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INVESTIGATION OF GENDER DIFFERENCES IN FAMILIAR PORTFOLIO CHOICE

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Abstract. The prevailing assumption holds that investors include in their portfolios securities that they know well, are located near their place of residence, or align with their fields of interest. This article analyse familiarity in investment through gender perspective and their fields of interest. Women and men field of interest is defined by enabling online magazines' article's themes. The aim of this paper is to investigate gender-based behavioural differences in investment decisions – i.e. to define women's and men's fields of interests and value investment portfolios. Portfolios differ according to whether they are formed from securities that are consistent with women's fields of interest, men's fields of interest or both women's and men's fields of interest. Textual analysis was employed to identify men's and women's fields of interest. Investment portfolios were built using mean variance (MV) and Black–Litterman (BL) models. The analysis revealed that portfolios built from men's fields of interests are more diversified than are portfolios built either from women's fields of interests or from both men's and women's fields of interest. Analysing 12 portfolios' efficiency revealed that women's portfolio returns are more stable than are men's. Moreover, the study demonstrated that time impacts investment portfolio returns to a greater extent than do gendered fields of interest. The article complements the existing knowledge about bias in investor familiarity, which results from differences in men's and women's fields of interest.

Keywords: behavioural finance, investment psychology, gender differences, familiarity bias, investment decisions, media analytics, textual analysis, investment portfolio.

JEL Classification: G11, G41.

Introduction

The ubiquity of online media has revolutionised the world. Statistics reveals that in recent years, people are increasingly choosing online magazines and papers over printed ones. Online magazines are quite diverse; for example, some specifically target female audiences, while

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others target male audiences. Based on the target audience, in turn, the topics magazines discuss also vary to address the interests of that audience.

In addition to choosing particular media, both men and women are free to choose particular investment vehicles. While most investors of both genders tend to invest in securities that are familiar to them and align with their areas of interests, men's and women's areas of interest differ. Analysing male- and female-targeted online magazines and the topics they address can help to define these gendered fields of interest. We argue that these fields can further be used to predict the particular industries and sectors in which men and women choose to invest. When industries and sectors are identified for men and women, stocks' selection and portfolio process begin. Portfolios are build using two different portfolio creation methods: Mean variance (MV) and Black-Litterman (BL). According to portfolio analysis, it revealed, that portfolios which are built based on women's field of interest, the results are more stable compared to the portfolios which are built based on men's field of interest.

The aim of this paper is to investigate gender differences in investment decisions by defining women's and men's fields of interests and the value investment portfolios they build. We have completed the following steps to achieve these goals:

- Review previous research in the field;
- Outline this paper's methodology;
- Define men's and women's fields of interest and the portfolios they construct;
- Assess selected portfolios' efficiency;
- Present the results and discuss their implications.

Many authors have examined individuals' financial decisions and various aspects of investor behaviour. Kahneman and Tversky's work (Tversky & Kahneman, 1985, 1989; Kahneman & Tversky, 2013) includes the best known of these studies. While most extant research has focused on the tendency of investors to choose investment vehicles that are located within their region and employ their native language, researchers have yet to explore the tendency of investors to select vehicles that align with their fields of interest. This lacuna in the existing literature is all the more problematic because papers that analyse familiarity bias in terms of region or language may lose value as the globalisation process progresses. Efforts to examine investment decisions from the perspective of women's and men's fields of interest, however, do not depend on localisation or globalisation processes.

In Section 1, previous studies will be reviewed in the field of gender differences in the investment process. Section 2 describes the portfolio creation methodology used in this paper. Section 3 determines how the research was organized. Also, the performance and results of the created portfolios are. In the last Section, conclusions and findings of the study presented.

1. Analysis of the literature on gender differences in the investment process

In many countries, men and women enjoy equal opportunities to choose their profession and invest their assets, and societies generally seek to minimise gender differences and avoid gender-based discrimination. Nevertheless, the same societies hold a clear position on what is feminine and what is masculine. In this context, investing is traditionally classified as a male domain, and the European Commission has addressed the need to increase women's involvement in investing (Skonieczna & Castellano, 2020). We argue that achieving this goal requires understanding differences in men's and women's interests. Such gender differences are easiest to notice and assess by analysing online media.

1.1. Online magazines' reader profiles

The extant literature offers myriad ways of classifying readers. For example, Pfost et al. (2013) and Badulescu (2016) categorise readers based on the amount of time they spend reading online or printed texts. They identified four groups of readers. The first group reads both printed and online texts and spends a significant amount of their time doing so. While the second group also reads printed and online text, these readers spend less time reading. The third group reads only online texts, while the fourth group reads only printed text.

Applegate and Applegate (2004) divide readers into two types: highly engaged readers and readers who do not experience any desire to read. While highly engaged readers spend a greater number of hours with diverse types of texts, non-engaged readers spend an insignificant amount of their time reading, and the practice of reading has no effect on them, meaning, their future actions are not influenced what they read. The more time individuals spend reading and the more texts they read, the higher the level of comprehension they achieve and the greater the impact for their future decision (Guthrie & Wigfield, 1999). Ackerman and Goldsmith (2011) further confirm these relationships.

In recent years, reading has increasingly become an activity that individuals complete online (Coiro, 2011). According to Mitchell et al. (2016), younger generations tend to read news from online (50%) rather than printed (5%) sources. Thus, the number of online readers is increasing, and most of these readers are young people (Karim & Hasan, 2007). Coiro (2011) describes digital reading as screen-based reading of texts found on the Internet/online.

Scholars have also explored the ways in which various reading purposes influence reading behaviours (McKenna et al., 2012). According to Buzzetto-More et al. (2007), readers seeking to comprehend a text and understand a topic typically choose printed materials and read in their free time (McKenna et al., 2012; Putro & Lee, 2017). In fact, many studies have shown that when the purpose of reading is academic, individuals opt for printed texts (Baron, 2017; Farinosi et al., 2016). Furthermore, when academic readers encounter texts that are accessible only via the Internet, they are likely to print and read a hard copy of it. Academic readers, moreover, typically decide for themselves what and when they will read (De Naeghel et al., 2012; Krashen, 2005). In contrast, individuals who read for pleasure usually choose online sources, such online magazines (Buzzetto-More et al., 2007).

Previous authors have thus divided readers based on the following criteria:

- Method of reading (printed vs online);
- Purpose of reading (leisure vs academic);
- Generation of readers (millennials vs older generations).

In conclusion, analysed authors confirm that there are different types of readers who have different purpose of reading online, however, there is an agreement that more and more people spend more time reading online every year and have higher influence on their decision, one of the decision – investment decision.

1.2. Investment decisions

Scholars have conducted much research in the area of investment decision-making. According to Frank et al. (2013), the investment decision-making process is complicated, and investors require a significant amount of information prior to making any investment decision. Wu et al. (2012) and Kent Baker and Ricciardi (2015) agree, emphasising that the investment decision-making process is strategic and influenced by specific factors. According to Pool et al. (2012), professional investors, in particular, make their investment decisions based on empirical research. Individual investors, meanwhile, tend to choose familiar investment vehicles and those that are associated with their fields of interest.

Behavioural finance research, however, emphasises the opposite phenomenon: investors do not always make rational investment decisions. Work in this field asserts that investment decisions are influenced by emotions and are, therefore, non-rational decisions. For example, Jureviciene and Ivanova (2013), Soni and Desai (2021), Jaiswal & Kamil (2012) confirm that behavioural biases affect investment decision. Similarly, Kent Baker and Ricciardi (2015) and Hala et al. (2020) assess the effects of various biases on investment decisions. The key biases they discuss are overconfidence, trust and control, disposition, mental accounting, heuristics, self-control and framing, familiarity, risk-taking behaviour and anchoring. Familiarity bias is also discussed by Dong et al. (2021) and Liu et al. (2018). Although investors cannot avoid all behavioural biases, they can avoid investment losses by acknowledging such biases and taking them into consideration when making investment decision.

Other authors (Bayyurt et al., 2013; Eckel & Grossman, 2008; Dickason et al., 2017; Gentjan et al., 2021; Stavytskyy et al., 2020) emphasize gendered behavioral differences. These studies affirm that men are more confident than women. In other words, men are willing to take greater risks because of their higher social and economic status, more extensive investment knowledge and other social and psychological factors. Nevertheless, some research in the field contradicts these findings. While reporting that the most important factor determining investor confidence is gender, Estes and Hosseini's (2001) and Mikelionyte and Lezgovko (2021) empirical results indicate that women are much more confident than men in their investment decisions.

Dickason and Ferreira (2019) reveal that marital status can also affect investment decisions. More specifically, married men and women tolerate lower levels of risk then do unmarried or divorced men and women.

Many authors have analysed familiarity bias (French & Poterba, 1991; Tesar & Werner, 1995; Kang & Stulz, 1997). The majority of these authors emphasise geographical familiarity; in other words, they focus on the tendency of individuals to invest in vehicles with which they are familiar and that are located near them. Riff and Yagil's (2016) empirical results demonstrate that inventors tend to invest in the stocks they consider familiar rather than those about which they have more knowledge. For example, investor will choose to invest in the company, which is located next to his house rather than into the one, which he was analysing. Akhter and Alam (2001) similarly highlight product familiarity. Their study reveals that decision-making is characterised by gender differences based on the information men and women encounter online. More specifically, men are more likely than women to make decisions based on online information.

Analysed authors affirm that investment decision is impacted by many factors such as overconfidence, trust and control, disposition, mental accounting, heuristics, self-control and framing, familiarity, risk-taking behavior, anchoring. The other authors argue, and their studies reveal that investment decision is not only impacted by behavioural factors, but also gender has big role in it. In conclusion, investment decision is influenced by gender and factors which are broadly discussed in Behavioural Finance Theory.

2. Methodology of investigation

The current study involved several steps, which are presented sequentially in Figure 1. The massive online media industry, which continues its rapid development, influences its readers' decisions in particular ways. Analysing online magazines, moreover, can reveal men's and women's fields of interests. Because the prevailing assumption holds that people invest in securities with which they are familiar – i.e. those in their fields of interest, such an analysis can also illuminate men's and women's investment decisions.

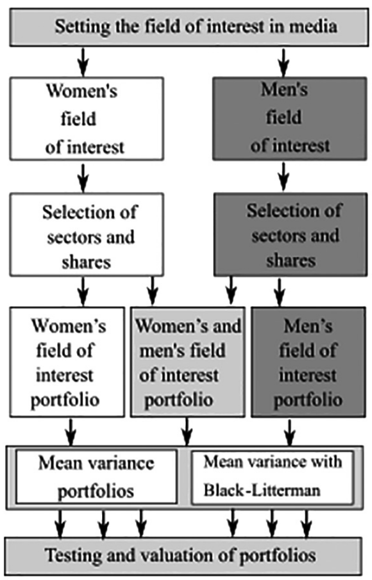

Figure 1. Scheme of investigation

Analysing portfolios formed on the basis of men's and women's fields of interest can, for example, help to answer the following questions: Do women's and men's portfolio exhibit sufficient levels of diversification? Are women's and men's portfolio return acceptable? Is it worthwhile to invest in gendered fields of interest (i.e. only men's or only women's fields of interest)?

Analysing online magazines, defining women's and men's fields of interest, forming investment portfolios on the basis of these interests and analysing their results are necessary to answer these questions.

Defining men's and women's fields of interest in media. First, we analysed online media. A Google search identified the 12 most popular online magazines that represent themselves as men's or women's magazines. Recognising that all online magazines follow a clear organisational structure, we employed this structure and the themes of articles in to determine women's and men's fields of interest in online media. We assume that online magazine's editor-in-chief analyse their readers profile and offer to read articles which are interesting for them and offered themes in articles define their fields of interest.

Second, we used these fields of interest to identify the sectors that best represent women's and men's interests. Women's fields of interests spanned the beauty, fashion, style, health, sports, travel and entertainment sectors. The majority of online magazines devote the largest proportion of their content to beauty, fashion and style, which, based on our expectations, suggests that women are likely to invest in the fashion industry. Men's fields of interest spanned households, sports, cars, news broadcasting and technology, which suggests, in turn, that men should invest in these sectors' securities. We employed MATLAB Code 1 (10–20 December 2021) to visualise women's and men's interests. Figure 1 depicts this step in detail.

Having defined women's and men's fields of interest and the associated sectors, we next utilised Yahoo Finance's industry classifications to select 10 securities from the sectors of interest. The selected securities had at least five years of monthly historical data. Our analysis utilised the following company abbreviations from Yahoo Finance: LRLCY for L'Oréal S.A., TGT for Target Corp., IPAR for Inter Parfums Inc., REV for Revlon Inc., EL for The Estée Lauder Companies Inc., ULTA for Ulta Beauty Inc., ELF for e.l.f. Beauty Inc., BBWI for Bath & Body Works Inc., CPRI for Capri Holdings Ltd., TPR for Tapestry Inc., RL for Ralph Lauren Corp., JWN for Nordstrom Inc., GPS for The Gap Inc., M for Macy's Inc., KSS for Kohl's Corp., TL for Tesla, 6CA.F for Cartier Resources Inc., MTN for Vail Resorts Inc., MSGS for Madison Square Garden Sports Corp., BATRA for The Liberty Braves Group, RACE for Ferrari N.V., SPOT for Spotify Technology S.A., AAPL for Apple Inc., UFPI for UFP Industries Inc., CENT for Central Garden & Pet Company, CCOEY for Capcom Co. Ltd., ZNGA for Zynga Inc., ATVI for Activision Blizzard Inc., EA for Electronic Arts Inc. and NKE for NIKE Inc.

Portfolio formation. We created portfolios using two methods: the classical mean variance portfolio optimisation method (Markowitz, 1952, 2009) and the mean variance with Black–Litterman portfolio optimisation method (Black & Litterman, 1990; Xiao & Valdez, 2015; Min et al., 2021; Tang et al., 2021).

The mean variance portfolio optimisation method employs a covariance matrix and mean of historical asset returns, which is calculated by taking historical five-year monthly stock price data.

The mean variance with Black–Litterman portfolio optimisation method does not require the presentation of expected returns which are generally unknown to investors. The method constructs equilibrium equations by using a covariance matrix and blended asset returns in a portfolio optimisation and then compares stock prices using a selected index – in our case, the Dow Jones Industrial Average (DJIA) index, which reflects market changes in all industries. Idzorek (2007) explains all steps of this optimisation method in detail. Table 1 below compares the two portfolio optimisation methods.

We utilised MATLAB Code 2 (4–12 January 2022) to generate visualisations and numerical values for the mean variance portfolio optimisation and mean variance with Black–Litterman portfolio optimisation methods.

Table 1. Comparison of portfolio optimisation methods (source: MathWorks, 2022)

	Mean variance optimisation	Black–Litterman approach
Asset mean	Mean of historical asset returns	Blended asset returns estimated from analyst views and equilibrium returns
Asset covariance	Covariance of historical asset returns	Covariance of historical asset returns + estimated uncertainty of the blended asset returns

Testing and valuation of portfolios. We assessed portfolio performance in 2020 and 2021. The portfolios were compiled on the first day of the selected year, using only the data known at that time, and they closed on the last day of the selected year. The 2020 portfolio was built just before the COVID-19 pandemic commenced, but at the time, information about the pandemic was quite limited. The 2021 portfolio was built using data from the same companies but during a time when the COVID-19 pandemic was already rampant and forcing companies to adapt. We selected the following indicators to measure the portfolios' performance:

a) Return on investment reflects the investor's expectations and is calculated with the following formula:

$$R(p) = \frac{Final\ value\ of\ investment - initial\ value\ of\ investment}{Cost\ of\ investment} \times 100\%. \tag{1}$$

b) Riskiness is inevitable, especially in light of prevailing market conditions. Risk is calculated via the portfolio's standard deviation.

c) The Sharpe ratio measures the ratio of the return to the risk of the sub-portfolio, taking into account the risk-free return:

$$\text{Sharpe ratio} = \frac{R(p) - r}{\sigma_p}, \tag{2}$$

where $R(p)$ represents the return of the portfolio, r represents the risk-free rate and σ_p represents the standard deviation of the portfolio.

In this way, we constructed 12 portfolios with various fields of interest, optimisation methods and time lags. We then conducted a multidimensional comparison of these portfolios' performance to examine the impact of familiarity bias on investors.

3. Research of portfolios based on gender fields of interest

Familiarity bias dictates the tendency of investors to focus on investment vehicles they know and understand. While it is logical to invest in fields where one has the most knowledge and experience, the theory of financial behaviour asserts that investor bias, in fact, leads to repetitive mistakes. The following analysis tests these competing assertions across different areas of investor interest and different time intervals and using different portfolio optimisation methods.

3.1. Setting the field of interest

After identifying the 12 most popular men's and women's online magazines, we analysed the constant sections of each – i.e. the sections that do not change as the individual sections change. Focusing on the constant section is important to avoid seasonality in the topic. Table 2 presents the distribution of constant sections in the selected online magazines.

Table 2. Distribution of sections in women's and men's media (source: created by authors)

Constant sections in journals	Women	Men
Beauty, style and fashion	12	3
Health, well-being and fitness	10	2
Sex, relationships, love, family and parenting	9	1
Food and cocktails	6	2
Lifestyle	5	2
Travel	4	0
Homes (W), grooming and gear (M)	4	10
Culture	4	2
Celebrities and entertainment	3	0
Craft and business	3	3
News and tours		4
Hobbies and interests separately divided into the following categories:		19
Separate sport activities		5
Technology		4
Cars		2
Adventure		2
Sci-Fi		1
Airplanes		1
Space		1
Watches		1
Military		1
Science		1

Overall, topics are more repetitive in women's magazines, with three topics found in almost all journals. Meanwhile, men's magazines are more specialised. We even combined the different hobbies into one to summarise.

Word clouds. Word clouds offer a visualisation tool for word statistics in a data set. Although word clouds do not provide empirical evidence to answer the research questions, they do reveal the topics that are emphasised in the area of analysis.

Figure 2 presents the words most commonly used in women's and men's online magazines. The word cloud for women's media reveals that the majority of words are related to beauty, fashion, shopping, health, food, videos, style, love, home, fitness, 'well-being', crafts and travel.

Figure 2. Word clouds for women's and men's media (source: created by authors)

The word cloud for men's media reveals that key words are more concentrated there than in women's media. The key words in men's media are news, features, videos and gear.

Based on the world clouds, we assigned the most frequently words to specific industries and then grouped the industries into sectors according to their official classification. The word clouds thus enabled us to identify the dominant words that identify the industry and sector. The results indicate that light industry dominates women's and men's fields of interest. Among the dominant industries in which women should invest are manufacturing of clothes, shoes, cosmetics, home appliances, food and beverages. The dominant industries in which men should invest are quite narrow and consist of cars, consumer electronics and communication.

Proceeding with the investigation, we selected 10 securities from the companies that represent light industry.

3.2. Creation of portfolios

Next, to analyse any differences in men's and women's portfolios and their diversification levels, we created 12 portfolios. Four of the 12 were based solely on women's fields of interest, four were based solely on men's fields of interest and four were based on the interests of both women and men.

To not only compare the differences in men's and women's investment portfolios but also assess the impact of time, we created separate portfolios for investments made at the beginning of 2020 and investments made at the beginning of 2021.

Figure 3 presents the two portfolios based solely on women's interests, which were created with the mean variance and Black–Litterman models at the beginning of 2020 and 2021. In both years, the portfolios created with the Black–Litterman models exhibited a higher level of diversification than did those created with the mean variance model. While noting these differences in diversification levels, we observe that the two models nevertheless included the same securities: Revlon (REV), Estée Lauder (EL), Inter Parfums (IPAR), Target Corporation (TGT) and L'Oréal S.A. (LRLSY).

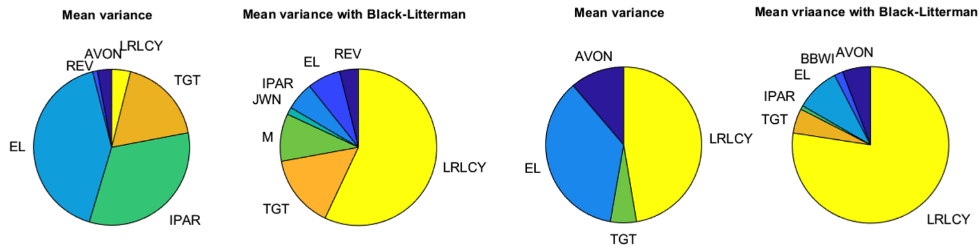

Figure 3. Women's fields of interest (W) 2020 (on the left) and 2021 (on the right) (source: created by the authors)

The women's portfolio created using the Mean variance model exhibited a lower level of diversification and proposed to invest 60% in one stock: L'Oréal S.A. (LRLSY). In the Black–Litterman portfolio created at the beginning of 2021, moreover, this stock assumed an even stronger position, representing more than 75% of all assets. Meanwhile, the mean variance model for 2021 proposed to decrease the number of stocks in the portfolio to four and add a new stock – Avon (AVON), which was not included in the portfolio at the beginning of 2020.

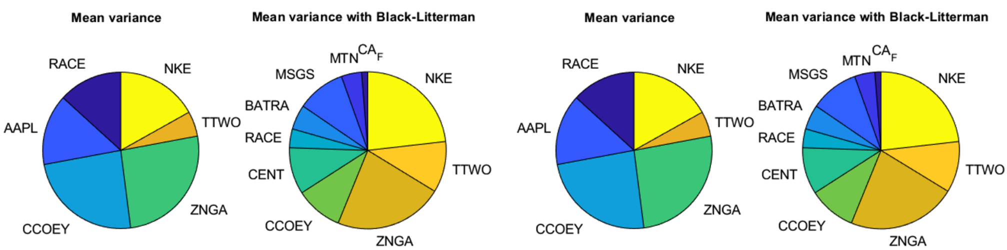

Figure 4. Men's fields of interest (M) 2020 (on the left) and 2021 (on the right) (source: created by the authors)

Figure 4 presents the four portfolios created solely based on men's fields of interest. Compared to the portfolios that were created solely based on women's interests, these portfolios exhibited higher levels of diversification. The mean variance model proposed to include fewer stocks in the men's portfolios than did the Black–Litterman model. However, stock choices remained nearly identical.

Figure 5 presents the portfolios created based on both women's and men's fields of interest. The mean variance and Black–Litterman models included various securities from men's

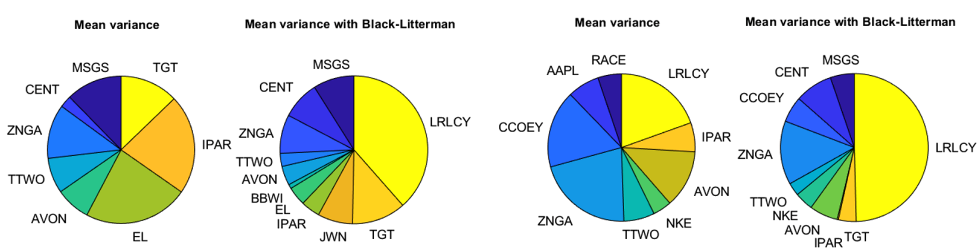

Figure 5. Women's and men's fields of interest (WM) 2020 (on the left) and 2021 (on the right) (source: created by the authors)

and women's fields of interest. However, securities from women's fields of interest dominated the portfolios created at the beginning 2020 and 2021.

L'Oréal S.A., which falls within women's fields of interest, comprised the largest component of the four combined portfolios, and this security assumed an even more dominant position in the portfolios created at the beginning of 2021. This suggests that neither the model nor the time period matters; in all cases, the models selected securities associated with women's fields of interest.

3.3. Valuation of portfolios efficiency

Table 3 presents the investment performance of all 12 portfolios and the DJIA index. The year 2020 was successful for all portfolios, with all performing better than the DJIA index. In fact, 2020 was the most successful year for the portfolios created based solely on men's fields of interest (M), with these portfolios achieving 55% investment returns. The year 2021, however, was not successful for either portfolio created solely based on men's fields of interest (M) or for the mean variance model's portfolio created based on women's and men's fields of interest (MW), all of which suffered losses. Both portfolios created solely based on women's fields of interest (W) performed better in 2021 than in 2020 and exceeded the growth of the DJIA index. The portfolios created solely based on women's field of interest (W) produced stable returns while investment returns based solely on men's fields of interest (M) ranged from –2.92% to 55%. Diversification using shares from both fields of interest (WM portfolio) did not yield clear benefits, especially in 2021.

Table 3. Portfolios' return on investment

Year	DJIA	Mean variance portfolio			Mean variance with Black–Litterman		
		W	M	WM	W	M	WM
2020	6.11%	18.34%	55%	23.09%	23.47%	36.85%	27.61%
2021	21.43%	29.32%	–2.92%	–4.22%	32.05%	–0.77%	11.56%

The risk assessment in Table 4 reveals that all of the (M) portfolios entailed the lowest risk, with a maximum risk of 10.1. The (M) portfolios were also more diversified than the (W) portfolios. The greatest risk was associated with the (WM) portfolios created via the mean variance model. For all (W) and (WM) portfolios, however, 2021 was riskier than 2020. The greatest return on investment-to-risk ratio, expressed via the Sharpe ratio, occurred in 2020 for both (M) portfolios and the mean variance with Black–Litterman (W) portfolio. The poorest results were obtained when a portfolio's return on investment was negative.

Across all of the investment portfolios studied, 2020 was more successful than 2021, despite the significant challenges the former posed in adapting to the conditions of the COVID-19 pandemic. Returns on investment in 2020 ranged from 18.34% to 55%. Meanwhile, in 2021, three portfolios suffered losses, although, by this time, the global economy had already adapted to the new conditions. Portfolios based solely on women's fields of interest (W) achieved stable positive results but entailed the highest risk. Meanwhile, portfolios based

Table 4. Risk and sharpe ratios of portfolios

	Mean variance portfolio			Mean variance with Black–Litterman		
	Risk					
	W	M	WM	W	M	WM
2020	22.197	8.6068	52.872	6.4519	10.106	28.812
2021	68.586	6.2545	55.0313	38.288	7.7214	29.716
	Sharpe ratio					
2020	0.0075	0.0668	0.0044	0.0338	0.0338	0.0095
2021	0.0036	–0.012	–0.0014	0.0069	–0.006	0.0022

solely on men's fields of interest (M) achieved the greatest returns and average losses, but they entailed the lowest risk. Our investigation found that combining women's and men's fields of interest benefitted neither male nor female investors.

In this study we analysed familiarity bias in portfolio choice through creating different portfolios of men's fields of interest, women's fields of interest and women's and men's fields of interest which revealed that portfolio based on women's fields of interested generated greater and stabler portfolio results. However, for the future studies, study can be extended and enable another methods to identify investor's fields of interest. Also, the length of analysis can be extended, because in this study we analysed only two years period.

Conclusions

This paper examined differences in investment portfolios created solely based on women's fields of interest, solely based on men's fields of interest and based on both women's and men's fields of interest.

To define men's and women's fields of interests, we extracted data from an online web page and then analysed these data in Excel. The analysis revealed that prevailing opinions regarding men's and women's areas of interest are accurate. Women's fields of interests include fashion, style and beauty, while men's fields of interests include cars, technology and news.

We then created 12 portfolios using mean variance and Black–Litteram models. Four of these portfolios were based solely on women's fields of interest, four were based solely on men's fields of interest and four were based on both men's and women's fields of interest. To facilitate the comparisons, we created separate portfolios for investments commencing at the beginning of 2020 and for investments commencing at the beginning of 2021. Because information on COVID-19 was limited at the beginning of 2020 and, in fact, the virus had not yet been declared a pandemic, the portfolios created for 2020 could not evaluate the pandemic's impact on investment decisions. However, the portfolios created at the beginning of 2021 were able to evaluate COVID-19's impact. Comparing portfolios from these two years revealed differences in the diversification levels of men's and women's portfolios. While the level of diversification decreased in women's portfolios as COVID-19 spread around the world, the same was not true for men's portfolios.

Overall, in this study, the investment period exerted a more significant impact on investment success than did gendered fields of interests. Furthermore, portfolios based solely on women's fields of interest produced stable results, while portfolios based solely on men's fields of interests produced extreme estimates in terms of returns on investment and the Sharpe ratio; however, these male-oriented portfolios were consistently associated with the lowest degree of risk. The bias of familiarity that affects investment decisions is thus more understandable based on this study's findings. Although selecting investment vehicles that more closely align with the investor's interest does not guarantee investment failure, it does narrow the investment options.

Research limitations and future research possibilities. Despite its contributions, this study also entails limitations. First, the current study analysed only a limited number of selected online magazines. Second, the study period spanned only two years. For future research, number of magazines and analysed period could be extended and since this research did not study portfolios comprised of stocks associated with gender-neutral fields, such as food and health, research could be extended to this field. Also, in this study was chosen US based companies, in the future research can be explored other exchanges and comprised developed and emerging markets.

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