Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 5, 1362-1374
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i5.1837

Evaluation of golfers' performances in the ladies professional golf association tour based on bootstrapped data envelopment analysis and latent growth curve model

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Abstract: A latent growth curve model and bootstrapped data envelopment analysis were used to examine the performance and changes in professional golfers on the Ladies Professional Golf Association tour. The panel data for both analyses were obtained for the last three seasons (from 2020 to 2022). The dependent variable was the official money list of players, whereas the independent variables consisted of efficiency factors, technical factors (number of birdies, eagles, and hole-in-ones), mental factors (driving and putting accuracies), and career length. Each factor, other than the efficiency factor, was determined by the weighted combination of parenthesized variables using principal component analysis and was measured as two latent variables of the intercept and the slope of the growth pattern for the three seasons. The efficiency factor was measured using data envelopment analysis and its z with the output factors of scoring average and the percentage of rounds in the 60s, and the input factors of driving distance, greens in regulation, number of putts per green hit in regulation, and sand savings. The results confirm the homogeneity in players' efficiency and prove Penick's claim that golf performance is dependent on various factors and that golf is psychological.
Keywords: *Efficiency factor, Growth, Mental factor, Money list determination, Technical factor.*

1. Introduction

Golf has become increasingly popular since the mid-15th century and saw noticeable growth during the COVID-19 pandemic because this could be played as an indoor sport as well. In Korea, the number of golfers increased by 16.4% between 2017 and 2021 - a trend that is expected to continue (Kim, [1]). The growth in golf's popularity has also resulted in more people wanting to become professional golfers. Notably, the average money list per Ladies Professional Golf Association (LPGA) event exceeds $3 million, with the best player in a year earning more than $4 million (LPGA, [2]).

Golf is one of the most challenging sports to master. One study ranked golf 51st on the list of toughest sports, 5th if martial arts such as boxing and mixed martial arts and extremely dangerous sports like bungee jumping were excluded, and 5th–7th in the ability to react quickly to sensory perception and the ability to evaluate and react appropriately to strategic situations [3].

This implies that good shooting techniques and mental stability are essential for becoming good golfers. In fact, Penick, et al. [4] insisted that both professional and amateur players display substantial variation in performance depending on their technical level and mental state, and suggested various training approaches to technical and psychological skills, as well as many famous sayings about golf skills. Thus, this study is interested in how these technical and mental factors are related to the seasonal results of players to find some useful insights into how we can become good golfers and how coaches teach players and beginners for their improvement.

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Moy and Liaw [5], Callan and Thomas [6], Yun, et al. [7], Choi, et al. [8], Kim [9], and Park and Chae [10] defined technical variables such as driving distance, sand saves, greens in regulation, and putts per round, and technical result variables such as scoring average for each type of holes, birdies per round, and eagles per round as substitute factors reflecting the technical level of players. However, there are some differences between researchers. Technical factors indicate an individual's ability to react quickly to sensory perceptions.

Psychologists such as Seiler [11], McCaffrey and Orlick [12], Jeong and Baek [13], and Kim and Kim [14] have listed anxiety, commitment, goal setting, tournament planning, focus control, distraction control, and evaluation as mental/psychological variables related to golf excellence. Additionally, Penick, et al. [4] pointed out that driving and putting accuracies as performance measures are most closely related to the mental state of players. In fact, a golf player saying, "It's not that I'm anxious because I cannot shoot well, but it's that I can't shoot well because I'm anxious" applied best to driving and putting accuracies. Mental factors indicate an individual's ability to appropriately evaluate and react to strategic situations.

For performance measures of seasonal results, scoring averages, official money, winning odds, rounds in the 60s, and top 10 finishes are available (Moy and Liaw [5]; Callan and Thomas [6]; Park and Chae [10]; Davidson and Templin [15]; Schmanke [16]; Scully [17]; Finley and Hasley [18]; Chung and Yeo [19]).

Davidson and Templin [15] are considered forerunners in the research on determinants of golfers' season results using a regression-based model. Moy and Liaw [5], Callan and Thomas [6], Schmanke [16], Scully [17], Finley and Hasley [18], Chung and Yeo [19], Belkin et al. [20], Wiseman et al. [21], Dorsel and Rotunda [22], and Park and Chae [23] followed their research searching for technical mental factors affecting season result of players in several golf tournaments like LPGA, PGA, and SPGA. The scoring average or official money was used as a dependent variable, and technical and career variables were used as independent variables. Although the results vary across studies, the main finding of the abovementioned research is that the power of technical and mental (accuracy) factors is well supported, whereas mental factors are more effective than technical factors. Career did not explain the variability in the seasonal results. This research also adds efficiency as an independent factor to technical and mental factors to examine their effect on the official money list as a seasonal result for professional golf players in the LPGA. Koorse and Warren [24], Fried, et al. [25], and Chung and Yeo [19] have studied the productivity or efficiency of golfers. By evaluating players' efficiency using data envelopment analysis (DEA), they specified some season results as outputs and some technical factors as inputs. Efficiency refers to players' ability to connect techniques with low scores. The present study decomposes technical and technical-result variables into technical factors, which are used as independent factors, and others as DEA inputs, as shown in the following sections.

Furthermore, we examined the growth of players in terms of technical and mental factors, efficiency, and money lists in the three seasons. Although Davidson and Templin [15], Belkin et al. [20], and Kim and Min [26] analyzed panel data on golfers, they differ from this study in that they were not interested in the growth of players or the various roles of independent factors in the regression model. Moy and Liaw [5] recommended this type of research for studying improvements in factors and results over time.

The rest of the paper is structured as follows. Sections 2 and 3 introduce the research approach and data, respectively. Section 4 presents the results of the empirical analysis. Finally, Section 5 summarizes the study.

2. Data and Research Methods

The data were obtained from the top 60 players in the 2020 season money list ranking of the LPGA. We extracted each value from the site one by one from the LPGA official homepage [2]. Only 52 players were included because 8 players were included in only one of the 2021 and 2020 seasonal statistics.

As observed, the dependent variable of LGCM the players' official money list (Moy and Liaw [5]; Callan and Thomas [6]; Park and Chae [10]; Schmanke [16]; Chung and Yeo [19]). The two technical variables used to generate technical factors, which were independent variables in LGCM, were the numbers of birdies and eagles (Park and Chae [10]; Chung, et al. [27]). The number of hole-in-ones was omitted because of the lack of variation across players. For mental factors, another independent variable of LGCM, although we ideally should have conducted a survey of the players on their psychological capital, this was impossible because of our lack of access to LPGA players. We decided to find indirect measures reflecting the mentality of players and concluded that driving and putting accuracies qualify (Penick, et al. [4]).

The input-output specifications for DEA came from Fried, et al. [25] by modifying their inputs and outputs. They included driving accuracy in DEA as an input, but we used it for mental factors and money awarded per event as only one output factor, while we used the scoring average and the ratio of rounds in the 60s like Chung and Yeo [19].

Table 1 summarizes the variables in the 2022 season data used for the LGCM, PCA, and DEA analyses. The 2021 and 2020 season data are summarized in this manner. As shown in Table 1, there are substantial variations in all the variables, suggesting the need for further analysis. Notably, a mental variable, total number of putts per 18 holes, an output factor of efficiency evaluation, and scoring average were used in the analysis after reverse coding from 36 and 100, respectively, because they are considered better when their values are small rather than large. Additionally, both technical variables (the numbers of birdies and of eagles) and an output factor of efficiency evaluation (rounds in the 60s) were used in the analysis after dividing by the total rounds played by each player.

Table 1.
Summary of the 2022 season data.

Variables		**N**	**Min.**	**Max.**	**Mean**	**Standard deviation**
D	Official money list ($1,000)	52	131.874	4,364.403	1,053.231	802.769
M	Driving accuracy (%)	52	64.13	85.93	74.99	5.48
M	Total # of putts per 18 holes (Putting accuracy)	52	28.61	31.67	29.87	0.55
T	Birdies	52	101	396	263.35	53.78
T	Eagles	52	0	11	5.60	3.19
X	Career (Years)	52	3	16	8.81	3.74
E/X	Driving distance (yds.)	52	240.64	279.25	258.29	9.29
E/X	Greens in regulation (%)	52	67.07	77.69	71.86	2.63
E/X	# of putts per green hit in regulation	52	1.72	1.85	1.79	0.03
E/X	Sand saves (%)	52	30.30	66.25	48.52	6.98
E/Y	Scoring average	52	68.99	71.93	70.62	0.68
E/Y	Rounds in the 60s	52	7	49	25.94	8.02

Note: D: Dependent variable of LGCM, M: Mental factors of PCA, LGCM, T: Technical factors of PCA, LGCM, E/X: Input factor of DEA, X: Independent variable of LGCM, E/Y: Output variable of DEA.

Our study used four research methods. Principal component analysis (PCA) was used to integrate sub-factors for mental and technical factors, while DEA was used to evaluate the efficiency of players.

DEA bootstrapping was also used to obtain more robust efficiency scores. Finally, the latent growth curve model (LGCM) was used to estimate the relationship between independent factors (career, mental ability, technical ability, and efficiency) and dependent factors (money list) and examine their growth in mental ability, technical ability, efficiency, and money list) during the 2020–2022 seasons.

Specifically, PCA coefficients that explain at least 80% of the variance were used to create an integrated variable for mental and technical abilities in every season. Minitab 16 software was used for the PCA (Srivastava [28]; Lind, et al. [29]). DEA, which is a nonparametric approach for estimating the efficient frontier and efficiency scores, was implemented with four input and two output factors for each season, and a Banker, Chames and Cooper (BCC) model is used assuming variable returns to scale (Charnes, et al. [30]). Bootstrapped-DEA approach (Mooney and Duval [31]) was also run 2,000 times for each season to avoid sampling errors due to the small sample size. The Lingo 14 optimizer was used for DEA, and an application developed by the authors in Microsoft Visual Studio 2010, integrated with the Lingo 14 optimizer, was used for the bootstrapping analysis.

In the LGCM, the observed variables are repeated measures of a variable, and the latent variables are constructs representing patterns of change in a variable. Two latent variables are specified to represent the patterns of change: intercept and slope. The intercept represents the outcome-measure level at which time equals 1, and the slope represents the linear or quadratic rate at which the outcome measure changes (Preacher et al. [32]). This research selected the linear rate change for the estimate of the latent variable, slope, because golfers seem to progress relatively slowly but stably. The LGCM was designed and implemented using IBM AMOS 22 (Lee and Lim [33]).

3. Results and Discussion

As observed, the results of this research consist of three parts: the efficiency scores of players, implying the ability of players to connect their techniques to a final score; the PCA result to integrate two variables (sub-factors) into a factor for mental and technical factors; and the LGCM result to find influencing factors on the money list and represent the growth of players in factors.

3.1. Efficiency

To examine how the four inputs are related to the two outputs, a DEA based on BCC was implemented, and the results are illustrated in Table 2. As seen in this study, players were very efficient, and there was little variation among players. This result did not change when the sample size was extended to the top 180 players. This implies that all players playing professional tournaments are quite efficient and homogeneous.

Table 2.
Summary of efficiency scores.

	Player efficiency		
	2022	**2021**	**2020**
N	52	52	52
Min.	0.9267	0.9254	0.9092
Max.	1.0000	1.0000	1.0000
Mean	0.9777	0.9701	0.9603
Standard deviation	0.0208	0.0233	0.0244

Table 3 summarizes the DEA bootstrapping results. Each player is resampled 1,267, 1,268, and 1,276 times for each season in a 2,000 times bootstrapping averagely, and is still very efficient. The median score for each player was used for the LGCM (Mooney and Duval [31]).

Table 3.
Summary of efficiency bootstrapping result.

Season	2022	2021	2020
Average # included in bootstrapping	1,267	1,268	1,276
Mean	0.9779	0.9745	0.9669
Median	0.9788	0.9725	0.9654

3.2. PCA

PCA was implemented to create a variable that integrated the two sub-factors for mental and technical factors. PCA generates a number of artificial variables called principal components by linearly integrating the original variables, and a principal component explaining the variance in variables is mostly used to make a variable to integrate the original variables. Table 4 presents the results of the study. Putting accuracy was given a far greater weight than driving accuracy for mental factors, and the number of birdies was given a greater weight than the number of eagles among the technical factors. The percentage of explained variance was greater than 80%.

Table 4.
PCA results for mental and technical factors.

Mental factor coefficient			Technical factor coefficient		
Drive accuracy	Putt average	C.O.D.	Birdies	Eagles	C.O.D.
0.404	0.915	0.840	0.999	0.043	0.990

By multiplying the abovementioned coefficient with the observed values of the corresponding variables, we generated the independent factors (mental and technical) for the LCGM. Table 5 summarizes the calculated mental and technical factors. Substantial variation among players was confirmed. These variables were included in the LGCM.

Table 5.
Summary of PCA scores for mental and technical factors.

Season	Factor	N	Min.	Max.	Mean	Standard deviation
2022	Mental	52	71.21	97.61	86.43	5.15
	Technical	52	2.66	4.50	3.44	0.41
2021	Mental	52	67.74	99.10	84.22	5.57
	Technical	52	2.40	4.45	3.46	0.39
2020	Mental	52	75.35	109.76	85.89	6.27
	Technical	52	2.32	5.05	3.29	0.41

3.3. The LGCM

Because the LGCM was based on a structural equation model, it was necessary to examine the reliability of the observed sub-factors (2022, 2021, and 2020 season values) of the efficiency, mental, technical, and money-list slopes and intercepts. The Cronbach's α of these categories were 0.59, 0.82, 0.69, and 0.64, respectively, implying that these were reliable (Srivastava [28]). Moreover, the appropriate relationships among the calculated subfactors were confirmed through a correlation analysis as presented in Table 6, which shows that the dependent variables—official money in 2022, 2021, and 2020—have some significant correlations with independent variables and factors, except career variables. Furthermore, mental factors (e.g., mental 2022, 2021, and 2020), which may be examined for the role of mediator between other independent and dependent factors, demonstrated some significant correlations with other sub-factors and independent factors except variable career. These relationships are important motivations for this study.

Table 6.
Correlations among variables of LGCM.

	Money 2021	**Money 2020**	**Efficiency 2022**	**Efficiency 2021**	**Efficiency 2020**	**Mental 2022**	**Mental 2021**	**Mental 2020**	**Technical 2022**	**Technical 2021**	**Technical 2020**	**Career**
Money 2022	0.399**	0.304*	0.259	0.007	−.025	0.214	0.137	0.108	0.643**	0.320*	0.232	−0.093
Money 2021		0.646**	0.185	0.215	0.232	0.167	0.372**	0.384**	0.423**	0.575**	0.295*	−0.188
Money 2020			0.177	0.282*	0.377**	0.285*	0.445**	0.621**	0.455**	0.334*	0.625**	0.013
Efficiency 2022				0.328*	0.334*	0.784**	0.411**	0.293*	0.385**	0.182	−.027	0.231
Efficiency 2021					0.318*	0.372**	0.554**	0.332*	0.148	0.278*	0.187	.052
Efficiency 2020						0.368**	0.197	0.465**	0.159	0.194	0.453**	−0.097
Mental 2022							0.689**	0.517**	0.312*	0.176	−.023	0.153
Mental 2021								0.625**	0.279*	0.275*	0.139	0.152
Mental 2020									0.221	0.115	0.312*	−0.031
Technical 2022										0.550**	0.426**	−0.163
Technical 2021											0.305*	−0.339*
Technical 2020												0.016

Note: * $p<0.05$, ** $p<0.01$

Four LGCMs (Figure 1) were implemented (Preacher et al. [32]). Models 1 and 2 illustrated cases in which all independent factors affected the dependent factor directly, without the assumption of a moderation effect. Model 1 included the possibilities of all relationships between intercepts, slopes, and intercepts and slopes, whereas Model 2 included the possibilities of relationships between intercepts and slopes. Models 3 and 4 illustrated cases in which all independent factors directly affected the dependent factor with the assumption of the moderating role of mental factors because all other factors can affect the money list through mental factors (McCaffrey and Orlick [12]; Kim and Kim [14]). Model 3 also included the possibilities of all relationships between intercepts, slopes, and intercepts and slopes, whereas Model 4 included the possibilities of relationships between intercepts and slopes, as in Models 1 and 2.

Table 7 presents the results of the growth of players across the three seasons for all factors. As shown in Table 7, because the slopes of all factors have positive values, players seem to make some efforts, such as exercise, fitness, swing alignment, and psychological skills training to improve their games (Penick, et al. [4]; Yun, Kim, and Kang [7]; McCaffrey and Orlick [12]; Kim and Kim [14]; Davidson and Templin [15]).

Table 7.
Result of the growth of players.

		Official money	Efficiency	Mental ability	Technical ability
Model 1	Intercept	42.089	96.550	84.550	3.327
	Slope	30.934	0.667	0.940	0.055
Model 2	Intercept	42.089	96.551	85.072	3.321
	Slope	30.606	0.673	0.690	0.060
Model 3	Intercept	42.089	96.551	85.405	3.326
	Slope	30.579	0.669	0.512	0.057
Model 4	Intercept	42.089	96.674	84.849	3.318
	Slope	30.568	0.641	0.790	0.062

Figure 1, Figure 2, Figure 3, Figure 4, and Table 8 present the LGCM results for the four models. Because measures of fitting for Model 1 do not look acceptable, while those for the other three models appear to be acceptable (Lee and Lim [33]), the result from Model 1 will not be interpreted, although it supports the power of technical factors on the money list; therefore, the results from Models 2, 3, and 4 are interpreted here. Without any assumption of mediation role of mental factor, Model 2 showed that technical intercept affects money list intercept positively, which implies that technical level of players in 2020 season affected money list in this season positively, and technical slope also affected money list slope positively, which implies that improvement in technical ability brought up the increase in money list. Moreover, the efficiency slope positively affected the money list slope, which means that improvement in efficiency led the money list to increase, and the mental intercept affected the money list intercept positively, which means that the mental ability of players in the 2020 season positively affected the money list in this season.

Assuming the mediating role of mental factors, Model 3 supported the mediating power of mental factors on efficiency. The mental intercept had a perfectly positive mediating effect on the efficiency intercept. The indirect effect of the efficiency intercept on the money list intercept through the mental intercept was calculated as $3.864 \times 5.390 = 20.827$, and the direct effect was 0. Regarding the efficiency slope, the mental slope had a partially negative mediating effect. The indirect effect of efficiency slope on money list slope through mental slope was calculated as $3.524 \times 197.891 = 676.224$, the direct effect was −698.491, and total effect was −22.267, which is negative. This means that maintaining the current high efficiency and not trying to improve efficiency helps increase the money list. The result from Model 4 added a perfect mediating effect of the mental slope from the technical

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 5: 1362-1374, 2024
DOI: 10.55214/25768484.v8i5.1837

slope (indirect effect = 1,194.876) and the direct effect of the technical intercept on the money list intercept to the result from Model 3 and changed the perfect mediating effect of the mental intercept from the efficiency intercept into a partial mediating effect (indirect effect = 32.994, direct effect = 28.250, total effect = 61.244). The effect of the efficiency slope on the money list slope differed from the result of Model 3 (indirect effect = 2,783.645, direct effect = −2,819.587, total effect = −35.941), which was similar to the result of Model 3. This result may be explained as follows: because the effort to improve efficiency may be very stressful to players and even high efficiency may make players concentrate less on each shot during rounding, high efficiency may lead to unsatisfactory rounding results and the loss of money. However, when this high efficiency is mediated by mental factors, players may recover their concentration and overcome stress, which can positively affect their monetary lists. Consequently, although efficiency seems to have a slightly negative total effect on the money list, it may show a positive total effect on the money list in another research.

In any model, the career variable does not have any clear relationship with the money list intercept and slope, as in the past literature. This may be explained by the prematurity of players with short careers, and the aging curve phenomenon of players with long careers (Signorile [34]).

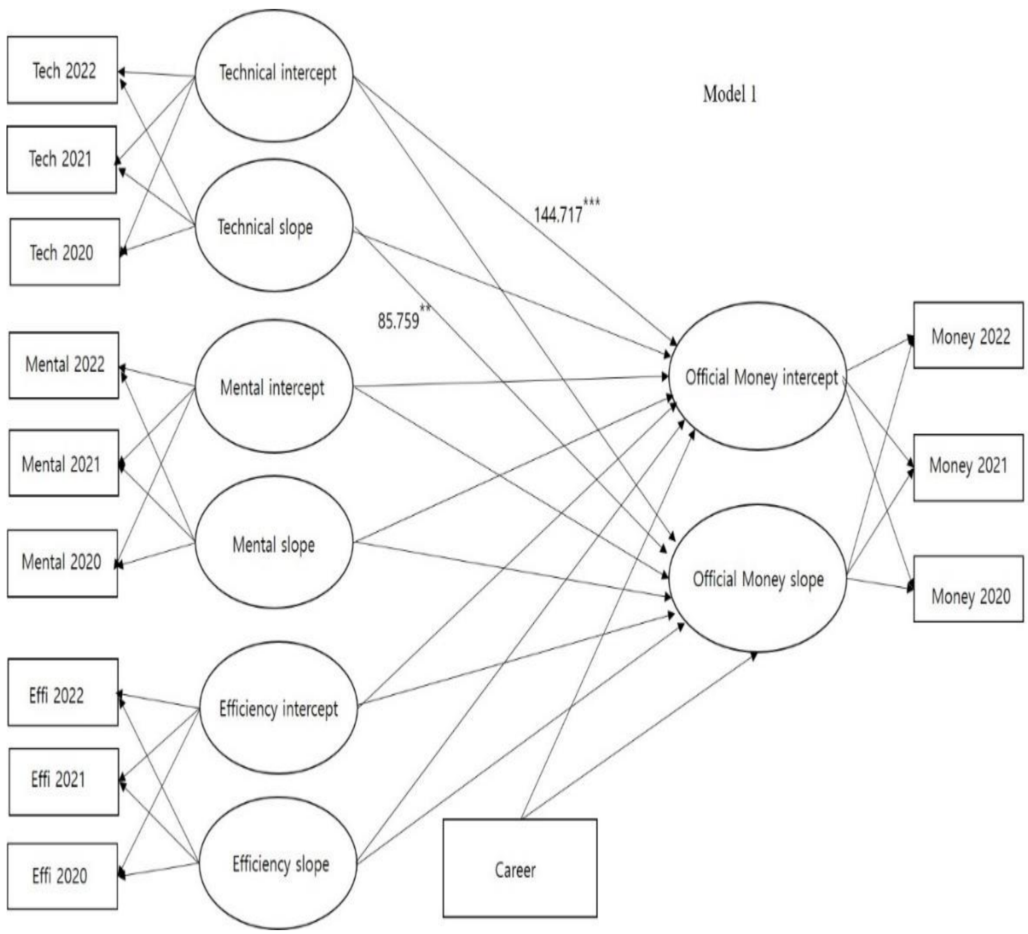

Figure 1.
The model 1 and result of LGCM.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 5: 1362-1374, 2024
DOI: 10.55214/25768484.v8i5.1837

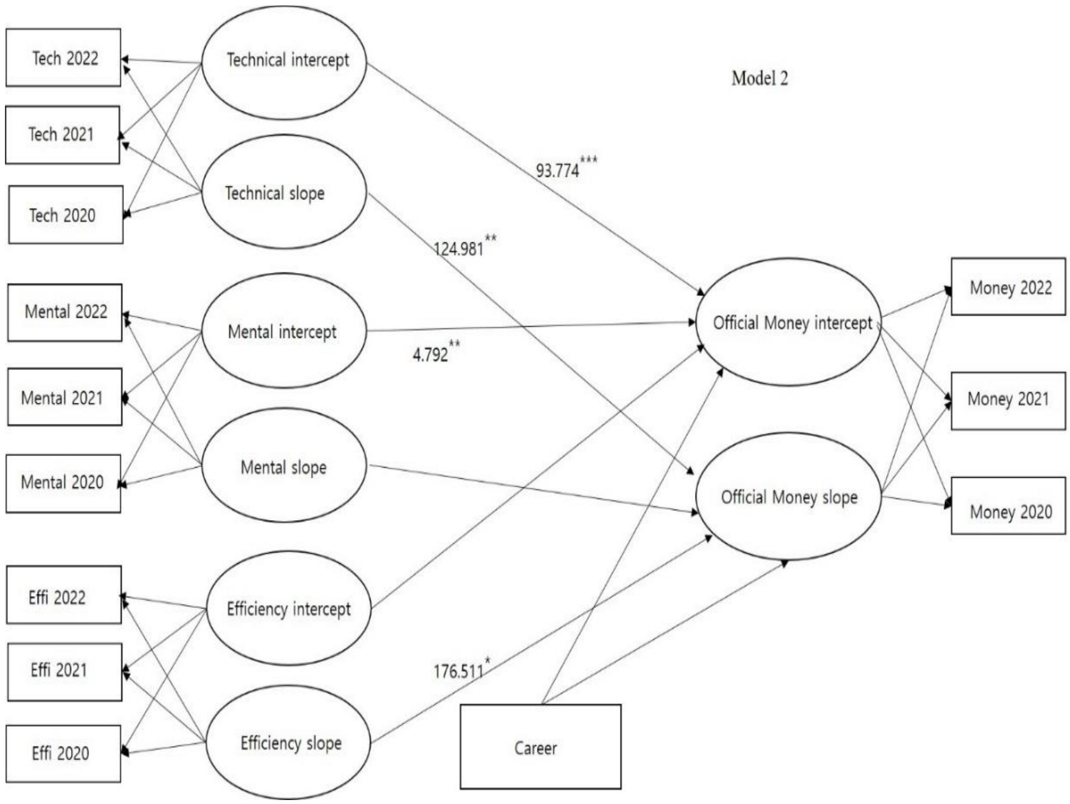

Figure 2.
The model 2 and result of LGCM.

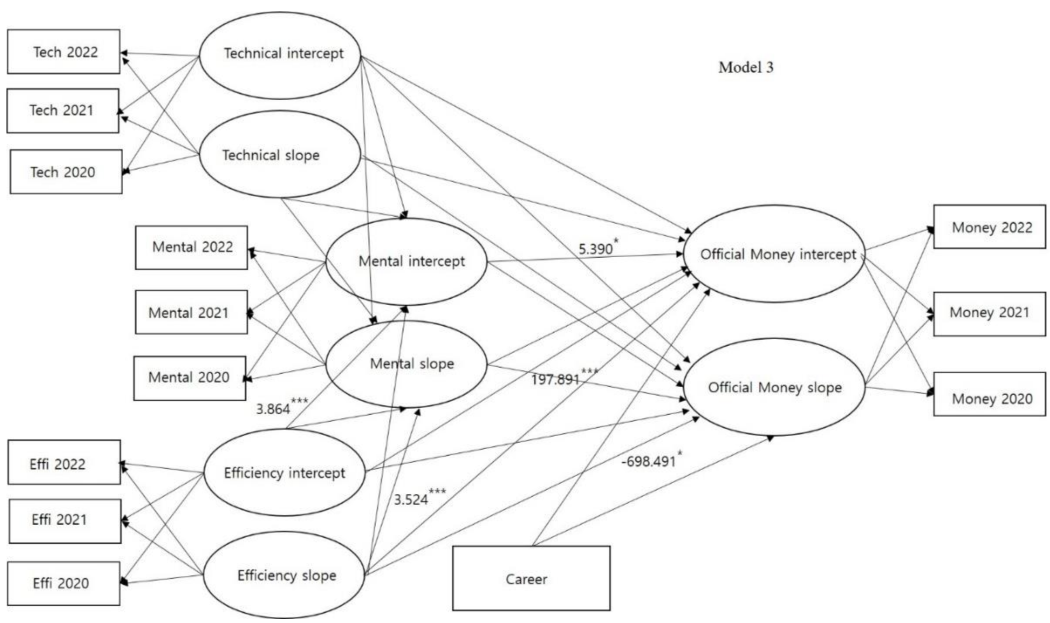

Figure 3.
The model 3 and result of LGCM.

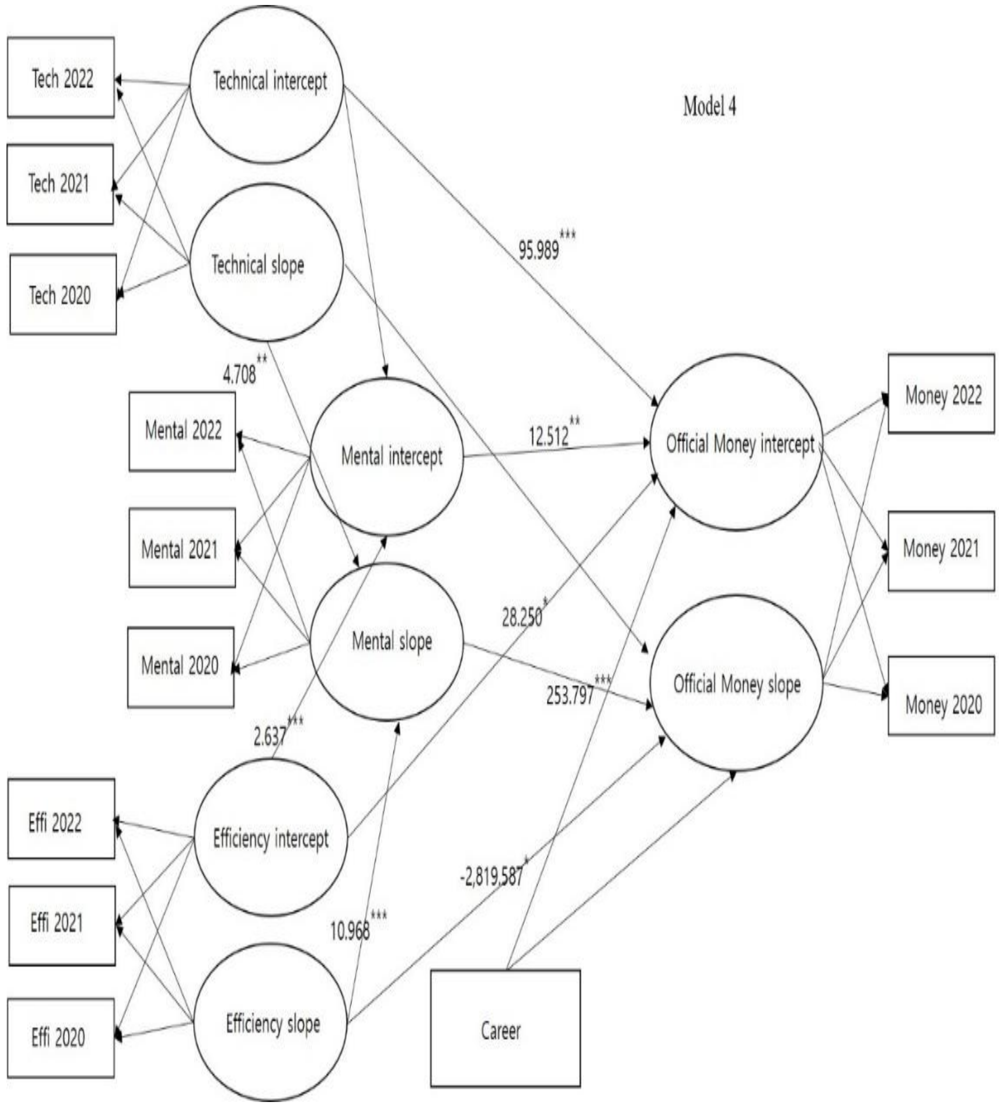

Figure 4.
The model 4 and result of LGCM.

Table 8.
Result of LGCM.

Model 1						
GFI	**TLI**	**CFI**	**NFI**	**RMSEA**	**AGFI**	χ^2/df
0.703	0.527	0.612	0.526	0.114	0.542	1.668***
Significant paths			B	S.E.	C.R.	
Money intercept ← Technical intercept			144.717***	24.813	5.832	
Money slope ← Technical slope			88.759**	32.678	2.716	
Model 2						
GFI	**TLI**	**CFI**	**NFI**	**RMSEA**	**AGFI**	χ^2/df

0.851	0.926	0.965	0.842	0.078	0.852	
Significant paths			**B**	**S.E.**	**C.R.**	
Money slope ← Efficiency slope			176.511*	105.407	1.675	1.312**
Money intercept ← Technical intercept			93.774***	20.193	4.644	
Money slope ← Technical slope			124.981**	29.968	4.170	
Money intercept ← Mental intercept			4.792**	2.515	1.813	
Model 3						
GFI	**TLI**	**CFI**	**NFI**	**RMSEA**	**AGFI**	χ^2/df
0.866	0.977	0.968	0.972	0.098	0.891	
Significant paths			**B**	**S.E.**	**C.R.**	
Mental slope ← Efficiency slope			3.524***	1.001	3.516	1.491**
Mental intercept ← Efficiency intercept			3.864***	1.124	3.442	
Money slope ← Efficiency slope			−698.491*	370.752	1.914	
Money intercept ← Mental intercept			5.390*	3.476	1.334	
Money slope ← Mental slope			197.891**	83.821	2.395	
Model 4						
GFI	**TLI**	**CFI**	**NFI**	**RMSEA**	**AGFI**	χ^2/df
0.926	0.988	0.976	0.915	0.093	0.904	
Significant paths			**B**	**S.E.**	**C.R.**	
Mental slope ← Technical slope			4.708**	1.794	2.624	
Mental intercept ← Efficiency intercept			2.637***	0.478	5.517	
Mental slope ← Efficiency slope			10.968***	3.702	4.854	
Money intercept ← Technical intercept			95.989***	25.497	3.765	1.441**
Money intercept ← Efficiency intercept			28.250*	15.141	1.866	
Money intercept ← Mental intercept			12.512**	5.902	2.553	
Money slope ← Efficiency slope			−2,819.587*	1561.664	1.667	
Money slope ← Mental slope			253.797***	76.272	3.328	

Note: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

4. Conclusions

This study aimed to investigate the differences between players ranked on the official money list, which lists the total award money won by LPGA players and is their most crucial performance measure. To examine what factors affect it and whether they grow over seasons, four LGCMs were developed and implemented using mental, efficiency, and technical factors as independent factors, and players' career as an independent variable.

This research led to the following useful and natural conclusions. The efficiency of the top-ranked players is homogeneous and high. However, it does not look very good for players to try to improve it much and really to become very efficient because it may negatively affect the money list. Moreover, if the stress of becoming efficient and high efficiency itself can be neutralized, more money can be offered to players. Therefore, players must be coached and trained to improve their mental balance and efficiency. Moreover, to earn more money, players should focus on improving their techniques to obtain more birdies. As observed, because the mental factor does not affect the money list directly, it plays an essential role in the mediation through which technical factors and efficiency affect the money list, and should be well controlled and trained.

This type of research using LPGA statistics enables players and coaches to evaluate the current status of players and decide which factors should be improved, and players and coaches invest time and money in making more earnings. In the future, this research should be extended by including more players in the analysis and by performing a survey of players' psychological capital to accurately measure mental factors (Peterson et al. [35]).

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