively, for a capital of $10,000, different cumulative percentages will be obtained for increases and decreases. A 5% increase will result in an approximate 63% increase at the end of 10 years, while a 5% loss over ten years will correspond to a total decrease of approximately 40% (Gonzalez & Svenson, 2014).

Furthermore, this effect will impact the increases or decreases in the same direction if the rates continue to grow (Stango & Zinman, 2009). Therefore, decisions involving exponential decay show less deviation, and individuals' predictions in this regard yield more accurate results compared to exponential growth (Timmers & Wagenaar, 1977).

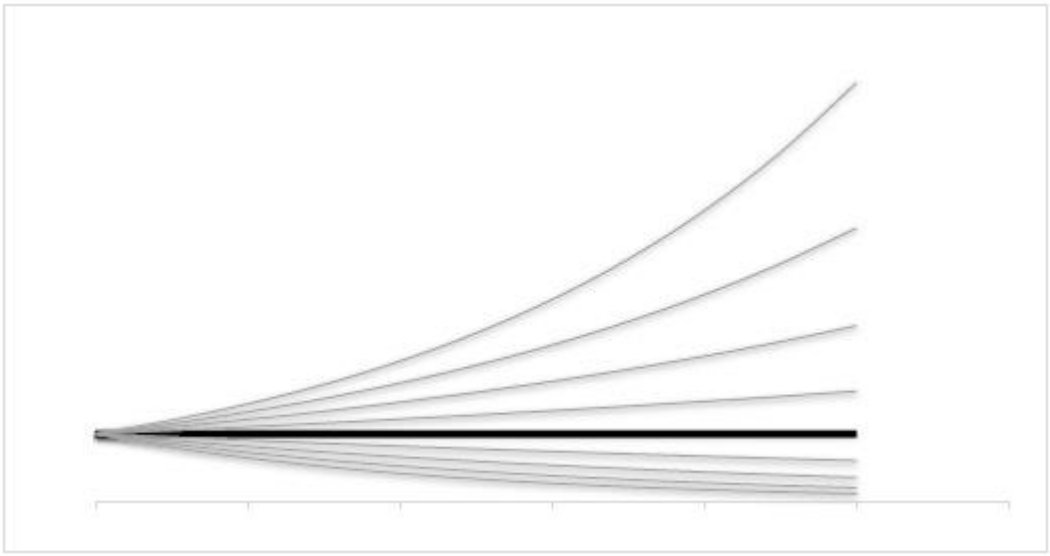

Figure 2.2. Exponential Increase and Decrease

In most studies conducted on the exponential growth bias, participants were subjected to retesting after being provided with education or information regarding the points where they made errors to determine the effect's certainty. The findings suggest a reverse relationship between the exponential growth bias and financial literacy or financial education on the subject (Almenberg & Gerdes, 2012).

For instance, in a laboratory study conducted by Eisenstein and Hoch (2005), participants were informed about the Rule of 72 in the subsequent stage of the study after obtaining substantial evidence regarding the phenomenon. It was observed that the rate of falling into the bias decreased by 50% (Eisenstein & Hoch, 2005).

Similar results indicate that emphasizing the exponential growth of savings makes participants more willing to save for retirement (McKenzie & Liersch, 2011; Song, 2013; Goda et al., 2012).

Therefore, the decrease in the bias is negatively correlated with asset accumulation, savings, and investments. Generally, investment and savings are directly related to the exponential growth bias. On the other hand, it should be noted that empirical studies show that participants' demographic characteristics do not affect the phenomenon (Goda et al., 2014). However, cultural differences can have an impact (Keren, 1983).

Moreover, the exponential growth tendency, a calculation bias, is observed in individuals with numerical skills, although the intensity of demonstrating the bias may be lower (Soll et al., 2013). Therefore, financial literacy, which includes familiarity with financial products and concepts in addition to basic calculations, can reduce the intensity of these biases, even though it cannot wholly prevent individuals from falling into behavioral biases.

Hence, as the level of financial literacy decreases, individuals tend to borrow more (Agarwal et al., 2009), save less (Lusardi & Mitchell, 2007), and have lower potential for participation in the stock market (Banks & Oldfield, 2007).

2.3. Cognitive Reflection

2.3.1. Definition of Cognitive Reflection

Cognitive reflection refers to the ability of individuals to resist the tendency to give an initial response that comes to their mind (Frederick, 2005). Cognitive reflection involves determining whether an individual instinctively or thoughtfully responds in a situation where they need to reason to find the correct answer, avoiding an initial instinctive response that may be incorrect.

Cognitive reflection is studied through the "dual-process theory." The dual-process theory, proposed by William James, explains how an event can occur in two different ways or as a result of two different processes. One of these processes is often implicit (unconscious or automatic), while the other is explicit (conscious or controlled).

For example, in the process of buying a car, the individual may be aware of factors such as price, speed, engine capacity, etc., but may not be conscious of other factors that influence the choice, such as the color of the vehicle, brand value, or the second-hand market (Baars, 1986).

2.3.2. Cognitive Reflection Test (CRT)

Cognitive reflection is measured through a test known as the Cognitive Reflection Test (CRT). Frederick initially developed the CRT in 2005, and consisted of three questions. However, due to concerns regarding its internal validity, particularly confidence, the instrument was later expanded to a seven-question test by Toplak in

2011, including the previous three questions. The updated test increased the internal validity of the CRT, raising the Cronbach Alpha values from previous measurements of 0.64 (Liberali et al., 2012), 0.60 (Morgan et al., 2013), and 0.66 (Campitelli & Gerrans, 2014) to 0.72 (Toplak et al., 2014).

Frederick's (2005) definition of cognitive reflection is fascinating as it suggests including a thinking tendency within the concept. This is noteworthy because Toplak et al. (2011) argue that thinking tendency is a subjective measurement concept, whereas the CRT is an objective performance measure.

From this perspective, if the CRT truly measures thinking tendencies, it would also represent a significant advancement in measuring them (Campitelli & Gerrans, 2014). Furthermore, researchers have differing views on whether the CRT is a measure of ability and thinking tendency or simply a measure of thinking tendency. Cokely and Kelley (2009) associated the CRT with reflection or careful, comprehensive, but not necessarily normative detailed cognition.

On the other hand, Campitelli and Labollita (2010) argue that cognitive reflection is not only an ability or thinking tendency to resist intuitive responses but also a triggering ability or thinking tendency. Additionally, Campitelli and Labollita (2010) suggest that the cognitive reflection measured by the CRT is related to a broader concept of Baron's (2000) actively open-minded thinking (Baron, 2000; Campitelli & Labollita, 2010).

Another research group considers the CRT not as a measure of thinking tendency but as a measure of ability, although they treat this ability differently from general cognitive abilities (Campitelli & Gerrans, 2014). Therefore, the evidence in the literature regarding cognitive reflection being a thinking tendency is weak, and the authors argue that the CRT directly measures rational thinking ability or frames its tendency towards reasoning errors resulting from flawed information processing (Toplak et al., 2011).

It is understood that the CRT is a strong predictor of various independent forms of reasoning, such as Analogical Reasoning, Bayesian Reasoning, Causal Reasoning, Covariation Detection, and Temporal Discounting (Frederick, 2005; Toplak et al., 2011).

Reflective responses regarding CRT items predict correct or normative logical patterns, while intuitive responses predict incorrect or misleading ones (Shtulman & McCallum, 2014). From an economic perspective, cognitive reflection has been associated with better performance in Bayesian reasoning and reduced biases in decision-making (Sirota & Juanchich, 2011).

Significant relationships have been found between CRT scores and classical decision anomalies such as randomness error, base rate neglect, gambling fallacies, framing, endowment effect, sunk cost, conservatism bias, and anchoring (Stanovich & West, 2008; Oechssler et al., 2009; Bergman et al., 2010; Hoppe & Kusterer, 2011; Liberali et al., 2012).

As Kahneman and Frederick (2002) stated, the CRT represents a test designed to elicit individuals' intuitive (System 1) or analytical-rational (System 2) responses, or their emotional/impatient or cautious/patient character, in the way they would respond with their initial instinctive response (Stanovich & West, 2000), (Brocas & Carrillo, 2008; Kahneman & Frederick, 2002).

The dual process of the emotional/impatient and cautious/patient mental systems is referred to by different names: fast and slow thinking, hot and cold, affective and evaluative, and automatic and controlled thinking (Camerer et al., 2005). In simple terms, the intuitive system relies on quick, first-impression responses without consulting relevant cognitive resources, while the analytical system systematically evaluates available information (Baldi et al., 2013).

System 1 and System 2 processes are closely related to the concepts of effort and cost. System 2 allows individuals to solve complex and novel problems accurately and frequently. However, this effort comes at a cost: the individual needs to focus on the problem, be slow and careful, set aside other thoughts and actions during that period, and concentrate seriously on the problem.

On the other hand, System 1 has a lower computational capacity than System 2, and the effort expended is proportionally minimal. System 1 needs to be more decisive in solving various problems the individual has not experienced before, and there is a high possibility of missing details. However, it has a fast response and does not hinder other thoughts or actions in the individual's mind at that moment (Toplak et al., 2014).

Individuals demonstrate a conservative approach to cognition due to their persistent inclination towards the System 1 process, which has low computational costs. Because considering the limited effort, time, and energy, the less computational capacity used for one task, the more effort, time, and energy will be available for other tasks.

Within a time frame, System 1 makes numerous calculations and routine evaluations. System 1 involuntarily generates intuitions in the individual's mind without issuing explicit commands, often related to the distances of surrounding objects, thoughts about someone encountered for the first time, and whether an unanalyzed endeavor will be successful. These intuitions are frequently unexplainable or indefensible by the individual (Kahneman, 2011).

The division of labor between System 1 and System 2 is nearly perfect; it minimizes mental effort and maximizes performance for an event. The main reason for this efficiency is the overall competence of System 1 in its work.

System 1 makes accurate models for familiar events, produces correct short-range predictions, and reacts quickly to demanding situations. However, the problematic aspect of System 1, which also constitutes the fundamental research question in behavioral sciences, is that it leads individuals to specific systematic errors.

Furthermore, since System 1 operates automatically and is an unconscious structure that cannot be switched off at will, it is challenging to prevent the behavioral biases that occur in the individual's mind (Kahneman, 2003). Kahneman exemplifies the actions that individuals frequently take regarding the functioning of System 1 as follows (Kahneman, 2011):

- Determining whether one object is farther away or closer than another object
- Involuntarily turning towards a sudden sound
- Answering a 2x2 question
- Driving on a road with no traffic
- Completing the sentence "Hide the straw..."
- Reading signs written in large fonts.

Kahneman (2011) also utilizes the following image to illustrate the fast thinking of System 1.

Figure 2.3. Quick Thinking - System 1

Source: Kahneman D., Thinking, fast and slow, 2011.

When initially looking at the image, one may perceive a figure of a woman with black hair, appearing angry and about to yell. However, the woman in the picture could also be an opera singer.

Kahneman (2011) explains that the particular representation formed in our minds is automatically generated without any conscious command of our brains (Kahneman, 2011).

Another principle of operation for System 1 is the effects of association and triggers. Kahneman (2011) explains the concept of association as follows:

Bananas ***Vomiting***

By using the example of the words "bananas" and "vomiting," Kahneman (2011) illustrates how the reading of these words automatically triggers a causal connection between bananas and vomiting in the reader's mind. This associative interaction suggests that words evoke memories, and these memories, in turn, evoke emotions, leading to facial expressions and various physiological changes in the body.

Another effect related to association and priming is the Florida Effect. In a laboratory experiment, students were shown words that evoke associations with old age, such as "Florida, forgetful, bald, gray, wrinkled." Then, they were asked to walk to another classroom at the other end of a corridor. During this walk, their walking speeds were measured, and it was found that the students walked slower than usual.

In another experiment, significant differences were found between placing election ballot boxes for the proposal of increasing funds allocated to education in Arizona in the year 2000, either in schools or in regular public institutions.

Another effect related to association and priming is the Lady Macbeth Effect. In this experiment, participants were given a suggestion such as "imagine stabbing your co-worker in the back," Afterward, they showed a greater inclination towards purchasing soap, detergent, and disinfectant products during their regular shopping routines.

In another interesting experiment related to priming, an honesty box called the "honesty jar" was placed in front of a coffee machine used by office workers, where individuals could voluntarily contribute money to cover the expenses. Throughout the week, either a flower or a poster featuring a pair of eyes looking directly at the individuals, as shown below, was placed near the box.

The graph demonstrates that during weeks with a flower, the donations were low, whereas during weeks with the eyes (especially with an angry expression), higher donations were collected (Kahneman, 2011).

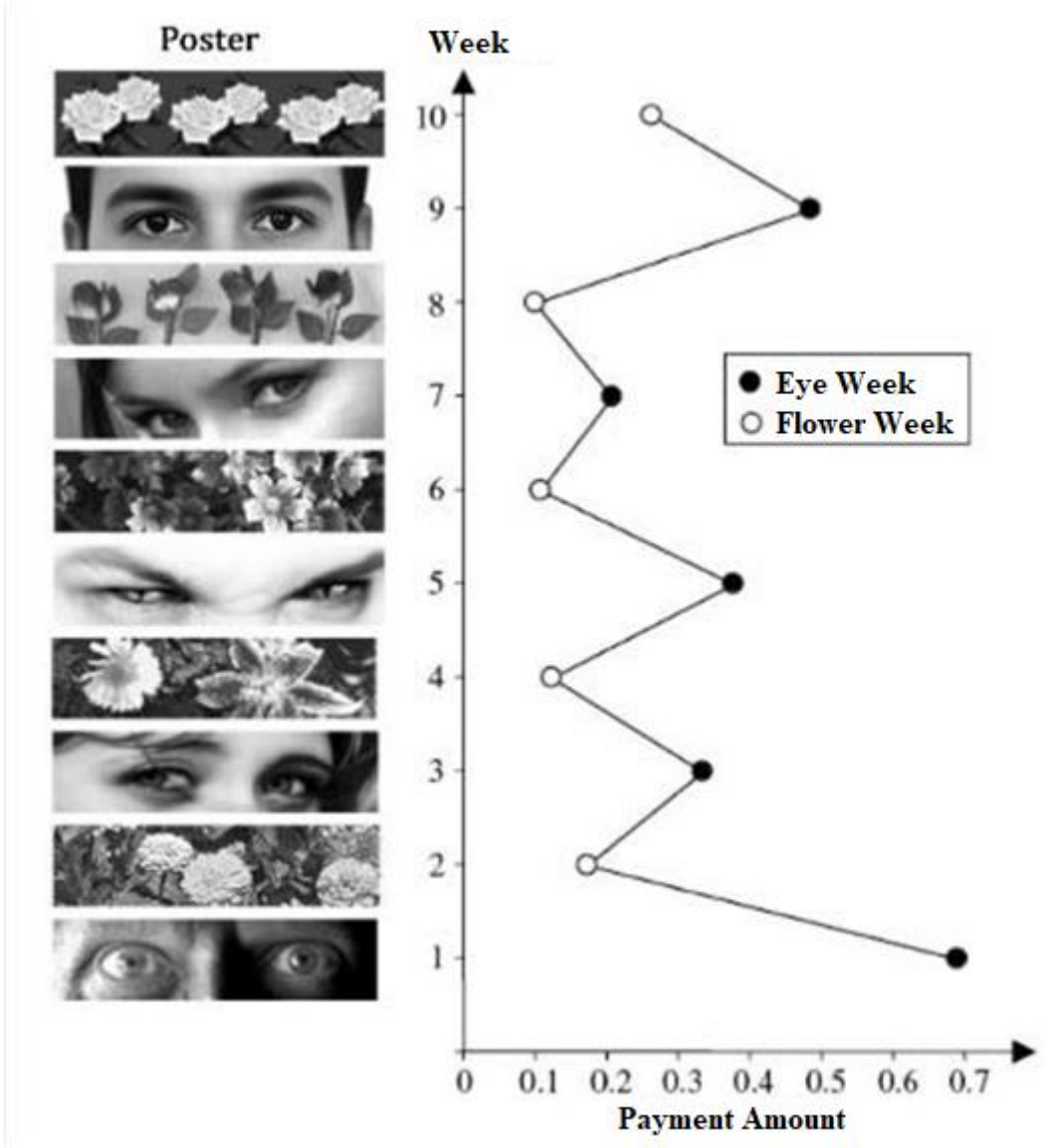

Figure 2.4. Trigger Effect

Source: Kahneman D., Thinking, fast and slow, 2011.

Another topic related to System 1 i cognitive ease, where System 1 determines whether System 2 is needed for any encountered situation. Conditions such as tension, difficulty, stress, etc., reduce cognitive ease and decrease errors caused by cognitive comfort.

For example, during a cognitive reflection test conducted with students at Princeton University, the students were divided into two groups. One group was given questions written in small, gray, and faint font. The font that caused cognitive tension led to higher CRT scores for this group. While 90% of the students who read the three-question test

in regular fonts made at least one mistake, the corresponding percentage for the other group was significantly lower at around 35%.

When it comes to beliefs or preferences that have strong connections in terms of logic or association, or when data comes from a trusted or liked source, System 2, due to its laziness, transfers all tasks to System 1. For example:

Adolf Hitler was born in 1892.

Adolf Hitler was born in 1887.

In propositions, the probability of the mind believing information written in bold fonts is higher.

A study conducted in Switzerland found that the names or abbreviations of unfamiliar and newly introduced stocks also had a similar effect. Names such as "Emmi" and "Comet" were found to have higher trading activity during the initial market entry phase compared to names like "Ypsomed" and "Geberit."

In summary, an individual's discomfort or unhappiness prevents the relaxation that a happy mood would create on System 2, suppressing intuitions and the individual behaving more cautiously (Kahneman, 2011, pp. 71-84). In the sentence "When a cemented thing does not fit the current context of activated ideas, the system detects an anomaly," the word "cemented" after the word "context" signals to our mind reading with System 1 that there is a deviation from the norm, triggering a shift to System 2.

This error, known as the norm effect or Moses Illusion, is often illustrated with the following example:

"Moses took how many animals of each kind onto his ark?"

Kahneman attributes that most individuals do not perceive any anomaly in this sentence to the concept that Moses is not a far-fetched notion from Noah. However, if the same sentence were written as "George W. Bush took how many animals of each kind onto his ark?" almost all individuals would directly identify the anomaly (Kahneman, 2011).

Kahneman illustrates a similar situation through the following example:

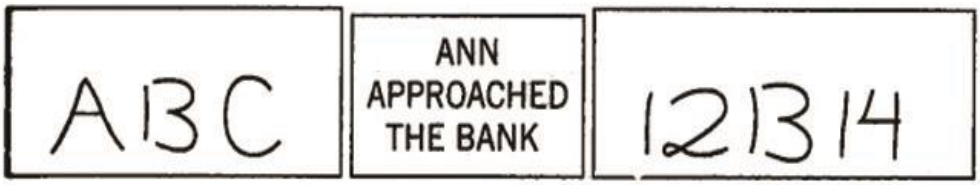

Figure 2.5. Norm Effect

Source: Kahneman D., Thinking, fast and slow, 2011.

In the above image, which represents System 1's tendency to jump to automatic conclusions, almost all individuals read the first image as ABC and the second as 12 13 14. However, the first image can also be read as A 13 C and the second as 12 B 14. However, due to familiarity and associative effects, System 1 directly perceives the first group as a set of letters and the second group as a set of numbers (Kahneman, 2011).

Kahneman exemplifies individuals' actions related to the functioning of System 2 as follows (Kahneman, 2011):

- Filling out a tax return form
- Comparing the price, weight, etc., of two similar products while shopping
- Walking at a pace faster than your average walking speed
- Trying to pick out someone's voice in a noisy environment
- Parking a car in a tight space.

System 2 directs an individual's attention to mentally taxing tasks. The functioning principle of System 2 is mainly associated with subjective experiences related to action, preference, and focus (Kahneman, 2011). Influenced by E. Hess's (1965) article on pupil dilation, Kahneman discovered that individuals' pupils dilate according to the difficulty level of the task during System 2's taxing tasks (Hess, 1965; Beatty & Kahneman, 1966).

Kahneman (2011) provides a simple example to represent the slow thinking of System 2:

$$17 \times 24 = ?$$

In the case of multiplication mentioned above, a definitive answer does not readily form in the individual's mind. In such cases, the individual needs to summon the cognitive program learned in primary school and perform the calculation. Kahneman describes this process as a conscious, taxing, and orderly mental work (Kahneman, 2011).

System 2 is aware of the limited mental capacities of individuals. For instance, when the driver next to you is about to make a critical lane change, you instinctively stop talking and know the driver will not focus on what you are saying (Kahneman, 2011).

Furthermore, in the Invisible Gorilla experiment conducted regarding System 2, participants were shown a video of a basketball game between two teams, one wearing white shirts and the other wearing black shirts. The participants were asked to ignore the players in black shirts and count the number of passes made by the players in white shirts. In the middle of the video, a woman dressed in a gorilla suit walks through the center of the court (for 9 seconds), and at the end of the video, the participants are asked if they noticed the woman. In the experiment conducted with thousands of participants, half of them stated that they did not notice the occurrence (Simons, 2010).

2.4. Behavioral Finance and Cognitive Reflection

Individuals' cognitive abilities (or "IQ") vary differently, leading to differences in essential and trivial matters. Those with higher cognitive ability generally live longer, earn higher incomes, have a broader working memory, exhibit faster reaction times, and may be more susceptible to visual illusions (Jensen, 1998). However, despite the existence of various phenomena associated with IQ, there have been few studies aimed at understanding or defining the impact of cognitive ability on judgment and decision-making.

In studies on time preference, risk preference, probability weighting, ambiguity aversion, endowment effect, anchoring effect, and other related topics, the possible

effects of cognitive abilities are rarely examined. Decision researchers often focus more on the overall effects of specific experimental manipulations and may overlook the role of cognitive abilities.

Therefore, individual differences (such as intelligence or another factor) are often considered an alternative source of "unexplained" variance. Additionally, most studies are typically conducted on university students who are assumed to be homogeneous. Determining performance differences in cognitive tasks may necessitate using terms such as "IQ" and "aptitude." However, specific individuals can sometimes criticize these terms due to their association with discriminatory policies.

In summary, researchers may only investigate uninteresting topics believed to lack variability or perceived as potentially problematic. However, as Lubinski and Humphreys (1997) pointed out, the existence of a neglected factor does not cease its function, and there is no valid reason to disregard the possibility that general intelligence or various cognitive abilities may be significant determinants in decision-making processes.

In their study, Oechssler, Roider, and Schmitz (2009) introduce the three-item "Cognitive Reflection Test" (CRT) as a simple measure of a cognitive ability type. They aim to demonstrate that CRT scores can predict significant decision-making tendencies in decision theories, such as expected utility theory and probability theory tests.

This relationship is sometimes so strong that preferences function as an expression of cognitive ability and require a theoretical explanation. The study examines the relationships between CRT and critical decision-making features such as time and risk preferences. It compares these relationships with other cognitive ability or cognitive "style" measures, namely the Wonderlic Personnel Test (WPT), the Need for Cognition Scale (NFC), and self-reported SAT and ACT scores. It is noted that CRT exhibits significant differences between males and females, and the discussion explores how these differences relate to gender disparities in time and risk preferences. The final section discusses the interpretation of the relationships between cognitive abilities and decision-making features.

In the relevant study, Oechssler, Roider, and Schmitz (2009) replicated the relationship between time and risk preferences and cognitive abilities. Additionally, they

examined the relationship between cognitive abilities and standard errors, conservatism, and anchoring effects. A fundamental finding is that individuals with lower cognitive abilities are more susceptible to behavioral biases.

The study by Hoppe and Kusterer (2011) on the topic investigates the relationship between cognitive abilities and behavioral biases. The researchers examine the base rate fallacy, overconfidence, and endowment effect. Additionally, they explore an interesting question raised by Oechssler, Roider, and Schmitz (2009). This question investigates whether individuals exhibiting conservatism bias (i.e., weighting the base rate heavily) are less sensitive to the base rate fallacy (i.e., underweighting the base rate).

However, the obtained findings do not support this hypothesis. Specifically, it has been observed that individuals with lower cognitive abilities exhibit both the base rate fallacy and the conservatism bias more prominently. Regarding overconfidence, participants with higher CRT scores were significantly more confident in their self-evaluations. Finally, it was observed that test scores did not influence the endowment effect, which is noteworthy in both the low and high CRT groups.

3. METHODOLOGY

In this part of the study, information about the research method, including the type of research, universe and sample, data collection method and tools, and analysis method, is presented.

3.1. Research Type and Design

This study aimed to determine whether there were differences between the cognitive reflection levels of university students and behavioral biases such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. In addition, it also aimed to examine if cognitive reflection levels and behavioral biases of university students differed according to their demographic characteristics. In line with this purpose, this descriptive and cross-sectional quantitative research was conducted in a relational screening model.

3.2. Population and Sample

University students are the architects of the future economies of countries. At this point, students with great importance should be evaluated regarding behavioral finance and cognitive reflection (Yıldırımer et al., 2011). University students represent a frequently referenced target population regarding behavioral biases and cognitive reflection literature (Cokely & Kelley, 2009; Eisenstein & Hoch, 2005; Frederick, 2005; Hoppe & Kusterer, 2011; Tversky & Kahneman, 1986). On the other hand, Ankara is the fourth province with the highest number of university students (CHE, 2023). Therefore, the research universe consists of students attending four-year programs at universities in Ankara province. According to statistics published by the Council of Higher Education, 355,048 university students in the academic year 2022-2023 in Ankara province (CHE, 2023). The minimum sample size representing a universe of this magnitude with a confidence interval of 0.95 and a margin of error 0.05 has been calculated as 384. The sample of the study consists of 388 university students selected through a simple random sampling method from within this universe.

3.3. Data Collection

In the research, primary data was collected using the online survey method. Data were collected from students of Hacıbayram Veli University, TED University, Gazi University, and Ankara Yıldırım Beyazıt University. The research data was collected between June and July 2023. The link to the online questionnaire form was distributed to participants through email, social media, WhatsApp, and similar platforms.

Before the survey application, participants were presented with an information form related to the research. In this form, the purpose of the research was explained to the participants, and it was stated that participation in the research was based on voluntariness. In addition, participants were informed that they could withdraw from the research at any time, that their identity information would not be asked, that the anonymously collected data would not be shared with third parties and that it would only be used for scientific purposes. After this information, participants gave their voluntary participation consent and participated in the survey application.

The questionnaire form (see Appendix 1) prepared for data collection within the scope of the research consists of two sections. The first section includes five questions about participants' gender, age, department, class, and place of birth. The second section of the questionnaire form contains a total of 18 questions. The questions in this section were taken from Polat's (2019) study. Information about the variables that these questions measure is provided in Table 3.1.

Table 3.1. Scales Used in the Research

Scale	Source	Number of Items
Cognitive reflection	Frederick (2005) Toplak et al. (2011)	3, 4, 5, 6, 8, 10, 11
Overconfidence	Hoppe & Kusterer (2011)	13, 14, 15, 16, 17, 18
Base rate neglect	Minda (2015)	1
Exponential growth bias	Stango & Zinman (2009)	7, 12
Mental accounting (Sunk cost)	Stanovich & West (1998)	2, 9

3.4. Data Analysis

Data underwent a preliminary review before the analyses. A total of 505 participants contributed data to the study. However, during this preliminary review, it was determined that the responses of four participants were blank. Additionally, the responses of four participants were found to be inconsistent (for instance, selecting both female and male options for gender). Moreover, 109 participants indicated that they looked up the answers to the survey questions online. Due to these reasons, 117 participants were excluded from the study, and the analyses were conducted with the data obtained from the remaining 388 participants.

For data analysis in the study, SPSS v26 software was utilized. The distributions of participants based on cognitive reflection, financial behavioral biases, and demographic characteristics were examined through frequency analysis. Skewness and kurtosis values of variables were assessed to determine whether the data followed a normal distribution. Chi-square test, t-test, and ANOVA analysis were employed for testing the research hypotheses.

3.5. Limitations and Assumptions

An essential limitation of the study is the inability to control whether participants sought help to answer the survey questions. Therefore, participants were asked if they received assistance in answering the survey questions, and those who reported receiving assistance were not included in the research. It was assumed that the remaining participants answered the survey questions without assistance.

Another limitation of the study is the sample. The research data was obtained from university students in Ankara province. A study with data obtained from a different sample might yield different results.

Another limitation is that the data was collected in a single period, and the research was conducted cross-sectionally. The data does not cover an extended period or involve repeated measurements. Since the data do not cover an extended period or include repetitive measurements, the variation of the relationships with time could not be examined.

Furthermore, the structured data collection through the survey method is also a limitation. Since the data was not gathered using qualitative methods such as interviews or focus groups, it lacks the depth of information that could lead to more in-depth findings about the relationships between variables.

3.6. Research Hypotheses

As Kahneman and Frederick (2002) stated, the Cognitive Reflection Test (CRT) represents a test in which individuals will either provide answers that align with their intuitive (System 1) or analytical-rational (System 2) character. In simple terms, the intuitive system involves quickly providing initial impressions and intuitive responses without relying on relevant cognitive resources. On the other hand, the analytical system systematically evaluates existing information (Baldi et al., 2013). Regarding CRT elements, analytical responses predict accurate or normative logical patterns, while intuitive answers anticipate incorrect or misleading ones (Shtulman & McCallum, 2014). Within this framework, CRT has been indicated as a strong predictor of many forms of reasoning (Frederick, 2005; Toplak et al., 2011). In line with this, cognitive reflection has been associated with better reasoning performance and reduction of decision-making biases (Sirota & Juanchich, 2011). Numerous studies have found significant relationships between CRT scores and behavioral biases (Albaity et al., 2014; Alós-Ferrer & Hügelschäfer, 2016; Bergman et al., 2010; Hoppe & Kusterer, 2011; Liberali et al., 2012; Noori, 2016; Oechssler et al., 2009; Polat & Duman, 2020; Sinayev & Peters, 2015; Stanovich & West, 2008; Thomson & Oppenheimer, 2016; Yiğit, 2022). Therefore, the following hypothesis can be suggested:

H_0: There are no significant differences between the cognitive reflection levels of university students and behavioral biases.

H_1: There are significant differences between the cognitive reflection levels of university students and behavioral biases.

Cognitive reflection and behavioral biases may vary among individuals, and these variations can be associated with demographic characteristics. There are studies in the literature investigating the relationship between behavioral biases and demographic factors (Albaity et al., 2014; Brañas-Garza et al., 2019; Leeper, 2015; Ludwig & Achtziger, 2021; Noori, 2016; Polat & Duman, 2020; Sinayev & Peters, 2015; Temel,

2019; Yıldırımer et al., 2021; Yiğit, 2022). Similarly, studies in the literature also explore the association between behavioral biases and demographic factors (Arslan & Boztosun, 2022; Baker et al., 2019; Bashir et al., 2013; Beatrice et al., 2021; Polat & Duman, 2020; Küçükdurmaz, 2019). These studies suggest that different demographic groups may exhibit varying levels of cognitive reflection and behavioral biases such as overconfidence, base rate neglect, exponential growth, and mental accounting. In this context, understanding the potential relationships between individuals' levels of cognitive reflection, behavioral biases, and demographic characteristics can contribute to a better understanding. Therefore, the following hypotheses can be suggested:

H_0: Cognitive reflection levels of university students significantly do not differ according to their demographic characteristics.

H_2: Cognitive reflection levels of university students significantly differ according to their demographic characteristics.

$H_{0:}$ Behavioral biases of university students significantly do not differ according to their demographic characteristics.

H_3: Behavioral biases of university students significantly differ according to their demographic characteristics.

4. FINDINGS

In this part of the study, the findings reached in the analysis of the data obtained in the research are reported.

4.1. Demographic Statistics

The frequency analysis results reflecting the participants' distribution according to their demographic characteristics are presented in Table 4.1.

Table 4.1. Demographic Statistics of the Participants

Varible	**Category**	**n**	**%**
Gender	Female	200	51.5
	Male	188	48.5
Age	19	46	11.9
	20	66	17.0
	21	78	20.1
	22	72	18.6
	23	61	15.7
	24	35	9.0
	25+	30	7.7
Grade (Class)	1	65	16.8
	2	127	32.7
	3	69	17.8
	4	83	21.4
	4+	44	11.3

As seen in Table 4.1, 200 female participants (%51.5) and 188 male participants (%48.5) participated in the research. Participants are mostly 21 (n=78; %20.1) and 22 (n=72; %18.6). It is observed that the majority of the participants are in the second grade (n=127; %32.7). The distribution of participants according to their demographic characteristics is also presented visually in Figure 4.1.

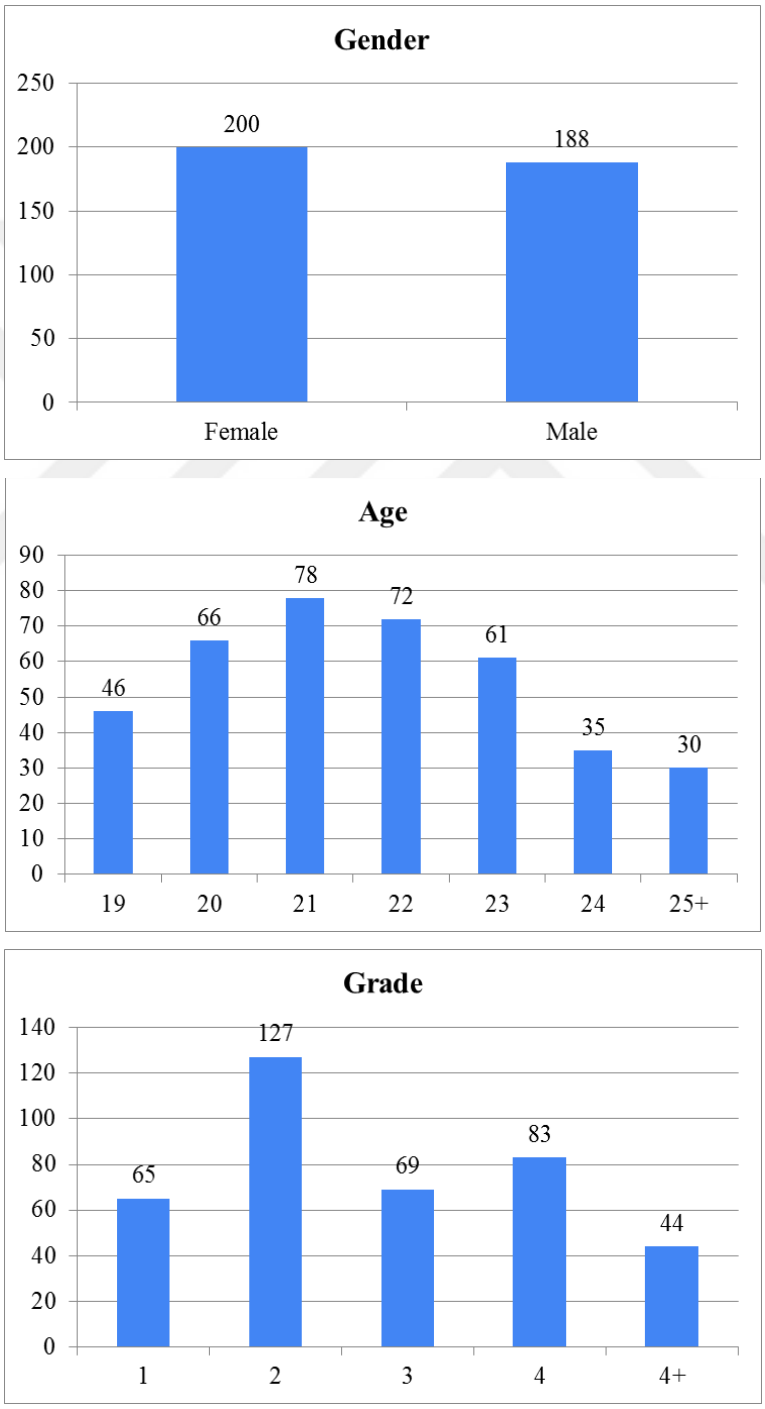

Figure 4.1. Demographic Statistics of the Participants

In addition, it has been observed that most participants are studying in the computer engineering department (n=43; %11.1) and were born in Ankara (n=104; %26.8). The distribution of participants according to their departments and birthplaces can be found in Appendix 2 and 3.

4.2. Descriptive Analysis

4.2.1. Findings Regarding Cognitive Reflection

Participants were presented with seven questions to measure their cognitive reflections. The responses provided by the participants are shown in Table 4.2.

Table 4.2. Responses to Cognitive Reflection Questions

Questions	Wrong (Intuitive)		Correct (Analytic)	
	n	%	n	%
q3_racket/ball	190	49.2	196	50.8
q4_machine	143	37.0	244	63.0
q5_water lily	152	40.4	224	59.6
q6_farm	284	73.8	101	26.2
q8_stock market	94	24.6	288	75.4
q10_lesson	165	43.2	217	56.8
q11_demijohn	171	45.0	209	55.0

In Table 4.2, it can be observed that participants gave the most correct answers to the "Q8: Stock Market" question (n=288; 75.4%) and the least to the "Q6: Farm" question. Participants' average correct answer score is 3.81 (sd=1.80). Participants who gave correct answers to 0-3 out of the seven questions are categorized as "intuitive," while those who answered 4-7 questions correctly are categorized as "analytic" in terms of cognitive reflection levels (Toplak et al., 2011; Polat, 2019). The distribution of participants according to their cognitive reflection categories is shown in Table 4.3.

Table 4.3. Distribution of Participants According to Cognitive Reflection Groups

Cognitive Reflection	n	%
Intuitive	162	41.8
Analytical	226	58.2
Total	388	100.0

As seen in Table 4.3, it is determined that 162 participants (41.8%) are in the intuitive category, while 226 participants (58.2%) are in the analytic category.

4.2.2. Findings Regarding Overconfidence Bias

Participants were presented with five questions to measure their overconfidence biases. The responses provided by the participants are shown in Table 4.4.

Table 4.4. Responses to Overconfidence Bias Questions

Questions	Wrong		Correct	
	n	%	n	%
q13_distance	257	67.3	125	32.7
q14_yalova	204	53.1	180	46.9
q15_einstein	188	48.7	198	51.3
q16_author	115	29.7	272	70.3
q17_acreage	317	82.1	69	17.9

In Table 4.4, it can be observed that participants gave the most correct answers to the "Q16: Author" question (n=272; 70.3%), while the least correct answers were given to the "Q17: Acreage" question (n=69; 17.9%).

The participants' average correct answer score out of the five questions was 2.18 (sd=1.20). On the other hand, participants were also asked to estimate how many questions they answered correctly. Participants estimated they answered an average of 3.45 (sd=1.30) questions correctly. This indicates that participants tend to have an overconfidence bias.

Participants were divided into three groups based on the difference between their actual correct answer count and their estimated correct answer count. Accordingly, participants who estimated a higher number of correct answers than they gave were categorized as "overconfident," participants who estimated a lower number of correct answers were categorized as "underconfident," and participants who accurately estimated their correct answer count were categorized as "correct assessment/no bias" (Hoppe & Kusterer, 2011). In this context, the distribution of participants according to their overconfidence bias groups is shown in Table 4.5.

Table 4.5. Distribution of Participants According to Overconfidence Bias

Group	**n**	**%**
Correct assessment (no bias)	71	18.3
Overconfident	265	68.3
Underconfident	52	13.4
Total	388	100.0

As shown in Table 4.5, 265 participants (68.3%) exhibit overconfidence bias, while 52 participants (13.4%) show underconfidence bias. On the other hand, it was determined that 71 participants (18.3%) did not show any confidence bias.

4.2.3. Findings Regarding Base Rate Neglect Bias

A question was posed to measure participants' base rate neglect bias. In this question, participants were asked to predict a woman who reads a scientific magazine on the Ankara metro. Within this context, participants were allowed to choose either "the woman has a doctoral degree" or "the woman is not a university graduate." The option "the woman has a doctoral degree" indicated base rate neglect bias. This is because participants selecting this

response focus on specific information about the woman reading a scientific article, disregarding the overall proportions of women's educational levels (Minda, 2015). In this context, the distribution of participants' base rate neglect bias is presented in Table 4.6.

Table 4.6. Distribution of Participants According to Base Rate Neglect Bias

Base Rate Neglect Bias	n	%
Unbiased	307	79.1
Biased	81	20.9
Total	388	100.0

As seen in Table 4.6, it was determined that the majority of the participants (n=307; 79.1%) did not exhibit the base rate neglect bias.

4.2.4. Findings Regarding Exponential Growth Bias

To measure participants' exponential growth bias, they were asked two questions involving an exponential function (q7 and q12) and were asked to predict future values. Exponential growth bias, technically, is a result of individuals linearizing functions containing exponential terms. In other words, exponential growth bias involves significantly underestimating future values by ignoring the incremental effect. Within this context, participants' responses reflecting exponential effect indicate the absence of exponential growth bias, whereas responses reflecting linear thinking point to exponential growth bias (Stango & Zinman, 2008). In this framework, the distribution of participants' exponential growth biases is presented in Table 4.7.

Table 4.7. Distribution of Participants According to Exponential Growth Bias

Exponential Growth Bias	n	%
Unbiased	158	40.7
Biased	230	59.3
Total	388	100.0

As seen in Table 4.7, it was determined that the participants mostly exhibit exponential growth bias (n=230; 59.3%).

4.2.5. Findings Regarding Mental Accounting Bias

Participants were presented with two questions (q2 and q9) containing the sunk cost effect to measure their mental accounting bias. Firstly, participants were asked to assume they had paid for a gym membership and were then questioned about how frequently they would exercise during a year-long period if they were to become injured. Secondly, participants were asked to imagine that they engaged in sports purely for enjoyment and without cost, and they were then questioned about their exercise frequency under the same scenario of a year-long injury. Participants indicating a higher likelihood of engaging in exercise when they had paid for the membership than when they did not pay indicated the presence of the sunk cost effect. Conversely, if participants reported a lower exercise likelihood under the paid scenario than the free scenario, this indicated a reverse sunk cost effect. When responses to both questions were the same, it demonstrated the absence of the sunk cost effect (Stanovich & West, 2018). In this context, the distribution of participants' mental accounting bias is presented in Table 4.8.

Table 4.8. Distribution of Participants According to Mental Accounting Bias

Mental Accounting Bias	n	%
Unbiased	282	72.7
Sunk cost effect	30	7.7
Reverse sunk cost effect	76	19.6
Total	388	100.0

As seen in Table 4.8, it was determined that the participants primarily did not exhibit mental accounting bias (n=282; 72.7%).

4.3. Hypothesis Tests

In this part of the study, the research hypotheses were tested respectively.

4.3.1. Differences in Behavioral Biases by Cognitive Reflection

The study's first hypothesis is "H1: University students' behavioral biases show significant differences according to their cognitive reflections." We present analyses for each behavioral bias in the following subsections to test the first hypothesis..

4.3.1.1. Overconfidence Bias by Cognitive Reflection

The results of the chi-square analysis conducted to examine the overconfidence bias of participants based on their cognitive reflections are presented in Table 4.9.

Table 4.9. Chi-Square Results for Overconfidence Bias by Cognitive Reflection

			Cognitive Reflection		Total
			Intuitive	Analytical	
Overconfidence Bias	Correct assessment	n	26	45	71
		%	16.0	19.9	18.3
	Overconfident	n	108	157	265
		%	66.7	69.5	68.3
	Underconfident	n	28	24	52
		%	17.3	10.6	13.4
Total		n	162	226	388
		%	100.0	100.0	100.0

$x^2(2) = 4.005; p = 0.135$

In Table 4.9, it can be observed that overconfident participants constitute a majority of both intuitive (n=108; 66.7%) and analytical (n=157; 69.5%) groups. Additionally, it

has been found that there is no significant difference in the overconfidence bias of participants based on their cognitive reflections ($\chi 2=4.005$; $p>0.05$). Accordingly, it was concluded that the participants' overconfidence bias was similar in both cognitive reflection groups.

4.3.1.2. Base-Rate Neglect Bias by Cognitive Reflection

The results of the chi-square analysis conducted to examine the base-rate neglect bias of participants based on their cognitive reflections are presented in Table 4.10.

Table 4.10. Chi-Square Results for Base-Rate Neglect Bias by Cognitive Reflection

			Cognitive Reflection		Total
			Intuitive	Analytical	
Base-Rate Neglect Bias	Unbiased	n	110	197	307
		%	67.9	87.2	79,1%
	Biased	n	52	29	81
		%	32.1	12.8	20,9%
Total		n	162	226	388
		%	100,0%	100.0	100.0

$x^2(1) = 21.206; p = 0.000$

Table 4.10 shows that most analytical participants do not exhibit a base rate fallacy (n=197; 87.2%). Additionally, most participants showing the base-rate neglect bias are from the intuitive group (n=52; 32.1%). Furthermore, a significant difference has been determined in the base rate neglect bias of participants based on their cognitive reflections ($\chi 2=21.206$; $p<0.01$). Accordingly, it was concluded that the base rate neglect bias was mainly exhibited by intuitive participants.

4.3.1.3. Exponential Growth Bias by Cognitive Reflection

The results of the chi-square analysis conducted to examine the exponential growth bias of participants based on their cognitive reflections are presented in Table 4.11.

Table 4.11. Chi-Square Results for Exponential Growth Bias by Cognitive Reflection

			Cognitive Reflection		Total
			Intuitive	Analytical	
Exponential Growth Bias	Unbiased	n	31	127	158
		%	19.1	56.2	40,7%
	Biased	n	131	99	230
		%	80.9	43.8	59,3%
Total		n	162	226	388
		%	100,0%	100.0	100.0

$x^2(1) = 53.685; p = 0.000$

As seen in Table 4.11, the majority of intuitive participants exhibit exponential growth bias (n=131; 80.9%), while the majority of analytical participants do not exhibit exponential growth bias (n=127; 56.2%). Furthermore, a significant difference has been found in participants' exponential growth bias based on their cognitive reflections (χ^2=53.685; p<0.01). Therefore, it can be concluded that intuitive participants tend to show a tendency towards exponential growth bias.

4.3.1.4. Mental Accounting Bias by Cognitive Reflection

The results of the chi-square analysis conducted to examine the mental accounting bias of participants based on their cognitive reflections are presented in Table 4.12.

Table 4.12. Chi-Square Results for Mental Accounting Bias by Cognitive Reflection

			Cognitive Reflection		Total
			Intuitive	Analytical	
Mental Accounting Bias	Unbiased	n	112	170	282
		%	69.1	75.2	72,7%
	Sunk cost effect	n	18	12	30
		%	11.1	5.3	7,7%
	Reverse sunk cost effect	n	32	44	76
		%	19.8	19.5	19,6%
Total		n	162	226	388
		%	100,0	100.0	100.0

$x^2(2) = 4.592; p = 0.101$

In Table 4.12, it can be observed that unbiased participants constitute the majority of both intuitive (n=112; 69.1%) and analytical (n=170; 75.2%) groups. Additionally, it has been found that there is no significant difference in the mental accounting bias of participants based on their cognitive reflections ($\chi 2=4.592$; $p>0.05$). Accordingly, it was concluded that the participants' mental accounting bias was similar in both cognitive reflection groups.

4.3.1.5. Evaluation of the First Hypothesis

As a result of the analyses carried out within the scope of testing the first hypothesis of the research, it was determined that the participants' base ratio neglect bias and exponential growth bias differed significantly according to their cognitive reflections. On the other hand, it was determined that the participants' overconfidence and mental accounting biases did not differ significantly according to their cognitive reflections. Based on these results, the H1 hypothesis was partially accepted.

4.3.2. Differences in Cognitive Reflection by Demographic Characteristics

The study's second hypothesis is "H2: Cognitive reflection levels of university students significantly differ according to their demographic characteristics". To

determine whether parametric or non-parametric analysis techniques should be used to test the second hypothesis, we examined to assess whether the data follows a normal distribution. The analysis performed in this context determined that the skewness value of the cognitive reflection variable was -0.336, and the kurtosis value was -1.897. It is stated that the skewness and kurtosis values should be between -3 and +3 in order for the data to be accepted as having a normal distribution (Gürbüz & Şahin, 2014). Accordingly, since the skewness and kurtosis values of the cognitive reflection variable were within the mentioned range, it was determined that the data were normally distributed. Therefore, parametric analyses were preferred in the differences test; a t-test was performed for two category variables, and ANOVA analysis was performed for variables with more than two categories. The following subsections present analyses for each demographic characteristic to test the second hypothesis.

4.3.2.1. Cognitive Reflection Levels by Gender

The results of the t-test conducted to examine the cognitive reflection levels of participants based on their gender are presented in Table 4.13.

Table 4.13. T-Test Results for Cognitive Reflection Levels by Gender

Gender	n	Mean	sd	t	df	p
Female	200	3,84	1,78	,318	386	,751
Male	188	3,78	1,82			

As seen in Table 4.13, it was determined that the cognitive reflection levels of the participants did not differ significantly according to their genders ($p>0.05$). Consistent with this finding, the results of the chi-square analysis regarding the distribution of the cognitive reflection groups of the participants by gender in Table 4.14 also indicate no significant difference ($p>0.05$). According to these results, it was concluded that male and female participants had similar cognitive reflection levels.

Table 4.14. Chi-Square Results for Cognitive Reflection by Gender

			Cognitive Reflection		Total
			Intuitive	Analytical	
Gender	Female	n	80	120	200
		%	49.4	53.1	51,5
	Male	n	82	106	188
		%	50.6	46.9	48,5
Total		n	162	226	388
		%	100,0	100.0	100.0

$x^2(1) = 0.521; p = 0.470$

4.3.2.2. Cognitive Reflection Levels by Age

The results of the ANOVA analysis conducted to examine the cognitive reflection levels of participants based on their age are presented in Table 4.15.

Table 4.15. ANOVA Analysis Results for Cognitive Reflection Levels by Age

Age	n	Mean	sd	F	p
19	46	3,48	1,60	,517	,796
20	66	3,68	1,91		
21	78	3,96	1,81		
22	72	3,79	1,88		
23	61	3,85	1,65		
24	35	3,97	1,72		
25+	30	4,00	2,00		

As seen in Table 4.15, it was determined that the cognitive reflection levels of the participants did not differ significantly according to their age ($p>0.05$). Consistent with this finding, the results of the chi-square analysis regarding the distribution of the cognitive reflection groups of the participants by age in Table 4.16 also indicate no significant difference ($p>0.05$). According to these results, it was concluded that participants of all ages had similar cognitive reflection levels.

Table 4.16. Chi-Square Results for Cognitive Reflection by Age

			Cognitive Reflection		Total
			Intuitive	Analytical	
Age	19	n	20	26	46
		%	12.3	11.5	11.9
	20	n	31	35	66
		%	19.1	15.5	17.0
	21	n	31	47	78
		%	19.1	20.8	20.1
	22	n	30	42	72
		%	18.5	18.6	18.6
	23	n	27	34	61
		%	16.7	15.0	15.7
	24	n	12	23	35
		%	7.4	10.2	9.0
	25+	n	11	19	30
		%	6.8	8.4	7.7
Total		n	162	226	388
		%	100.0	100.0	100.0

$x^2(6) = 2.204; p = 0.900$

4.3.2.3. Cognitive Reflection Levels by Grade

The results of the ANOVA analysis conducted to examine the cognitive reflection levels of participants based on their grade (class) are presented in Table 4.17.

Table 4.17. ANOVA Analysis Results for Cognitive Reflection Levels by Grade

Grade	n	Mean	sd	F	p
1	65	3,28	1,58	1,270	0,300
2	127	3,94	1,82		
3	69	3,81	1,88		
4	83	3,75	1,68		
4+	44	3,64	1,95		

As seen in Table 4.17, it was determined that the cognitive reflection levels of the participants did not differ significantly according to their grades ($p>0.05$). Consistent with this finding, the results of the chi-square analysis regarding the distribution of the cognitive reflection groups of the participants by grade in Table 4.18 also indicate no significant difference ($p>0.05$). According to these results, it was concluded that participants of all grades had similar cognitive reflection levels.

Table 4.18. Chi-Square Results for Cognitive Reflection by Grade

			Cognitive Reflection		Total
			Intuitive	Analytical	
Grade	1	n	32	33	65
		%	19.8	14.6	16,8
	2	n	53	74	127
		%	32.7	32.7	32,7
	3	n	26	43	69
		%	16.0	19.0	17,8
	4	n	38	45	83
		%	23.5	19.9	21,4
	4+	n	13	31	44
		%	8.0	13.7	11,3
Total		n	162	226	388
		%	100.0	100.0	100.0

$x^2(4) = 5.215; p = 0.266$

4.3.2.4. Evaluation of the Second Hypothesis

As a result of the analyses carried out within the scope of testing the second hypothesis of the research, it was determined that the cognitive reflection levels of the

participants did not differ significantly according to their demographic characteristics. Based on these results, the H2 hypothesis could not be supported.

4.3.3. Differences in Behavioral Biases by Demographic Characteristics

The third hypothesis of the study is "H3: Behavioral biases of university students significantly differ according to their demographic characteristics". To test the third hypothesis, We present analyses for each demographic characteristic in the following subsections to test the third hypothesis.

4.3.3.1. Behavioral Biases by Gender

The results of the chi-square test conducted to examine the overconfidence bias of the participants based on their gender are presented in Table 4.19. The results of the analysis show that the participants' overconfidence biases do not differ significantly according to their genders ($p>0.05$).

Table 4.19. Chi-Square Results for Overconfidence Bias by Gender

			Overconfidence Bias			Total
			Correct assessment	Overconfident	Underconfident	
Gender	Female	n	37	139	24	200
		%	52.1	52.5	46.2	51.5
	Male	n	34	126	28	188
		%	47.9	47.5	53.8	48.5
Total		n	71	265	52	388
		%	100.0	100.0	100.0	100.0

$x^2(2) = 0.702; p = 0.704$

The results of the chi-square test conducted to examine the base-rate neglect bias of the participants based on their gender are presented in Table 4.20. The results of the

analysis show that the participants' base-rate neglect biases do not differ significantly according to their genders (p>0.05).

Table 4.20. Chi-Square Results for Base-Rate Neglect Bias by Gender

			Base-Rate Neglect Bias		Total
			Unbiased	Biased	
Gender	Female	n	151	49	200
		%	49.2	60.5	51.5
	Male	n	156	32	188
		%	50.8	39.5	48.5
Total		n	307	81	388
		%	100.0	100.0	100.0

$x^2(1) = 3.281; p = 0.070$

The results of the chi-square test conducted to examine the exponential growth bias of the participants based on their gender are presented in Table 4.21. The results of the analysis show that the participants' exponential growth biases do not differ significantly according to their genders (p>0.05).

Table 4.21. Chi-Square Results for Exponential Growth Bias by Gender

			Exponential Growth Bias		Total
			Unbiased	Biased	
Gender	Female	n	82	118	200
		%	51.9	51.3	51.5
	Male	n	76	112	188
		%	48.1	48.7	48.5
Total		n	158	230	388
		%	100.0	100.0	100.0

$x^2(1) = 0.013; p = 0.908$

The results of the chi-square test conducted to examine the mental accounting bias of the participants based on their gender are presented in Table 4.22. The results of the analysis show that the participants' mental accounting biases do not differ significantly according to their genders (p>0.05).

Table 4.22. Chi-Square Results for Mental Accounting Bias by Gender

			Mental Accounting Bias			Total
			Unbiased	Sunk cost effect	Reverse sunk cost effect	
Gender	Female	n	145	14	41	200
		%	51.4	46.7	53.9	51.5
	Male	n	137	16	35	188
		%	48.6	53.3	46.1	48.5
Total		n	282	30	76	388
		%	100.0	100.0	100.0	100.0

$x^2(2) = 0.463; p = 0.793$

4.3.3.2. Behavioral Biases by Age

The results of the chi-square test conducted to examine the overconfidence bias of the participants based on their age are presented in Table 4.23. The results of the analysis show that the participants' overconfidence biases do not differ significantly according to their age ($p>0.05$).

Table 4.23. Chi-Square Results for Overconfidence Bias by Age

			Overconfidence Bias			Total
			Correct assessment	Overconfident	Underconfident	
Age	19	n	8	32	6	46
		%	11.3	12.1	11.5	11.9
	20	n	10	47	9	66
		%	14.1	17.7	17.3	17.0
	21	n	18	53	7	78
		%	25.4	20.0	13.5	20.1
	22	n	12	48	12	72
		%	16.9	18.1	23.1	18.6
	23	n	12	38	11	61
		%	16.9	14.3	21.2	15.7
	24	n	5	26	4	35
		%	7.0	9.8	7.7	9.0
	25+	n	6	21	3	30
		%	8.5	7.9	5.8	7.7
Total		n	71	265	52	388
		%	100.0	100.0	100.0	100.0

$x^2(12) = 5.572; p = 0.936$

The results of the chi-square test conducted to examine the base-rate neglect bias of the participants based on their age are presented in Table 4.24. The results of the analysis show that the participants' base-rate neglect biases do not differ significantly according to their age ($p>0.05$).

Table 4.24. Chi-Square Results for Base-Rate Neglect Bias by Age

			Base-Rate Neglect Bias		**Total**
			Unbiased	**Biased**	
Age	**19**	**n**	33	13	46
		%	10.7	16.0	11.9
	20	**n**	49	17	66
		%	16.0	21.0	17.0
	21	**n**	61	17	78
		%	19.9	21.0	20.1
	22	**n**	56	16	72
		%	18.2	19.8	18.6
	23	**n**	52	9	61
		%	16.9	11.1	15.7
	24	**n**	28	7	35
		%	9.1	8.6	9.0
	25+	**n**	28	2	30
		%	9.1	2.5	7.7
Total		**n**	307	81	388
		%	100.0	100.0	100.0

$x^2(6) = 7.657; p = 0.264$

The results of the chi-square test conducted to examine the exponential growth bias of the participants based on their age are presented in Table 4.25. The results of the analysis show that the participants' exponential growth biases do not differ significantly according to their age ($p>0.05$).

Table 4.25. Chi-Square Results for Exponential Growth Bias by Age

			Exponential Growth Bias		**Total**
			Unbiased	**Biased**	
Age	**19**	**n**	18	28	46
		%	11.4	12.2	11.9
	20	**n**	22	44	66
		%	13.9	19.1	17.0
	21	**n**	28	50	78
		%	17.7	21.7	20.1
	22	**n**	29	43	72
		%	18.4	18.7	18.6
	23	**n**	28	33	61
		%	17.7	14.3	15.7
	24	**n**	15	20	35
		%	9.5	8.7	9.0
	25+	**n**	18	12	30
		%	11.4	5.2	7.7
Total		**n**	158	230	388
		%	100.0	100.0	100.0

$x^2(6) = 7.662; p = 0.264$

The results of the chi-square test conducted to examine the mental accounting bias of the participants based on their age are presented in Table 4.26. The results of the analysis show that the participants' mental accounting biases do not differ significantly according to their age (p>0.05).

Table 4.26. Chi-Square Results for Mental Accounting Bias by Age

			Mental Accounting Bias			Total
			Unbiased	Sunk cost effect	Reverse sunk cost effect	
Age	19	n	33	4	9	46
		%	11.7	13.3	11.8	11.9
	20	n	47	7	12	66
		%	16.7	23.3	15.8	17.0
	21	n	54	6	18	78
		%	19.1	20.0	23.7	20.1
	22	n	51	7	14	72
		%	18.1	23.3	18.4	18.6
	23	n	47	2	12	61
		%	16.7	6.7	15.8	15.7
	24	n	25	3	7	35
		%	8.9	10.0	9.2	9.0
	25+	n	25	1	4	30
		%	8.9	3.3	5.3	7.7
Total		n	282	30	76	388
		%	100.0	100.0	100.0	100.0

$x^2(12) = 5.454; p = 0.941$

4.3.3.3. Cognitive Reflection Levels by Grade

The results of the chi-square test conducted to examine the overconfidence bias of the participants based on their grades are presented in Table 4.27. The results of the analysis show that the participants' overconfidence biases do not differ significantly according to their grade ($p>0.05$).

Table 4.27. Chi-Square Results for Overconfidence Bias by Grade

			Overconfidence Bias			Total
			Correct assessment	Overconfident	Underconfident	
Grade	1	n	12	42	11	65
		%	16.9	15.8	21.2	16.8
	2	n	24	88	15	127
		%	33.8	33.2	28.8	32.7
	3	n	13	42	14	69
		%	18.3	15.8	26.9	17.8
	4	n	17	58	8	83
		%	23.9	21.9	15.4	21.4
	4+	n	5	35	4	44
		%	7.0	13.2	7.7	11.3
Total		n	71	265	52	388
		%	100.0	100.0	100.0	100.0

$x^2(8) = 7.731; p = 0.460$

The results of the chi-square test conducted to examine the base-rate neglect bias of the participants based on their grades are presented in Table 4.28. The results of the analysis show that the participants' base-rate neglect biases do not differ significantly according to their grade (p>0.05).

Table 4.28. Chi-Square Results for Base-Rate Neglect Bias by Grade

			Base-Rate Neglect Bias		Total
			Unbiased	Biased	
Grade	1	n	48	17	65
		%	15.6	21.0	16.8
	2	n	98	29	127
		%	31.9	35.8	32.7
	3	n	51	18	69
		%	16.6	22.2	17.8
	4	n	71	12	83
		%	23.1	14.8	21.4
	4+	n	39	5	44
		%	12.7	6.2	11.3
Total		n	307	81	388
		%	100.0	100.0	100.0

$x^2(4) = 7.006; p = 0.136$

The results of the chi-square test conducted to examine the exponential growth bias of the participants based on their grades are presented in Table 4.29. The results of the analysis show that the participants' exponential growth biases do not differ significantly according to their grade (p>0.05).

Table 4.29. Chi-Square Results for Exponential Growth Bias by Grade

			Exponential Growth Bias		Total
			Unbiased	Biased	
Grade	1	n	22	43	65
		%	13.9	18.7	16.8
	2	n	44	83	127
		%	27.8	36.1	32.7
	3	n	32	37	69
		%	20.3	16.1	17.8
	4	n	37	46	83
		%	23.4	20.0	21.4
	4+	n	23	21	44
		%	14.6	9.1	11.3
Total		n	158	230	388
		%	100.0	100.0	100.0

$x^2(4) = 7.073; p = 0.132$

The results of the chi-square test conducted to examine the mental accounting bias of the participants based on their grades are presented in Table 4.30. The results of the analysis show that the participants' mental accounting biases do not differ significantly according to their grade ($p>0.05$).

Table 4.30. Chi-Square Results for Mental Accounting Bias by Grade

			Mental Accounting Bias			Total
			Unbiased	Sunk cost effect	Reverse sunk cost effect	
Grade	1	n	46	7	12	65
		%	16.3	23.3	15.8	16.8
	2	n	88	10	29	127
		%	31.2	33.3	38.2	32.7
	3	n	54	5	10	69
		%	19.1	16.7	13.2	17.8
	4	n	64	4	15	83
		%	22.7	13.3	19.7	21.4
	4+	n	30	4	10	44
		%	10.6	13.3	13.2	11.3
Total		n	282	30	76	388
		%	100.0	100.0	100.0	100.0

$x^2(8) = 4.650; p = 0.794$

4.3.3.4. Evaluation of the Third Hypothesis

As a result of the analyses carried out within the scope of testing the third hypothesis of the research, it was determined that the behavioral biases of the participants did not differ significantly according to their demographic characteristics. Based on these results, the H3 hypothesis could not be supported.

5. DISCUSSION

This study aimed to examine whether there were differences between the cognitive reflection levels of university students and behavioral biases such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. In addition, it also aimed to examine if cognitive reflection levels and behavioral biases of university students differed according to their demographic characteristics.

In the study, participant university students' cognitive reflection and behavioral bias levels were initially examined. According to the analysis results, it was determined that most participants belonged to the analytical group regarding cognitive reflection. This finding indicates that participants tend to make decisions based on analytical and rational thinking processes, which involve evaluating data and reaching logical conclusions, rather than relying on quick and experiential thinking associated with intuitive and automatic decision-making.

On the other hand, in the examinations related to behavioral biases, it was found that participants mainly exhibited overconfidence bias and exponential growth bias. At the same time, they mostly did not display base rate neglect bias and mental accounting bias. This finding indicates that participants overestimate their knowledge compared to actual values (overconfidence bias) and considerably underestimate future values by linearizing functions with exponential terms and neglecting increasing effects (exponential growth bias). Additionally, these findings suggest that participants do not consistently disregard overall probabilities by focusing on specific information (base rate neglect bias) and do not uniformly apply the same logical thinking while making financial decisions across different categories (mental accounting bias).

5.1. Discussion of First Hypothesis Test Findings

Within the scope of the first hypothesis test of the research, the behavioral biases of participating university students according to their mental reflections were examined.

In the investigation of participants' overconfidence bias, it was determined that there was no significant difference in overconfidence bias based on participants' cognitive reflections. According to this finding, there is no statistically significant

relationship between cognitive reflection and overconfidence bias. In other words, participants' cognitive reflection levels have yet to emerge as a decisive factor in influencing overconfidence bias. This result suggests that whether participants have low (intuitive) or high (analytical) cognitive reflection levels does not impact their tendency towards overconfidence bias.

In examining participants' base rate neglect bias, it was determined that there was a significant difference in base rate neglect bias based on participants' cognitive reflections. According to this finding, participants who exhibit base rate neglect bias are predominantly intuitive thinkers, while participants who do not exhibit base rate neglect bias are predominantly analytical thinkers. This finding indicates that the tendency towards base rate neglect bias is more associated with intuitive decision-making, and it is less prevalent among participants who generally possess higher analytical thinking abilities. This finding could be attributed to intuitive individuals, often adopting a quick and experience-based thinking style (Kahneman, 2011; Toplak et al., 2014). This predisposition to focus on specific information while disregarding general ratios might explain why those who think intuitively are more prone to base rate neglect bias.

In examining participants' exponential growth bias, it was determined that there was a significant difference in exponential growth bias based on participants' cognitive reflections. According to this finding, the majority of intuitive participants tend to exhibit exponential growth bias, whereas the majority of analytical participants do not show a tendency toward exponential growth bias. This finding suggests that the tendency towards exponential growth bias is more associated with intuitive decision-making and is less prevalent among participants who generally possess higher analytical thinking abilities. This conclusion could be attributed to the fact that intuitive thinkers tend to linearize functions with exponential terms and underestimate future values due to their quicker and often intuitive decision-making processes (Kahneman, 2011; Toplak et al., 2014).

In examining participants' mental accounting bias, it was determined that there was no significant difference in mental accounting bias based on participants' cognitive reflections. According to this finding, there is no statistically significant relationship between cognitive reflection and mental accounting bias. In other words, participants' cognitive reflection levels did not emerge as a determining factor for their tendencies

toward mental accounting bias. This result indicates that whether participants have low (intuitive) or high (analytical) cognitive reflection levels does not influence their tendencies toward mental accounting bias.

In the context of testing the first hypothesis, the results indicate that participants with low cognitive reflection, categorized as intuitive thinkers, tend to exhibit base rate neglect and exponential growth bias. At the same time, there is no significant difference in overconfidence bias and mental accounting bias based on their cognitive reflection levels. Some researchers argue that overconfidence is a psychological phenomenon that can be observed in all individuals, widely prevalent, and robust (Barber & Odean, 2001; Evans, 2006). Thus, the finding that overconfidence bias is similar in both intuitive and analytical cognitive reflection groups might be due to this characteristic nature of overconfidence bias. On the other hand, in this study, mental accounting bias was measured through sunk cost. Thaler (1999) emphasizes the uncertainty of the impact of sunk costs on behavioral decisions. For instance, research has shown that fans who purchased tickets to attend a sports event are more likely to attend the event even if they experience an obstacle (such as falling ill) on the day of the event, compared to those who received discounted or free tickets (Thaler, 1999).

Similarly, this study's lack of a significant difference in mental accounting bias based on cognitive reflection levels could be attributed to factors similar to those mentioned above. For instance, participants might have considered the gym membership fee (300 TL) low enough to disregard, concluding that there is no significant difference. Different results could be obtained when a higher membership fee is paid.

In summary, the study's results suggest that while cognitive reflection levels influence some biases, other factors, like the nature of the bias itself or specific contextual factors, might contribute to the lack of significant differences in some instances. These findings highlight the complex interplay between cognitive reflection and different biases, calling for further research to explore the underlying mechanisms and contextual factors that influence these relationships.

When similar studies in the literature are examined, it is seen that intuitive participants with low cognitive reflection levels have a high tendency to exhibit behavioral bias. On the other hand, in each of these studies, it was observed that a

different behavioral bias did not differ significantly according to cognitive reflection. For instance, a study conducted by Hoppe and Kusterer (2011) with 414 university students in Germany found results consistent with this study, indicating that intuitive participants are more likely to exhibit base rate neglect compared to analytical participants, while overconfidence bias does not significantly differ based on cognitive reflection. Another study by Polat and Duman (2020) with 716 university students aged 18-23 showed that intuitive participants are more likely to exhibit overconfidence bias, base rate neglect, exponential growth bias, and mental accounting bias than analytical participants. In studies conducted by Noori (2016) with 395 university students in Iran and by Oechssler et al. (2009) with 1250 university students in Germany, similar conclusions were reached where intuitive participants exhibited more overconfidence bias and base rate neglect compared to analytical participants. Another study by Leeper (2015) with university students in the United States found that intuitive participants are more likely to exhibit overconfidence bias, exponential growth bias, and mental accounting bias compared to analytical participants, while there was no significant difference in terms of base rate neglect based on cognitive reflection. In summary, a general statement can be made that participants with lower cognitive reflection, characterized as intuitive thinkers, exhibit a higher tendency towards various behavioral biases. However, it is crucial to consider the specific contexts, cultural factors, and demographic characteristics that might influence these relationships, as different studies have produced varying results based on their unique conditions.

5.2. Discussion of Second Hypothesis Test Findings

The analyses conducted to test the study's second hypothesis revealed that participants' levels of cognitive reflection did not significantly differ based on demographic characteristics such as gender, age, and class. In other words, it was determined that participants' cognitive reflection levels were similar across all gender, age, and class groups. These findings might indicate that demographic factors such as gender, age, and class generally do not significantly impact cognitive reflection abilities. This situation could be attributed to cognitive reflection being a systematically observable phenomenon in almost all individuals. In other words, it is a widely applicable trait (Polat & Duman, 2020).

Numerous studies in the literature have arrived at similar conclusions. For instance, in a study by Temel (2019) involving a total of 186 participants aged between 18 and 45, it was determined that the level of cognitive reflection did not significantly differ based on participants' gender, age, and education status. Similarly, in a study by Leeper (2015) conducted with university students in the US, it was observed that cognitive reflection was not associated with demographic characteristics. Other studies have also found that cognitive reflection levels did not significantly differ based on participants' gender (Ludwig & Achtziger, 2021; Noori, 2016; Yıldırımer et al., 2021), age, and class (Polat & Duman, 2020). On the other hand, contrary to the findings of this research, some studies have identified that cognitive reflection levels were higher among male and older participants (Albaity et al., 2014; Brañas-Garza et al., 2019; Polat & Duman, 2020; Sinayev & Peters, 2015). The discrepancies among research findings stem from contextual differences in the studies. In conclusion, it can be stated in a general sense that cognitive reflection does not differ significantly based on demographic characteristics; however, higher levels of cognitive reflection might be observed in males and older individuals.

5.3. Discussion of Third Hypothesis Test Findings

The analysis to test the third hypothesis revealed that participants' overconfidence bias, base rate neglect bias, exponential growth bias, and mental accounting bias did not significantly differ based on demographic factors such as gender, age, and class. In other words, participants' behavioral biases were found to be at similar levels across all gender, age, and class groups. These findings suggest that demographic factors such as gender, age, and class may not significantly influence the mentioned behavioral biases. The observed pattern may stem from the notion that these behavioral biases are prevalent across a wide range of individuals, reflecting a systematic tendency that is nearly universally applicable (Polat & Duman, 2020).

Similar results are evident in the literature. For instance, a study by Bashir et al. (2013) in Pakistan with 225 participants found that behavioral biases did not vary significantly based on participants' gender, age, and educational backgrounds. Arslan and Boztosun (2022), in a study with 408 participants in Kayseri, determined that overconfidence bias did not show significant differences concerning gender and age. Similarly, Polat and Duman (2020) found that behavioral biases did not differ across

participants' ages and classes. On the other hand, some studies in the literature report different findings from the present study. For instance, in the same study, Polat and Duman (2020) identified that female participants exhibited higher tendencies in base rate neglect bias and exponential growth bias. Küçükdurmaz (2019), with 307 participants, found that while overconfidence bias did not vary by gender, women showed higher levels of mental accounting bias. Another study by Beatrice et al. (2021) with 152 participants in Indonesia did not find significant gender-based differences in overconfidence bias and mental accounting bias but identified higher levels among the elderly participants. Baker et al. (2019), with 500 participants in India, reported that overconfidence and mental accounting biases did not differ by gender. In the same study, while mental accounting bias did not vary by age, overconfidence bias was higher among older participants (Baker et al., 2019). Variations in research findings are likely attributed to contextual differences among the studies. In conclusion, it can be stated broadly that behavioral biases do not significantly differ based on demographic characteristics, but tendencies toward higher behavioral biases might be observed among women and older individuals.

6. CONCLUSION AND RECOMMENDATIONS

This study aimed to examine whether there were differences between the cognitive reflection levels of university students and behavioral biases such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. In addition, it also aimed to examine if cognitive reflection levels and behavioral biases of university students differed according to their demographic characteristics. This descriptive and cross-sectional quantitative research was conducted in a relational screening model in line with this purpose. The study sample consisted of 388 participants selected through a simple random sampling method among students at universities in Ankara province. The research collected primary data using an online questionnaire that included questions about cognitive reflection and behavioral biases such as basic ratio neglect, overconfidence, mental accounting, and exponential growth bias. SPSS v26 software was utilized for data analysis in the study. Chi-square test, t-test, and ANOVA analysis were employed for testing the research hypotheses. As a result of the analysis, it was determined that intuitive participants with low cognitive reflection tended to exhibit more base ratio neglect bias and exponential growth bias compared to analytical participants. On the other hand, it was determined that overconfidence bias and mental accounting bias did not differ significantly according to the cognitive reflection levels of the participants. In addition, it was observed that cognitive reflection and behavioral biases did not differ significantly according to the demographic characteristics of the participants.

The study results highlight the importance of cognitive reflection in mitigating behavioral biases among university students. Therefore, educational programs should be developed and integrated into the university curriculum to enhance students' cognitive reflection levels and raise awareness about cognitive biases. Furthermore, these awareness initiatives could also be incorporated within universities' guidance and counseling services.

The study also has suggestions for future research based on its limitations. Firstly, the investigation needed help to control whether participants sought assistance to answer the survey questions. Future research could employ a study design that prevents participants from seeking help to attain more reliable results. Another significant

limitation is that this study focused on specific behavioral biases, including overconfidence, base rate neglect, exponential growth, and mental accounting. It is recommended that future research explore different behavioral biases.

Additionally, the data for this study was collected from university students in Ankara. Conducting research with a sample from different demographics could yield different results. Therefore, future studies should consider a diverse sample, including different age groups and educational levels. Lastly, this research relied on survey methodology. For more in-depth insights, future research could analyze data collected through qualitative methods such as interviews and focus groups.

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8. APPENDIX

Appendix 1. Questionnaire Form

Gender:	☐ Female ☐ Male
Age:	
Department:	
Grades (1,2,3,4 and 4+):	
Birthplace	

**** PLEASE ANSWER THE FOLLOWING QUESTIONS TO THE BEST OF YOUR ABILITY. PLEASE DO NOT USE EXTERNAL SOURCES.**

1. **Which of the following predictions about a woman reading a scientific journal on the Ankara subway would you consider a better prognosis?**

   ☐ **S**he has a PhD.

   ☐ The woman is not a university graduate.

2. **You paid 300 TL to join a 6-month fitness course. In the first week of your membership, you develop a problem with your leg. This problem is so painful that it prevents you from doing sports. Your doctor said that this problem would last for about one year at the hospital you went to.**

Estimate how many more times you will go to the gym in the six months of your membership:	
Estimate how many times you will go to the gym in the next six months after your membership ends:	

3. **The price of a racket and a ball is $1.10. The noise is $1.00 more expensive than the ball. How much does the ball cost?**

4. **If five machines produce five pieces in 5 minutes, how long will it take 100 machines to make 100 pieces?**

5. **There are water lilies on the surface of a lake. Every day, the amount of water lilies in the lake doubles. If the water lilies cover the entire lake in 48 days, how many days will it take to cover half of the lake with water lilies?**

6. **A man buys a farm animal for 60 TL. He sells it for 70 TL. He repurchases it for 80 TL and finally sells it for 90 TL.**

   How many TL is this person's profit?

7. **The room temperature with an initial temperature of 10°C increases by 10% of the current temperature at the beginning of each hour. After 24 hours, what is the temperature of the room?**

8. **At the beginning of 2018, Ahmet invested TL 8,000 in the stock market. Six months after his investment, the stocks he bought lost 80% of their value. In the following three months, the value of the investment increased by 75%. At this point, Ahmet;**

☐ Becomes bankrupt.

☐ Better off than when it started.

☐ Has made a loss.

9. **Assume that you enjoy doing sports. Suppose that one day you are injured while playing sports and have a leg problem, which will prevent you from playing sports for a long time. Your doctor told you that this problem will last about one year.**

Predict how many more times you will exercise in the next six months: ☐

Estimate how many times you will exercise in the next six months: ☐

10. **Suppose a student in a class gets the 15th highest and 15th lowest grade in a subject. How many students are in the class in total?**

☐

11. **If Ali can drink a carboy of water in 6 days and Ayşe can drink a carboy of water in 12 days, how long will it take them to drink a carboy of water together? (in days)**

☐

12. Sissa invented the game of chess to educate and entertain the Indian ruler. The ruler loved the game and wanted to reward Sissa for creating it. Upon this gesture of the ruler, Sissa made the following wish: "Give me grains of wheat, but only until I reach the sixty-fourth square of the chessboard, continuing with one grain of wheat on the first square, two grains on the second square, four grains on the third square, and so on, multiplying each time until I reach the sixty-fourth square. What is your best guess about Sissa's request?

13. In astronomical units, what is the distance between the Earth and the Sun??

☐ 587

☐ 1

☐ 4553

☐ 14

14. What is the approximate population of Yalova?

☐ 283.296

☐ 78.550

☐ 141.800

☐ 50.100

15. In what year did Albert Einstein die?

☐ 1955

☐ 1947

☐ 1961

☐ 1938

16. Who is the author of 'Madonna in a Fur Coat'?

☐ Halit Ziya Uşaklıgil

☐ Sabahattin Ali

☐ Reşat Nuri Güntekin

☐ Orhan Veli Kanık

17. Which of the following metropolises has the largest surface area?

☐ Shanghai

☐ Istanbul

☐ Los Angeles

☐ Moscow

18. **How many of the last five questions above do you think you answered correctly?**

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

19. **Have you looked at any of the answers to the questions in the questionnaire?**

☐ Yes

☐ No

Appendix 2. Distribution of Participants According to Their Departments

Department	**n**	**%**
Computer engineering	43	11.1
Finance	20	5.2
Business	19	4.9
Law	18	4.6
Nursing	16	4.1
Civil engineering	15	3.9
Medicine	14	3.6
Dentist	14	3.6
Mechanical engineering	13	3.4
Software engineering	12	3.1
Psychology	11	2.8
Economy	11	2.8
History	10	2.6
Child development and education	10	2.6
Architecture	10	2.6
Banking and finance	10	2.6
Philosophy	9	2.3
Sociology	9	2.3
Maths	8	2.1
Industrial engineering	8	2.1
Turkish language and literature	7	1.8
İnternational relations	7	1.8
Audiology	6	1.5
Gastronomy	5	1.3
Physical therapy and rehabilitation	5	1.3
Economy	5	1.3
Physical	5	1.3
Aerospace engineering	4	1.0
Classroom teaching	4	1.0
Electrical electronics Engineering	4	1.0
Healthcare management	4	1.0

Department	**n**	**%**
Chemical	4	1.0
Statistics	4	1.0
Social service	3	0.8
Energy systems engineering	3	0.8
Industrial design	3	0.8
Pharmacy	3	0.8
Graphic design	3	0.8
Nutrition and dietetics	3	0.8
Management information systems	2	0.5
Pre-school teacher	2	0.5
Public relations and promotion	2	0.5
Interior architecture	2	0.5
Vet	1	0.3
Accounting	1	0.3
Food Engineering	1	0.3
Radiology	1	0.3
Business economics	1	0.3
Restoration	1	0.3
Biology	1	0.3
Translation and interpreting	1	0.3
Medical secretarial	1	0.3
Geography	1	0.3
Tourism and hotel management	1	0.3
Mechatronic engineering	1	0.3
Science teacher	1	0.3
Engineering	1	0.3
Information/document management	1	0.3
Sports management	1	0.3
City and region planning	1	0.3
Office management	1	0.3
Grand total	388	100

Appendix 3. Distribution of Participants According to Their Birthplaces

Birthplace	**n**	**%**
Ankara	104	26.8
Antalya	30	7.7
İstanbul	24	6.2
Samsun	16	4.1
İzmir	14	3.6
Kayseri	11	2.8
Other	10	2.6
Amasya	9	2.3
Yozgat	7	1.8
Trabzon	7	1.8
Muğla	7	1.8
Konya	7	1.8
Yalova	6	1.5
Isparta	6	1.5
Bolu	5	1.3
Tokat	5	1.3
Aydın	5	1.3
Artvin	4	1.0
Aksaray	4	1.0
Burdur	4	1.0
Çorum	4	1.0
Kars	4	1.0
Kırşehir	4	1.0
Bursa	4	1.0
Nevşehir	4	1.0
Denizli	4	1.0
Sakarya	4	1.0
Eskişehir	4	1.0
Hatay	4	1.0
Adana	3	0.8
Elazığ	3	0.8
Ordu	3	0.8
Afyon	3	0.8

Birthplace	**n**	**%**
Sinop	3	0.8
Manisa	3	0.8
Gaziantep	3	0.8
Kırıkkale	3	0.8
Bartın	2	0.5
Van	2	0.5
Tekirdağ	2	0.5
Giresun	2	0.5
Zonguldak	2	0.5
Kocaeli	2	0.5
Sivas	2	0.5
Mersin	2	0.5
Uşak	2	0.5
Erzurum	2	0.5
Bayburt	2	0.5
Niğde	2	0.5
Çanakkale	2	0.5
Rize	2	0.5
Kastamonu	1	0.3
Bitlis	1	0.3
Batman	1	0.3
Kütahya	1	0.3
Bilecik	1	0.3
Malatya	1	0.3
Edirne	1	0.3
Siirt	1	0.3
Balıkesir	1	0.3
Kahramanmaraş	1	0.3
Hakkari	1	0.3
Çankırı	1	0.3
Ağrı	1	0.3
Şırnak	1	0.3
Gümüşhane	1	0.3

Appendix 4. Ankara Yildirim Beyazit University Ethics Committee Project Approval Form

ANKARA YILDIRIM BEYAZIT ÜNİVERSİTESİ (AYBÜ)
SOSYAL VE BEŞERİ BİLİMLER ETİK KURULU
PROJE ONAY BELGESİ

Ankara Yıldırım Beyazıt Üniversitesi Soyal Bilimler Fakültesi/Enstitüsü Tezli Finans ve Bankacılık bölümü akademisyenlerinden / öğrencilerinden Nurbanu Kurtulmuş'in, **Üniversite Öğrencilerinin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği** adlı araştırması değerlendirilmiştir.*(Bu kısım başvuru sahibi tarafından doldurulmalıdır)*

Proje etik açısından uygun bulunmuştur. [X]

Proje etik açısından geliştirilmesi gerekmektedir. [ ]

Proje etik açısından uygun bulunmamıştır. [ ]

AYBÜ SOSYAL VE BEŞERİ BİLİMLER ETİK KURULU KARARI (Etik Kurul tarafından doldurulacaktır)	
Araştırma kodu (Yıl – Araştırma sıra no)	2022-1344
Başvuru formunun Etik Kurula ulaştığı tarih	28.12.2022
Etik Kurul Karar toplantı tarihi ve karar no	03.01.2023/22-1344
Yer	Ankara Yıldırım Beyazıt Üniversitesi, Esenboğa Külliyesi
Katılımcılar	Formda imzası bulunan üyelerimiz toplantıya katılmıştır.

KURUL BAŞKANI VE ÜYELER:

Prof. Dr. Hakkı ODABAŞ	Başkan
Doç. Dr. Musa ÖZTÜRK	Üye
Doç. Dr. Ömer ASLAN	Üye
Doç. Dr. Özge GÖKBULUT ÖZDEMİR	Üye
Doç. Dr. Ali POLAT	Üye
Dr. Öğr. Üyesi Nur Betül ATAKUL	Üye
Dr. Öğr. Üyesi Recep YORULMAZ	Üye
Dr. Öğr. Üyesi Semih CEYHAN	Üye
Dr. Öğr. Üyesi Keziban Büşra KAYNAK EKİCİ	Üye
Dr. Öğr. Üyesi Gülay YAZICI	Üye
Öğr. Gör. Dr. İrem ŞENGÜL	Üye

Appendix 5. Ankara Haci Bayram Veli University Ethics Committee Project Approval Form

T.C.
ANKARA HACI BAYRAM VELİ ÜNİVERSİTESİ
Öğrenci İşleri Daire Başkanlığı

Sayı : E-13349523-302.08.01-176134
Konu : Araştırma İzni (Nurbanu KURTULMUŞ)

ANKARA YILDIRIM BEYAZIT ÜNİVERSİTESİ REKTÖRLÜĞÜNE
(Sosyal Bilimler Enstitüsü Müdürlüğü)

İlgi : 23.03.2023 tarihli ve E-13983731-300-181945 sayılı yazı.

İlgi'de kayıtlı yazınız ile; Üniversiteniz Sosyal Bilimler Enstitüsü Finans ve Bankacılık Anabilim Dalı Tezli Yüksek Lisans Programı öğrencisi Nurbanu KURTULMUŞ'un "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" adlı tez çalışması kapsamında Üniversitemizde öğrenim gören öğrencilerden bilgi alınarak elektronik ortamda çevrimiçi yöntemlerle araştırma yapmak için gerekli izinlerin verilmesi istenmektedir.

İlgi'de kayıtlı yazınız ile istenen anket çalışmasının Türk Müziği Devlet Konservatuvarı ve Tapu Kadastro Yüksekokulu dışındaki Üniversitemiz akademik birimlerinde yapılması Rektörlüğümüzce uygun bulunmuştur.

Bilgilerini ve gereğini arz ederim.

Fethullah GÜNER
Rektör a.
Genel Sekreter

Ek:19 Sayfa

Bu belge, güvenli elektronik imza ile imzalanmıştır.

Belge Doğrulama Kodu :BSF84J9546 Pin Kodu :89452 Belge Takip Adresi : https://turkiye.gov.tr/ebd?eK=5574&eD=BS584J9M6H&eS=176134

Adres:Ankara Hacı Bayram Veli Üniversitesi Yücetepe Mahallesi 85. Cadde No 8 06570 Çankaya / Ankara
Telefon:+90 (312) 231 73 60
Kep Adresi:hacibayramveli@hs01.kep.tr

Bilgi için: Canan BAYRAKTAR
Unvanı: Büro Personeli

Appendix 6. TED University Ethics Committee Project Approval Form

TED ÜNİVERSİTESİ

TED ÜNİVERSİTESİ
Rektör Yardımcılığı

Sayı : E-46409941-605.01-24668 31.01.2023
Konu : Araştırma İzni (Nurbanu KURTULMUŞ)

ANKARA YILDIRIM BEYAZIT ÜNİVERSİTESİ REKTÖRLÜĞÜNE
(Sosyal Bilimler Enstitüsü Müdürlüğü)
Cinnah Cad. Güven Mah. No:16 Çankaya / Ankara

İlgi : 26.01.2023 tarihli ve E-13983731-300-170199 sayılı yazı

Üniversiteniz Sosyal Bilimler Enstitüsü Finans ve Bankacılık Anabilim Dalı Tezli Yüksek Lisans Programı öğrencisi Nurbanu KURTULMUŞ'un "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" tez çalışması kapsamında, üniversitemiz öğrencileri ile anket çalışması yapması uygun görülmüştür.

Bilgilerinizi rica ederim.

Saygılarımla.

Prof. Dr. Oya GÜNERİ
Rektör Yardımcısı

Adres:Ziya Gökalp Cad. No:48 06420 Kolej-Çankaya/Ankara
Telefon:0 312 585 00 00 Faks:0 312 418 41 48
e-Posta:info@tedu.edu.tr Web:www.tedu.edu.tr
Kep Adresi:tedu@tedu.hs03.kep.tr
Bilgi için: Semra Şimşek
Unvanı: Rektör Yardımcısı Sekreteri

Appendix 7. Gazi University Ethics Committee Project Approval Form

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Öğrenci İşleri Daire Başkanlığı

Sayı : E-17311665-044-597942 27.02.2023
Konu : Anketler (Nurbanu KURTULMUŞ)

ANKARA YILDIRIM BEYAZIT ÜNİVERSİTESİ REKTÖRLÜĞÜNE
(Sosyal Bilimler Enstitüsü Müdürlüğü)

İlgi : 26.01.2023 tarihli ve E-13983731-300-170199 sayılı yazı.

Üniversiteniz Sosyal Bilimler Enstitüsü, Finans ve Bankacılık Ana Bilim Dalı tezli yüksek lisans programı öğrencisi Nurbanu KURTULMUŞ'un, "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" adlı tez çalışması kapsamında Üniversitemiz bünyesinde uygulama yapmasına izin verilmesine ilişkin ilgi yazınız Üniversitemiz akademik birimlerine iletilmiş olup, alınan cevabî yazılar ilişikte gönderilmiştir.

Bilgilerinize arz ederim.

Prof. Dr. Yücel GELİŞLİ
Rektör a.
Rektör Yardımcısı

Ek:Cevabî yazılar (10 adet)

Gazi Üniversitesi Öğrenci İşleri Dairesi Başkanlığı Rektörlük Kampüsü Emniyet Mah. Bandırma Cad. No: 6/6 06500 Yenimahalle/ ANKARA
Tel:0 (312) 212 68 40 Faks:0 (312) 202 28 08
e-Posta :ogris@gazi.edu.tr İnternet Adresi :www.ogris.gazi.edu.tr
Kep Adresi: gaziuniversitesi@hs01.kep.tr

Bilgi için :Talip Gümüş
Bilgisayar İşletmeni
Telefon No:312 202 28 06

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Spor Bilimleri Fakültesi Dekanlığı

Ek-4

Sayı : E-92236698-044-574827 30.01.2023
Konu : Anketler (Nurbanu KURTULMUŞ)

REKTÖRLÜK MAKAMINA
(Öğrenci İşleri Daire Başkanlığı)

İlgi : 27.01.2023 tarihli ve 17311665-044- 573356 sayılı yazı.

İlgi yazınız gereğince, Ankara Yıldırım Beyazıt Üniversitesi, Sosyal Bilimler Enstitüsü, Finans ve Bankacılık Ana Bilim Dalı tezli yüksek lisans programı öğrencisi Nurbanu KURTULMUŞ'un, "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" adlı tez çalışması kapsamında Fakültemiz bünyesinde uygulama yapma talebi Dekanlığımızca uygun görülmüştür.

Bilgilerinizi arz ederim.

Prof. Dr. Latif AYDOS
Dekan

Abant Sokak No:12 Gazi Mahallesi 06330 Yenimahalle/Ankara Türkiye
Tel:0 (312) 202 35 00 Faks:0 (312) 212 22 74
İnternet Adresi :http://gazi-universitesi.gazi.edu.tr/
Kep Adresi: gaziuniversitesi@hs01.kep.tr

Bilgi için :Tülay MUTLU
Bilgisayar İşletmeni
Telefon No:03122023501

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ Ek-5
Sağlık Hizmetleri Meslek Yüksekokulu Müdürlüğü

Sayı : E-46451316-044-575371 30.01.2023
Konu : Anketler (Nurbanu KURTULMUŞ)

REKTÖRLÜK MAKAMINA
(Öğrenci İşleri Daire Başkanlığı)

İlgi : 27.01.2023 tarihli ve 17311665-044- 573356 sayılı yazı.

İlgi tarih ve sayılı yazınıza istinaden Ankara Yıldırım Beyazıt Üniversitesi, Sosyal Bilimler Enstitüsü, Finans ve Bankacılık Ana Bilim Dalı tezli yüksek lisans programı öğrencisi Nurbanu KURTULMUŞ'un, "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" adlı tez çalışması kapsamında Yüksekokulumuz bünyesinde uygulama yapmasında sakınca yoktur.

Bilgilerinizi ve gereğini arz ederim.

Doç. Dr. Hakan TEKEDERE
Yüksekokul Müdürü

Emniyet Mahallesi Bandırma Caddesi No :6/1 06560 Yenimahalle/ANKARA
Tel:0 (312) 484 56 35 Faks:0 (312) 484 36 49
e-Posta :shmyo@gazi.edu.tr İnternet Adresi :http://www.shmyo.gazi.edu.tr/
Kep Adresi: gaziuniversitesi@hs01.kep.tr
Bilgi için :Murat Korgun
Bilgisayar İşletmeni

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ Ek-7
Mühendislik Fakültesi

Sayı : E-57779677-044-588062 14.02.2023
Konu : Anketler

REKTÖRLÜK MAKAMINA
(Öğrenci İşleri Daire Başkanlığı)

İlgi : 27.01.2023 tarihli ve 17311665-044- 573356 sayılı yazı.

İlgi yazınız ile istemiş olduğunuz, Ankara Yıldırım Beyazıt Üniversitesi, Sosyal Bilimler Enstitüsü, Finans ve Bankacılık Ana Bilim Dalı tezli yüksek lisans programı öğrencisi Nurbanu KURTULMUŞ'un, "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" isimli tez çalışması Fakültemiz Bölümlerine iletilmiş, gelen cevabi yazılar ilişikte gönderilmektedir.

Bilgilerinizi arz ederim.

Prof. Dr. Rahmi ÜNAL
Dekan

Ek:Bölümlerin cevabi yazıları (6 adet)

Gazi Üniversitesi Mühendislik Fakültesi Eti Mh. Yükseliş Sk. No: 5 06570, Maltepe / Ankara
Tel:0312 5823000 Faks:0312 2308434
e-Posta :mf@gazi.edu.tr İnternet Adresi :www.mf.gazi.edu.tr
Kep Adresi: gaziuniversitesi@hs01.kep.tr
Bilgi için :Meltem DEMİREL
Bilgisayar İşletmeni
Telefon No:0312 582 30 14

Evrak Tarih ve Sayısı: 31.01.2023-E.576403

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Mühendislik Fakültesi
Bilgisayar Mühendisliği Bölüm Başkanlığı

Ek-1

Sayı : E-17831024-044-576403 31.01.2023
Konu : Anketler

MÜHENDİSLİK FAKÜLTESİ DEKANLIĞINA

İlgi : 30.01.2023 tarihli ve 57779677-044- 574972 sayılı yazı.

İlgi yazınızda bahsi geçen çalışmayı araştırmacının kendi imkanları ile yapması uygun görülmüştür.
Gereğini arz ederim.

Prof. Dr. M. Ali AKCAYOL
Bölüm Başkanı

Gazi Üniversitesi Mühendislik Fakültesi Bilgisayar Mühendisliği Bölüm Başkanlığı
Maltepe 06570 Ankara TÜRKİYE
Tel:0 (312) 582 31 30 Faks:0 (312) 230 65 03
e-Posta :bmbbgazi.edu.tr İnternet Adresi :http://mf-bm.gazi.edu.tr
Kep Adresi: gaziuniversitesi@hs01.kep.tr

Bilgi için :Kezıban İlkay Aynacı
Birim Evrak Sorumlusu

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Mühendislik Fakültesi
İnşaat Mühendisliği Bölüm Başkanlığı

Ek-2

Sayı : E-89330503-044-576252 31.01.2023
Konu : Anketler

MÜHENDİSLİK FAKÜLTESİ DEKANLIĞINA

İlgi : 30.01.2023 tarihli ve 57779677-044- 574972 sayılı yazı.

İlgi yazınıza istinaden Ankara Yıldırım Beyazıt Üniversitesi, Sosyal Bilimler Enstitüsü, Finans ve Bankacılık Ana Bilim Dalı tezli yüksek lisans programı öğrencisi Nurbanu KURTULMUŞ'un, "Öğrencilerin Bilişsel Yansımalarına Dayalı Davranışsal Finans Önyargılarındaki Farklılıklar: Ankara Örneği" başlıklı tez çalışması kapsamında yapılacak uygulama ancak öğrencilerin uygun görüşleri doğrultusunda gerçekleştirilebilir.

Gereğini bilgilerinize arz ederim.

Prof. Dr. Murat MOLLAMAHMUTOĞLU
Bölüm Başkanı

Gazi Üniversitesi Mühendislik Fakültesi İnşaat Mühendisliği Bölüm Başkanlığı,
Celal Bayar Bulvarı, 06570, Maltepe – Ankara.
Tel:0 (312) 582 32 30 Faks:0 (312) 231 92 23
e-Posta :insaat@gazi.edu.tr İnternet Adresi :http://mf-im.gazi.edu.tr/
Kep Adresi: gaziuniversitesi@hs01.kep.tr

Bilgi için :Adile Erdoğan
Birim Evrak Sorumlusu
Telefon No:0312 582 32 30

T.C.
GAZİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Mühendislik Fakültesi
Kimya Mühendisliği Bölüm Başkanlığı

Ek-5

Sayı : E-37066414-730.08.03-577941 06.02.2023
Konu : Anketler / Nurbanu KURTULMUŞ

MÜHENDİSLİK FAKÜLTESİ DEKANLIĞINA

İlgi : 30.01.2023 tarihli ve 57779677-044- 574972 sayılı yazı.

İlgide kayıtlı yazınızda bahsi geçen anket çalışması bölümümüzce uygun görülmüş olup, Bölümümüz Öğretim Elemanlarına duyurulmuştur.

Gereğini bilgilerinize arz ederim.

Prof. Dr. Göksel ÖZKAN
Bölüm Başkanı

Gazi Üniversitesi Mühendislik Fakültesi Kimya Mühendisliği Bölüm Başkanlığı,
Celal Bayar Bulvarı, 06570, Maltepe / Ankara.
Tel:0312 5823530 Faks:0312 2308434
e-Posta :kimyamuhendisligi@gazi.edu.tr İnternet Adresi :http://mf-km.gazi.edu.tr/
Kep Adresi: gaziuniversitesi@hs01.kep.tr

Bilgi için :Yasemin AYKAŞ BİLGİLİ (Esme Kılıç Vekaletiyl
Birim Evrak Sorumlusu V.
Telefon No:03122023739