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Career expectations and optimistic updating biases in minor league baseball players

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ABSTRACT

Data on the likelihood of becoming a professional athlete are abundant and readily available, yet athletes consistently overestimate their chances of achieving the top levels of career success. Research is needed to examine whether athletes and others update their career expectations when seeing new information. In this study, minor league baseball players created a career tree estimating their probabilities of moving through the minor league system and then read personalized trees built by a C5.0 machine learning algorithm. After seeing the C5.0 trees, many players updated their expectations consistent with updating theory, especially when reevaluating their chances of being out of the system; however, there was evidence of asymmetric updating. Some acted opposite to what Bayesian reasoning would suggest. Analysis of the interview data reveals three themes that explain asymmetric and contrary updating. Players believed optimism is necessary for their baseball career, they neglected their reference group, and they saw information as possessing affective qualities. Using these three themes caused athletes to ignore some information and, occasionally, circumvent the updating process altogether.

1. Introduction

Researchers have found that athletes have unrealistic expectations of becoming professionals (Kennedy & Dimick, 1987; NCAA, 2019; Sailes, 1998). Athletes with unrealistic career expectations enter development systems with low pay (Pifer et al., 2020), make errors when negotiating and signing professional contracts (McCann, 2006), and avoid career planning (Park et al., 2012; Peptitpas et al., 1990). Athletes who experience unprepared and unplanned retirements suffer from anxiety and depression, they feel anger, disappointment, and regret, lack autonomy in their career decisions, and are less satisfied with their lives (Knights et al., 2019; Perna et al., 1999). Athletes are not the only people with unrealistic career expectations. Students frequently overestimate their salaries after graduation (Jones et al., 2020; Shepperd et al., 1996), which leads students to pick different majors than if their expectations were accurate (Wiswall & Zafar, 2015). Therefore, it is imperative to help athletes and others develop accurate career expectations.

Information about careers, such as probabilities published by the National Collegiate Athletic Association on the chances of becoming a professional athlete, should help athletes develop realistic expectations (Wiswall & Zafar, 2015). However, there has been little research into how athletes perceive career information, and there is no theory explaining how athletes update their expectations when shown new information. If athletes acted consistent with Bayesian theory, the leading normative theory for updating beliefs, they would alter their expectations when faced with new information (Silver, 2012). However, researchers have demonstrated that

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people make consistent errors when processing new information (Eli & Rao, 2012; Garrett & Sharot, 2017; Sharot et al., 2011). Athletes' updating practices might differ from normative recommendations, causing them to maintain unrealistic expectations even though they have the information needed to develop accurate expectations. Thus, the purpose of this study is to examine how athletes update their expectations when shown career information.

Although this study focuses on athletes, we expect it will advance research on careers more generally due to the importance of expectations and information in leading career theories. For example, outcome expectations are one of the central features of social cognitive career theories (Ireland & Lent, 2018; Lent & Brown, 2013), and expectations of success are one of the fundamental beliefs in the expectancy-value theory of achievement choices (Gao & Eccles, 2020; Wigfield & Eccles, 2000). Information about the world of work is also one of the critical ingredients of effective career choice interventions (Brown et al., 2003). However, Lent and Brown (2020) explained that career decision-making models have tended to assume people are rational decision-makers when there is growing evidence suggesting widespread cognitive biases and other errors in decision-making. Thus, it is likely that many people have unrealistic expectations about their careers, and it is vital to study whether they use information rationally when updating their expectations. Professional athletes are ideal for exploring these questions because they have clear, incremental career pathways that enable researchers to measure expectations. Researchers can also use public information on performance and career outcomes to determine whether athletes have accurate expectations (see also Richardson & McKenna, 2020).

To examine how athletes update their expectations when shown career information, we elicited career expectations from minor league baseball players. We then showed them personalized career predictions created by a C5.0 machine learning algorithm and data on every player drafted between 2003 and 2011. By analyzing athletes' responses to the C5.0 data, this study makes the following contributions. First, we examine how athletes' updating behaviors differ from recommendations of normative theory. Second, we use qualitative data to propose theoretical explanations for why athletes incompletely update. Third, we show that some athletes violate normative principles when updating, and we attempt to explain why. These theoretical contributions will serve as the groundwork for a better understanding of unrealistic career expectations, which will inform future research on careers and help counselors and other career development professionals intervene to encourage athletes and others to think more accurately about their careers.

1.1. *Updating theory*

If people were rational "econs," they would update their career expectations using the practices supported by Bayesian statistical theory (Kahneman, 2011; Silver, 2012). Bayesian principles recommend estimating prior probabilities and then updating those probabilities when encountering new information. More specifically, Bayes' theorem describes how to calculate posterior probabilities, from priors, given a new event. If used correctly, two people using Bayesian updating will converge on the same expectations about the future, irrespective of how their expectations differed, so long as they receive the same information (Silver, 2012). Bayesian theory is an ideal standard for updating practices because it describes how to use available information as effectively as possible to develop the most accurate expectations.

Applied to becoming a professional athlete, Bayesian athletes would estimate a prior probability of making it and use any events to estimate new posterior probabilities. For example, being selected by a travel team, being ranked by a prospect site, or seeing a personalized career prediction would provide information to update a prior probability to estimate a new posterior probability of becoming a professional. Thus, according to Bayesian reasoning (e.g., Kahneman, 2011), athletes should start with base rate expectations and incrementally adjust their expectations as they move further through the development pathway. Bayesian reasoning is indifferent to whether athletes start with high or low expectations, so long as they update in the direction implied by new information.

However, researchers have demonstrated that people do not always update their beliefs consistent with normative theory. Massey et al. (2011) found that fans' predictions of National Football League games remained optimistically biased over a season of games, despite accuracy incentives and extensive feedback. Although fans' predictions became more accurate over the season as they learned from experience (better calibration), they still exhibited optimism bias (consistent upward and downward errors). Massey et al. (2011) further showed that optimistic biases were explained mainly by fans' desires to see their favorite teams win over others. Therefore, although people can learn and update their beliefs, they also consistently fall short of rational models, which is likely to happen in career updating.

One theory explaining why people make updating errors is that they are optimistically biased when updating, which leads them to update their beliefs to a greater extent when receiving information perceived as good than when receiving information perceived as bad (Eli & Rao, 2012; Garrett & Sharot, 2017; Sharot et al., 2011). This asymmetry can lead to the persistence of positive beliefs regarding one's future, known as unrealistic optimism (Weinstein, 1980), which has been demonstrated for many life outcomes, including outcomes that people could mitigate with behavioral changes, such as earning a score on an exam or dying from lung cancer or heart disease (Shepperd et al., 2013). Given the persistence of unrealistic optimism in human psychology, it is possible that athletes and other workers asymmetrically update their career expectations when shown new career information.

1.2. *Optimistic performance cultures*

Athletes' unrealistically optimistic expectations might also be linked to dispositional optimism and optimism-based mental skills that are favored in sport and other performance contexts. Optimism, and related ideas, such as confidence, hope, and self-belief, are woven into the fabric of sports culture because of widespread scientific and anecdotal evidence that they help performance (Curry et al., 1997; Grove & Heard, 1997). Sport psychologists have recommended teaching optimism skills to improve athletes' mental toughness and performance (Nicholls et al., 2008). Elite and sub-elite athletes report higher dispositional optimism than non-athletes and less accomplished athletes (Bleichrodt et al., 2018; Venne et al., 2006).

The health and performance benefits of dispositional optimism are also well recognized outside of sport contexts. Optimists persevere, work longer hours, are healthier, and live longer (Puri & Robinson, 2007; Sharot, 2011; Taylor & Brown, 1988, 1994). Indeed, given the widespread prevalence of optimism and other positive illusions among humans, researchers have suggested they might have evolutionary advantages (Johnson & Fowler, 2011). Although dispositional and skill-based optimism have benefits, an unintended consequence is that athletes and other performers might have unrealistically optimistic attitudes toward their careers and new career information. However, we are not aware of any empirical work that has examined how athletes update their expectations.

In summary, although Bayesian updating is the ideal framework for updating expectations about the future, humans have many cognitive and emotional biases that can cause them to err when updating, and these biases might be pronounced and observable among athletes. To examine these topics, we asked the following research questions:

RQ1: How do athletes update their expectations when shown career information?
RQ2: In what ways do athletes' updating behaviors differ from practices suggested by normative theory?
RQ3: What reasons, justifications, or explanations do athletes give that might explain why their updating behaviors differ from normative theory?

2. Method

We conducted interviews with minor league baseball players using a career tree protocol to examine how athletes respond to career information. We chose minor league baseball players as participants in this study for three reasons. First, athletes advance through the minor league farm system one level at a time, making it ideal for measuring athletes' career expectations. Second, since there are abundant data on player performance and career trajectories, we could show players career predictions adjusted to account for personal circumstances (such as draft round, performance, position, and prior movement in the system). We expected players would be more likely to engage with personalized career predictions than with base rates, which are widely known and easily dismissed by athletes who have good reason to believe that they are better than average. Third, the minor leagues' low pay and poor work conditions make for a situation where it would be in many athletes' financial interests to choose a different occupation if they knew they would

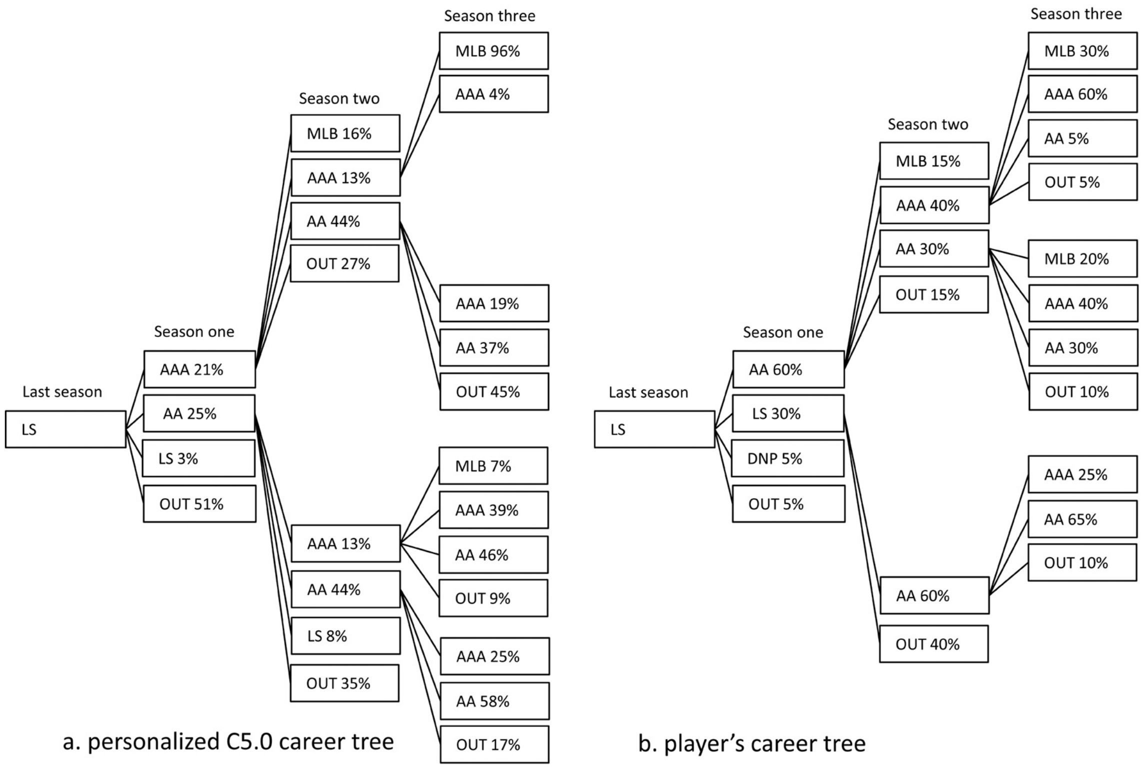

Fig. 1. Examples of career trees for a minor league baseball player's next three seasons built by a) the C5.0 machine learning algorithm and b) a player.

Note: Professional baseball is organized in classes (from highest to lowest): *MLB* = Major League Baseball; *AAA* = Triple-A (the highest level of minor league play); *AA* = Double-A; *LS* = Long Season. The lowest class of minor league baseball is *ST* = Short Season (Low-A and Rookie), although the player depicted in Fig. 1 is not predicted to appear in Short Season. Other abbreviations are *OUT* = Player leaves or is dropped from the minor league system forever, and *DNP* = Player does not play in the minor leagues for a season but returns later.

not make the Majors (Pifer et al., 2020). Therefore, minor league players should be interested in receiving the most accurate information about their career chances, making them ideal for collecting detailed qualitative data on career updating and theorizing how athletes update their expectations.

2.1. Participants

The instruments used in this study were piloted with five college baseball players recruited using snowball sampling. Participants for the final study were recruited using an email sent by a players' advocacy group to its members. The recruitment email notified players that we were seeking English-speaking athletes to study career expectations and that participants would receive a $50 Amazon gift card. The advocacy group sent emails to approximately 250 players. Twenty-two players responded to the email and were interviewed. One player's data was removed from the final sample because he had spent too long (> 6 years) in the minor leagues for our algorithm to provide a prediction. After the first round of interviews, the sample was evaluated based on two criteria: saturation of themes so that no new information emerged from the interview questions; and stratification of the sample, measured by the proportion of players at different levels of the minor league system. Every stage of the minor league baseball career was represented in our sample: Triple-A (14%), Double-A (24%), Long-Season A (24%), Short-Season A (24%), and Rookie (14%). This was interpreted as a desirable stratification for ensuring the findings represented players at different levels in the minors. The average age of the participants was 23.8. Most players identified as White or Caucasian (81%), one player identified as Latin American (5%), one player identified as bi-racial (5%), and one player identified as White and Asian-American (5%).

2.2. Instruments

Interviews were conducted using three instruments: a C5.0 career tree, a player-built career tree, and an interview guide.

2.2.1. C5.0 career trees

We created personalized career trees for each player, estimating his probability of reaching one of seven classifications over the next three seasons of his career: the Majors (MLB), any given level in the minor leagues (Short Season, Long Season, Double-A, Triple-A), out of the minor league system due to being dropped, injured, or quitting (OUT), or did not play for a season (DNP) (see Fig. 1). Trees were created using an advanced classification method known as C5.0 in *R* statistical software version 3.5.3. C5.0 is a machine learning method that extracts informative patterns from data and attempts to predict a case's class from any number of associated variables (Kuhn & Johnson, 2013).

As detailed in another study describing the creation of our C5.0 model (Pifer et al., 2020), we used data collected from The Baseball Cube (thebaseballcube.com) for all players signed from 2003 to 2011 in MLB First-Year Player Drafts. We collected players' draft records, biographical information, performance statistics in affiliate baseball from 2003 to 2018, and their minor league classification from 2003 to 2018. We split the dataset into pitchers and position players. We used the C5.0 models to predict the probability of a player reaching a given classification during each season given his overall draft number, college attendance, handedness, height, weight, the highest classes achieved in any other prior seasons, age, and relevant performance stats from that prior season (for fielders: on-base percentage, slugging average, at-bats, and strikeouts per at-bat; for pitchers: walks and hits per inning pitched, earned runs average, strikeouts per nine innings, innings pitched, percentage of starts, and percentage of closes).

The models were cross-validated on out of sample data and correctly classified players at least 50% of the time and as often as 85% of the time, which is reasonable considering the model had to choose between seven possible classifications each year. Imperfect prediction is an inherent limitation of risk estimators used in expectations research (Shepperd et al., 2013). We decided that these models would serve as a reasonably accurate and valuable source of information for players to update their career expectations. However, our findings and discussion also consider whether athletes believed this information was relevant to their career expectations.

Before conducting each interview, we collected the participant's demographic information, minor league performance statistics, and past career information. We used this information in our C5.0 model to create a career tree predicting the next three years of his career advancement up to a maximum of six years, the point at which most minor leaguers are either out of the system or have a chance to become free agents. Each year, the model produced a set of probabilities related to the player's likelihood of reaching each classification (MLB, AAA, AA, LS, ST, OUT, DNP). The two most likely classifications (excluding OUT) were then used to predict consecutive years in the model. Fig. 1a shows an example C5.0 career tree for a player who finished his last season in Long Season (LS). The branches from the player's starting point in LS show that our model gives this player a 21% chance of making it to Triple-A (AAA) next season, a 25% chance of making it to Double-A (AA), a 3% chance of staying in LS, and a 51% chance of being out of minor league baseball (OUT). Our model then shows branches from AAA and AA; if he makes it to AA in the first season, our model predicts a 44% chance of staying in AA the year after, a 13% of being promoted to AAA, an 8% chance of being demoted to LS, and a 35% chance of being OUT.

2.2.2. Player-created career trees

To determine whether athletes would update their expectations, we asked players to build career trees to determine their prior probabilities before seeing our C5.0 career trees. Players were instructed to use the career tree to "estimate the likelihood of progressing through the minors over the next three years." A blank career template was created for participants that mimicked the career trees built by our model. Participants read a one-page instruction sheet for completing the trees before the interview. The interviewer also provided instructions during the interview session and reminded participants of the instructions. An example of a career tree built by a player is also provided in Fig. 1b; it has the same basic structure as the C5.0 tree, although the player made different estimates.

2.2.3. Interview guide

Career trees were elicited as part of an overall interview protocol that included a mixture of open-ended and close-ended questions. The first author developed the interview guide based on a literature review and refined it using pilot interviews with five college baseball players. After collecting and reviewing top-cited articles from google scholar on the topics of "unrealistic optimism," "optimism bias," and "career expectations," he created a table listing the theories explaining unrealistic expectations, including key sources, a summary of findings, and critiques offered in other articles. He drafted an interview guide translating the theories into the baseball context and shared it with the second author for discussion and critique. Interviews were then conducted with college players, and the first and second authors reviewed the audio files to revise the protocol.

The final protocol had four parts. In the first part, players were asked about their background in baseball and questions concerning their aspirations and expectations in professional baseball. In the second part, players created career trees. In the third part, we showed players our C5.0 model-built career trees using the following description:

> Here is a career tree based on data from every player drafted between 2003 and 2011. We chose that timeframe because most players have finished their careers, so we can see how their careers played out. Based on your draft position, your player position, and your career trajectory so far, as well as your age, average performance, height, weight, and handedness, this is the career tree that shows how players like you, but drafted between 2003 and 2011, moved through their career. Our model correctly predicts career progression between 50% and 85% of the time, depending on the year. It also holds your average performance constant for future seasons, so it will underestimate your progress if you perform better than you have, and it will overestimate your progress if you perform worse than you have.

Players were asked to review the tree, comment on the probabilities, and ask any questions. Next, we asked players to compare their career tree to our C5.0 career tree. Lastly, we asked players the following questions to elicit their updating behavior: "If you had another go at drawing your career tree, would you change anything and, if you would change something, what would you change?" "Does this information about career trajectories change your expectations? In what ways?" "Does this information change your aspirations or your goals?" "Do you think this information is important or useful for minor league baseball players? And if so, why?" Lastly, we prompted follow-up questions with the players and asked them about optimism and realism in baseball.

2.3. Data collection and analysis

Interviews were conducted over Zoom using video chat. Zoom allows screen sharing so that the participant and the interviewer could watch the career trees being built. Interviews were audio-recorded and transcribed. Interview times ranged from 41 min to 90 min, and the average interview was 61 min. Career trees were also captured in a visual format for later analysis.

The mixed-method data analysis procedure consisted of four steps. First, we extracted the overall probabilities of making it to the Majors, the overall probabilities of being out of the minor league system, and the probability of progressing each season from players' career trees. Second, the same probabilities were extracted from the C5.0 career trees. The C5.0 probabilities were then subtracted from the players' probabilities to compute a difference score representing whether the player overestimated or underestimated his chances according to each variable. For example, if the player's tree estimated a 20% chance of making it to the Majors in the next three years, but our model estimated a 13% chance, the player received a difference score of +7%, representing that he overestimated his chances of making it by 7%.

Third, the interviews were coded for information regarding updating behavior. A priori categories were drawn from updating research (Eli & Rao, 2012; Garrett & Sharot, 2017; Kahneman, 2011; Massey et al., 2011; Sharot et al., 2011) and unrealistic optimism research (Shepperd et al., 2013; Weinstein, 1980) to guide coding. Additionally, we used open coding to allow for additional themes to emerge. Two authors (first and third) independently coded a subset of interviews using a priori and open coding. They compared and discussed their interpretations to produce a codebook that they agreed covered the various updating behaviors and attitudes present in the sample. Next, the authors, working independently, deductively coded the interviews and compared their coding to check interrater reliability (see below). Differences in coding were discussed until consensus was reached.

Lastly, for three variables—the overall probability of reaching the Majors, the overall probability of being out, and the average probability of advancing to higher classifications—players were grouped according to whether their estimates were accurate, underestimates, or overestimates. Since a 95% confidence level is generally accepted in statistics, we defined accurate predictions as being within 5% of the C5.0 model predictions; underestimates were 5% or more lower than the C5.0 model predictions; overestimates were 5% or more higher than the C5.0 model predictions. Players' updating behavior and justifications were then analyzed according to their group membership to explore any thematic differences between groups. We compared athletes' behavior with normative theory—specifically, if athletes were "rational," then underestimates should lead to updates in an upward direction, and overestimates should lead to updates in the downward direction. However, there were many inconsistencies in players' updating behaviors that we sought to explain using the interview themes.

2.4. Ethics

We prepared for the ethical issue that participating or advising athletes might lose their jobs if teams learned they were associated with our research projects. Therefore, we focused on measures that protected athletes' identities. We did not anticipate any ethical issues arising from presenting athletes with career predictions for three reasons. First, this study was motivated by unpublished athlete-partnered research to improve work conditions in minor league baseball, where we found teams withheld information from players. Players wished they received more information about their progress and rated "communication between front office and players" as one of their top three unmet developmental needs. Thus, we designed this study to see if we could help meet that need by providing players with objective information about their progress and chances. Following Sunstein's (2015) ethics of nudging, a choice architecture with incomplete information already existed in minor league baseball, and we aimed to change the choice architecture and improve athletes' autonomy by providing more information. Second, data on the likelihood of making it to the MLB is publicly available and frequently discussed by family members, friends, and the media, so we expected players to be familiar with the base rate chances of success, which are very low. Third, we explained the limitations of our data and method in straightforward language and were careful not to overstate our results' predictive power so athletes could decide whether the information was relevant.

2.5. Trustworthiness

All three authors have taken classes on qualitative design and data analysis. Additionally, the first author has led seven projects collecting and analyzing qualitative data. The second author specialized in analytics and was responsible for the C5.0 algorithm. The third author has served as a qualitative data coder on three projects. We used three strategies to ensure the trustworthiness of the findings. The first and third authors independently coded a subset of the updating data, and Krippendorff's alpha was calculated to evaluate the level of agreement between coders. Calculations ($a = 0.91$) exceeded 0.8, which was interpreted as high intercoder reliability (Hayes & Krippendorff, 2007). Second, the authors consulted with each other throughout the data collection and analysis to test their data interpretations. Lastly, the findings were shared with current and former players serving as administrators for a player advocacy organization to discuss and critique. They agreed with our interpretation of the interviews but recommended we mention that incorrect updating was encouraged by the MLB and its affiliates, who benefited from employing athletes with unrealistically optimistic expectations.

3. Results

Most players' prior probabilities required updating according to our C5.0 predictions. Across three career tree measures, only 10% to 19% of players made predictions within 5% of our C5.0 model (Table 1). The remaining athletes made predictions more than 5% above or below the C5.0 data and, therefore, should be expected to use new information to update their expectations. Moreover, players consistently made optimistic predictions. Most players overestimated their chances of making it to the Majors (76%), underestimated their chances of being out of the minor league system (76%), and overestimated their chances of being promoted (76%).

Players were also motivated to know their actual chances of making it to the MLB. Every player said they aspired to make it to the MLB, suggesting that they played in the minor leagues to make it to the Majors rather than have a long minor league career. Indeed, all participants would consider other occupations if they knew they had no chance of making it to MLB because players recognized that they sacrificed income, family, education, and career advancement to pursue a Major League career. Therefore, participants seemed motivated to gain information about their careers that could help with decision-making.

3.1. Updating behavior

Many participants exhibited updating behavior after being shown the C5.0 predictions (Table 2). Players were most likely to update their career trees, with 67% of athletes changing their career tree after seeing the model data. These athletes recognized that their career trees were not consistent with reality. For example, one player said, "I thought I was being realistic, but my tree is super optimistic compared to this tree. It's like night and day difference" (Player5). The most common discrepancy athletes noticed between their expectations and the data was the probabilities assigned to being out of Major League-affiliated baseball. For example, when shown the model tree, one player said, "I think what's interesting is that the out percentage, especially at the top of the tree… That's something I didn't even really realize." Later, when asked about the differences between his tree and the model tree, he said, "[my tree] is definitely different in the fact that there's no out percentage" (Player11). He also updated his career tree by increasing the chances of being out, which was the most common update made by players. Other pessimistic updating included decreasing one's chances of making it to the MLB, decreasing one's promotion probabilities, and increasing one's chances of repeating a level.

In addition to pessimistic updating, some participants updated in an optimistic direction. Two players increased their probability of making it to the MLB, and one player decreased his chances of being out. Interestingly, both players that increased their chances of

Table 1
Accuracy of players' expectations before receiving C5.0 trees.

	Underestimate (< -5%)	Accurate (± 5%)	Overestimate (> +5%)
MLB total	14%	10%	76%
OUT total	76%	14%	10%
Average probability of advancing	5%	19%	76%

Table 2
Percentage of players observed updating after receiving new information.

	Percentage
Player updated career tree	67%
Information caused player to change expectations	19%
Information caused player to change aspirations	0%
Players who did not show any updating behavior	24%

making it to the MLB did so despite their prior probabilities overestimating their chances of making it compared with the C5.0 model. In other words, even though the new information was pessimistic compared with their prior probabilities, they used it as if it were optimistic. Overall, 14% of players updated optimistically, 47% of players updated pessimistically, and 5% of players made updates that had optimistic and pessimistic components.

Even though most players changed their career trees in the face of new information, only 19% said the information changed their expectations, and half of these players updated their expectations optimistically rather than pessimistically. There was only one player who exhibited updating behavior that might help with a later career transition. He said,

> So it kind of gives me an idea or kind of makes me want to, not quit, but just have a plan B. Maybe think about doing something else. Because maybe baseball, not everyone's going to make it. And if you didn't get higher rounds or if you're not doing really good, there's just a smaller chance for you to go, maybe you actually have a plan B. That's what I am actually taking out of it. (Player1).

The other players said that the information did not change their expectations much, if at all. Lastly, no players said that the information changed their aspirations.

3.2. Asymmetric and contrary updating

Updating behaviors inconsistent with normative theory were evidenced in four ways. First, five athletes exhibited no updating behavior. Only one of the five had accurate predictions that warranted maintaining his prior expectations in the face of new information; the other four athletes overestimated their chances of making it to the MLB, underestimated their chances of being out, or overestimated their chances of promotion. They could have used the C5.0 information to change their career trees, but they showed no updating intentions.

Second, even though many athletes used C5.0 information to update their career trees pessimistically, they did not update their career trees as much as suggested by the C5.0 model. For example, a player faced with an 83% chance of being out in his fourth season, a 96% chance of being out in his fifth season, and a 99% chance of being out in his sixth season added a chance of being out to his tree, but only for his sixth season (Player2). Conversely, athletes who used the information to update their career trees optimistically often updated their expectations to the full extent or even further than the C5.0 model predicted. For example, one player who discovered that the C5.0 model gave him a chance to make it to the MLB increased his probabilities of making it even though his original predictions' cumulative probability was already higher than our model predicted. Collectively, players were more likely to update their trees to match the C5.0 model when presented with optimistic information than when presented with pessimistic information, which is consistent with findings of asymmetric updating in other studies (Eli & Rao, 2012; Garrett & Sharot, 2017; Sharot et al., 2011).

Third, players were more likely to say their expectations changed after receiving optimistic information. For example, one player said, "I actually think it improves my perception of my actual objective chances based on what I've already put in, which is really cool" (Player3), and another said, "If anything, it gives me a little bit more optimism but that's it" (Player20). Even though most players received pessimistic information regarding their careers, they often selected optimistic parts and ignored the overall pessimistic picture. For example, an athlete said, "It's useful knowing that at least it's not zero percent. At least there's a chance. Statistically, there's a chance and that's enough to keep going and keep putting the work in" (Player15). In contrast, only two athletes mentioned a pessimistic change in their expectations, and for one of the players, it was "just a little bit" of a change (Player2).

Fourth, there were four instances where athletes seemed to use the information in ways opposite to Bayesian updating. As already noted, two players increased their chances of making it to the MLB despite receiving pessimistic information. For example, a player who gave a 20% chance of being in the MLB in his third season was shown data predicting a 5% chance of making it; then, when asked what he would change, he said, "I would have put MLB at 100% in year three" (Player12), in an apparent violation of updating principles. Other departures from Bayesian updating included three athletes asking for a copy of pessimistic C5.0 trees for motivation. For example, one player took a screenshot of the C5.0 tree and said, "This is awesome. I might put this as my background. I like this a lot." When we asked him what he liked about it, he said, "I just like how the numbers are so minuscule to being successful" (Player16). He and other players seemed to take the pessimistic C5.0 information as a reason to increase their motivation rather than a reason to reassess their expectations.

3.3. Explaining contradictory updating behavior

In this section, we seek to explain inconsistencies in minor league baseball players' updating behaviors. First, we consider whether athletes found this information to be accurate and important. Note that some players had criticisms of the data we showed them. Three players possessed information that we did not include in the C5.0 model that gave them a good reason to think our model would be inaccurate. For example, one player who had spent time in independent leagues noted that the model neglected prior performances because it was limited to affiliate baseball statistics. Two other players had inside information about where they would be starting next season, giving them a more confident prediction about next season's progression. However, other than these exceptions, the remaining participants did not share any evidence that caused them to doubt the predictions.

Moreover, most athletes said the data were accurate and important. For example, one player said, “Yeah, now that I really see the numbers it makes a lot of sense as to how many people are out of baseball within the first three years” (Player17). Another said, “I think it's pretty spot-on” (Player16). Overall, 76% of participants agreed that the information was important for baseball players, and an additional 19% thought the information could be important depending on the player. Therefore, players had reason to see the C5.0 predictions as an important source of information.

However, although players believed the information was accurate, important, and useful, our predictions offered them some room to select what was relevant. For example, we were careful to explain the limitations of our data, notably that the predictions were not perfectly accurate and that we used prior performance to predict future performance. Some players used these limitations when explaining their reasons not to update, which are explored in the next section. For example, one player talked about how his last year's performance was underwhelming, and he expected to perform better in the future, which caused him to see our predictions as a lower bound for what he could expect. In addition to this player, we expect many athletes had unspoken reservations about the data. With these considerations in mind, we focus on what athletes said caused them to update their expectations incompletely.

3.3.1. Necessary optimism

All players in this sample believed that it was important to be optimistic and many believed that optimism was one of the essential baseball skills. A player explained,

> I think that is one of the most important qualities to have as a baseball player because … baseball is like a complete game of failure, and if you aren't optimistic then … the mental side of the game is just going to tear your physical side down, and you're not going to be able to perform well. Optimism is like one of the most important things definitely. (Player7).

Players also believed that optimism was necessary for thinking about their careers. One player said,

> If you were to almost flip [the career tree exercise] and ask the big leaguers who were very similar to me, … I bet that their chart would look similar to mine just because you have to be so mentally strong in order to be a big leaguer. (Player12).

The perceived necessity of optimism for baseball players manifested in a general belief that negative thoughts, including pessimistic thoughts about one's career, must be avoided. One player said, “I think that when you think negative, that attracts negative things to happen. And if you think positive, I think good things happen” (Player1). Players justified their incomplete updating behavior by referring to this self-fulfilling quality of negative and positive thoughts. For example,

> I definitely probably could have put … being out earlier, but I wouldn't be able to sleep at night if I knew I said that. You know what I mean? I just think the moment my mind lets myself say, “Hey, I actually have a chance of being out,” is the moment when I start struggling my next year playing, and remembering this conversation, like why did I sell myself short? (Player16).

Another player said,

> And when I made this, I didn't think that I was going to perform terribly, so I just don't want those negative thoughts. But if you just think of it as like, “I'm a computer, I have no emotion,” kind of deal, then the out percentage has to be a factor and there has to be that reality that it could happen. (Player11).

The importance of optimistic thinking was so vital that some players avoided thinking about being out of baseball:

> So I do sit there and some nights I'm just like, “Okay. What would I do if baseball's not here in my life anymore?” I think about it for 10 min and I'm just like, “Okay. Stop thinking about it, because you're not in that boat yet.” So I try to block it out. (Player2).

However, athletes also balanced optimism by maintaining a realistic perspective on their careers and the business of baseball. This player best described the balance between optimism and realism:

> I have realistic thoughts of making it and how the business works. I understand that, but at the same time, I override that with confidence. You try to block that out and say, “Oh, I don't really see it,” but I know it's there. I'm not dumb. (Player2).

Thus, although players knew how the minor league system worked, they used optimism as a tool to focus on positive thoughts and to help them succeed. Thus, it seems as though baseball players actively choose to be extra optimistic and to block out the reality of their situation because they believed it was necessary to succeed in their careers. Or, in the words of another player, “I think in order to [give it all to make the Majors] the best way you do have to kind of put the blinders on and … be a little bit ignorant if that makes sense” (Player18).

3.3.2. Reference group neglect

Players’ most common justification for incomplete updating was referring to themselves as being outliers or different or unique. This mindset allowed players to hold on to two seemingly contradictory ideas simultaneously: first, that the data was an accurate depiction of career trajectories in the minor leagues generally and, second, that the data did not apply to them personally. For example, one player said, “I don't argue [with] the data, I just am the outlier in my mind” (Player7).

Believing in oneself as an outlier was complemented by a tendency to stereotype other players, neglect others’ perspectives, and, consequently, see oneself as different. The most common examples of stereotyping were when participants explained that other players were unrealistic or other players suffered from limitations in work ethic, commitment, or other factors. For example, one player said, "There's a lot of lazy people, people that don't really care about making it that much further, 'they care' but they don't really care" (Player6). Another example comes from the following player who described other players as delusional:

> I think this could be very helpful for some people who … I run into a lot of players who I think are kind of delusional almost. They think a little bit higher of themselves than what might be realistic. I would like to show this to some of them. (Player14).

Ironically, this player overestimated his chances of making it by 10% and underestimated his chances of being out by 79%. Although he revised his estimate by allotting some probability of being out in three seasons, his expectations remained measurably different from his personalized C5.0 tree after updating, suggesting that he was also thinking higher of himself than was realistic. Stereotyping helped these two players see themselves as different.

Players neglected others' perspectives when they did not consider whether other players shared characteristics that were supposed to give players advantages over one another. For example, when we asked players what attributes, abilities, or characteristics gave them higher than average chances of making it to the Majors, players consistently mentioned "work ethic," "discipline," "resilience," "self-belief," and other psychological factors without recognizing that their counterparts also frequently listed the same psychological factors. While these psychological skills are relevant to becoming a professional baseball player, they do not provide any advantage to one player over another if all minor league systems also possess these qualities. For example, all but two players believed they worked harder than the average minor leaguer. Note that our sample size and sampling strategy make it impossible to rule out the possibility that we interviewed an exceptionally hard-working group of players. Nevertheless, by comparing themselves favorably to others, players were able to see themselves as different and, therefore, not represented in the data.

Indeed, many players referred to commonly referenced psychological characteristics when explaining why the C5.0 data did not apply to them. For example, this player explained his reasoning when comparing his tree to our C5.0 tree:

> I would say this [C5.0 career tree] is probably about what I would expect for someone drafted in the 25th round [like me]… Then I think I gave myself a much better chance of moving up through the levels, especially quicker, than this model shows, which makes sense, though, because I do believe in myself a little bit more than the average person or what history would tell you. (Player14).

When players discussed psychological factors, they focused on what they knew about themselves without considering whether the same attributes also applied to others, which caused them to elevate their chances compared with the reference group. For example:

> the out percentages are so wrong that … just because I know myself. That might not be the same situation for other players. If I'm healthy, unless there's another pandemic or something crazy like that, I won't be out of baseball. Again, this is my interpretation of it knowing myself better than the model does. Besides, I do think the predictions are definitely pretty accurate from a realistic standpoint. (Player6).

This player believed the C5.0 predictions were accurate for other players but believed they did not apply to him because he knew himself better. However, the characteristics that he believed influenced his chances of making it were "resilience," "humble," "routine oriented," "determined," and "motivated," which were also characteristics shared by other athletes in our sample.

Players' difficulty adopting others' perspectives, their tendency to reduce fellow athletes to stereotypes, and their belief in themselves as different or unique, created a situation where athletes neglected their similarities. Consequently, they acknowledged that the C5.0 information was accurate and important for players, in general, while also finding ways to select which of the C5.0 information applied to themselves. For example, one player facing a particularly pessimistic tree with a slight chance of success said, "I think it applies to me, but I think I'm those low percentages making it to AA, seven percent. So yeah, it applies to me, but I feel like I'm one of the outliers" (Player13).

3.3.3. Information as affect

The last factor that explains why baseball players violated updating principles when revising their career explanations is that they saw information about their careers differently from how Bayesian theory conceptualizes information. In Bayesian theory, information is *about* a state of the world—it is a fact that describes a situation and can be used to update predictions to bring hypotheses in line with reality. Baseball players recognize this quality of information, but they also see information as being *affective*; information also influences players and the world they live in—it helps bring certain situations into existence instead of others.

This affective quality of information is seen, for example, when players avoided thinking about their chances of being out of baseball because they believed that acknowledging information about their chances would also influence their chances. Participants had various ways of expressing the idea that the information could affect their chances, but they often believed that information would influence their mindset, which would then influence how they acted. For example, one player explained why he was not updating his tree to match the C5.0 data: "if your percentages aren't that high, I feel like you're not giving yourself that opportunity, mindset wise, to making it" (Player2). According to this player, providing a low probability would negatively affect his mindset and, in turn, his actions. Player3 summed up the common sentiment saying, "if you're not believing in yourself then you have no chance" (Player3).

However, the most interesting non-Bayesian responses were when players saw the information as a competitor or an antagonist to be defeated. For example, one player said,

> "But for me, I want to have you send me this. I'm going to put it in my room so I can see it. When I do get to the big leagues, I'm going to send it back to you and go, "You guys predicted there would be a two percent chance. I told you it was 100% and you were wrong." (Player12).

Another player said, "I definitely think it may motivate me to work harder and stuff, just have that drive to outdo these numbers" (Player10). By describing data as a challenge or a motivator, players did not describe information consistent with how statisticians would describe the same information. They described data as a challenge or motivator because they saw the information in affective terms rather than statistical terms. Seeing information in affective terms explains why some athletes violated Bayesian principles by increasing their expectations of making it to the Majors in the face of disconfirming information; in our participants' words, they were betting on themselves rather than describing a future set of possible events.

4. Discussion

The purpose of this study was to examine how athletes update their expectations when shown career information. Our findings show that most athletes updated their career trees when shown personalized career predictions created by a C5.0 machine learning algorithm. Athletes' updating behavior often followed general updating principles. For example, most athletes who underestimated their chances of being out of baseball increased their chances of being out after seeing their C5.0 tree. However, there was also evidence of updating asymmetries and some cases that contradicted Bayesian principles. These findings have implications for theory on career expectations and implications for career development professionals.

4.1. Theoretical implications

We theorize athletes' updating behaviors as being based in normative updating principles but with key asymmetries and exceptions. Athletes' updating behaviors in this sample were generally consistent with normative theory because they updated their trees after seeing credible information about their career chances, and they usually, but not always, updated their priors toward the probabilities presented in the new information. However, a simple updating framework is unlikely to predict updating behavior in athletes unless the framework accounts for asymmetric and contrary updating.

Regarding asymmetries, athletes updated their trees closer to C5.0 predictions after seeing optimistic information compared to when they saw pessimistic information; and some athletes did not update after seeing pessimistic information. Furthermore, athletes were more likely to say their expectations had changed after seeing optimistic information but rarely said their expectations changed after seeing pessimistic information. These findings are consistent with experimental research showing that people update their beliefs to a greater extent when receiving information perceived as good than when receiving information perceived as bad (Eli & Rao, 2012; Garrett & Sharot, 2017; Sharot et al., 2011). Therefore, this study shows that athletes exhibit asymmetric updating when revising their career expectations.

Regarding contrary updating, some athletes updated their expectations optimistically when faced with pessimistic information, which should not happen according to normative judgment theories. Scholars have considered non-Bayesian learning in other contexts, including overreactions and underreactions to information (Epstein et al., 2010); however, we are not aware of any prior theory that accounts for the behavior of some of the minor league baseball players in this sample who updated their expectations optimistically despite pessimistic information. Therefore, this study contributes to research showing that people can do the opposite of what is recommended by normative updating theories in certain naturalistic situations, such as minor league baseball (Wiswall & Zafar, 2015).

We also offered three theoretical explanations for departures from normative updating based on the interview data. First, athletes believed optimism was necessary for success, which caused them to act inconsistently with normative updating practices. Participants focused on positive thoughts, ignored negative thoughts, and updated their career expectations focusing on positive information. This finding is consistent with the considerable research showing people have unrealistic optimism about the future (Shepperd et al., 2013) and have optimistic biases when updating their beliefs (Garrett & Sharot, 2017; Sharot et al., 2011). However, our findings are unique because athletes believed that optimism was necessary, which is conceptually different from optimism bias (Weinstein, 1980). Our interviews show that players thought optimism was beneficial to their careers, and they actively chose to be optimistic. Players' perspectives were consistent with research finding optimists persevere, work harder, and enjoy many positive physical and mental health benefits (Puri & Robinson, 2007; Taylor & Brown, 1988, 1994). Sport psychologists have also identified optimism as a crucial skill for athletes (Berengui et al., 2013; Grove & Heard, 1997; Nicholls et al., 2008), and career researchers have identified optimism as a correlate of beneficial career attitudes (Eva et al., 2020). Therefore, although athletes with necessary optimism are likely to develop unrealistic expectations, it is also likely that necessary optimism benefits athletes. Future research is needed to explain when the benefits of optimism exceed the disadvantages of having unrealistic expectations and vice versa. Weinstein (1980) argued that the disadvantages of unrealistic expectations were greatest when they inhibit protective health behavior, such as smoking cessation or using protection during sex. If Weinstein's (1980) observation applies to career research, unrealistic expectations are likely to cause the most disadvantages when they inhibit productive career behavior, such as career planning. Otherwise, the benefits of optimism might outweigh the disadvantages of having unrealistic expectations.

The second explanation for why athletes departed from normative updating is reference group neglect (Camerer & Lovallo, 1999). Athletes exhibited an outlier mentality accompanied by a tendency to stereotype their peers and neglect other players' perspectives. This reference group neglect helped participants see the C5.0 information as selectively applying to them while acknowledging that the information applied to players in general. Reference group neglect is consistent with theories that explain persistent optimism biases (Camerer & Lovallo, 1999; Weinstein, 1980). Reference group neglect is likely to apply to other athletes. It helps explain why athletes maintain unrealistic expectations of becoming professionals, even when disconfirming information is abundant.

Although necessary optimism and reference group neglect help explain updating asymmetries, they do not explain the few examples of contrary updating observed in this study. Hence the final theoretical explanation—affective information—is necessary to explain why some athletes updated in the opposite direction implied by Bayesian principles. Affective information refers to situations where people see information as having affective qualities as well as descriptive qualities. Affective information is consistent with psychological research designed to include emotions, affect, and feeling in decision-making theory (Loewenstein et al., 2001; Peters & Slovic, 2000). Whereas theories of choice often assume that decision making is cognitive and consequentialist, newer perspectives, such as the risk-as-feelings hypothesis, argue that emotional reactions to risky situations often diverge from cognitive assessments of risk, leading emotional reactions to drive behavior instead of cognitive assessments (Loewenstein et al., 2001). The current research extends those theories by showing that information can be perceived as having affective qualities, leading to reactions at odds with statistical or analytical thinking. Affective information and the risk-as-feelings hypothesis are examples of System 1 thinking, which Kahneman (2011) described as operating "automatically and quickly" (p. 20), rather than System 2 thinking, which uses effortful mental activity and complex computations.

This article's theoretical themes collectively help explain why athletes have unrealistic expectations about succeeding in professional sports despite receiving information about their chances. Unrealistic expectations persist because necessary optimism and reference group neglect lead athletes to update their beliefs more when shown optimistic information than pessimistic information. Some athletes even circumvent the updating processes when faced with extremely pessimistic information by seeing information as affective. Therefore, unrealistic expectations can persist and become even stronger in the face of pessimistic information.

The overall finding that athletes make errors when updating career expectations is also transferable to other settings. Incomplete updating has been offered as one reason students have unrealistically high salary expectations (Jones et al., 2020; Shepperd et al., 2013; Wiswall & Zafar, 2015). Therefore, the findings of this study might also apply to students and other career hopefuls. Our findings are most transferable to careers, like professional baseball, where a few people achieve extraordinary success. Examples include talent-based industries like music, acting, writing, art, and professional gaming.

The theoretical themes of this study are also analytically generalizable to broader career research. Lent and Brown (2020) explained that most career decision-making models have assumed that people are rational decision-makers, whereas we have shown departures from rational updating in minor league baseball. Therefore, our study makes a generalizable contribution by showing that researchers cannot assume that people have accurate expectations or use information to update their career expectations accurately. Opportunities exist to extend popular career theories such as social cognitive career theory (Ireland & Lent, 2018; Lent & Brown, 2013) and expectancy-value theory (Gao & Eccles, 2020; Wigfield & Eccles, 2000). Taking expectancy-value theory as an example, high expectations of success lead to greater career achievement motivation; however, if those expectations are persistently unrealistic, people might be allocating their motivation to careers with lower chances of success and lower actual payoffs.

Moreover, given the widespread endorsement of optimism as a health, wellness, and performance strategy outside of sport, it is likely that our interview findings, and especially the theme of necessary optimism, will resonate with other careers. Indeed, the career optimism construct has gained popularity in career research (Eva et al., 2020; Rottinghaus et al., 2005). Athletes' unrealistic career expectations are one potential adverse effect of optimism (Eva et al., 2020). However, future research needs to determine whether unrealistic optimism leads to negative career outcomes since dispositional optimism and optimism-based skills have protective and motivating effects that might be more beneficial than having accurate expectations (Grove & Heard, 1997; Nicholls et al., 2008; Sharot, 2011; Taylor & Brown, 1988, 1994).

4.2. Practical implications

These findings also have implications for career counselors and athlete development practitioners. Practitioners can use the career tree protocol described in this study to help people think about their career trajectories and chances of "making it." Career trees can be used in any career with multiple potential outcomes— although it is best suited for careers that advance incrementally and when career outcomes are mutually exclusive. For example, tenure track professors in many fields focus on the number of publications per year when contemplating their chances of promotion. Career trees could easily be adapted to assign probabilities to publication output or other similar outcomes. Adding base rate data will help tenure track professors reflect on their expectations of receiving tenure, which will have many implications, such as deciding between optional retirement plans and pensions, maintaining work-life balance, and testing the job market during the tenure probationary period.

A promising finding of this study is that most athletes updated in some way, even if they did not always update their expectations fully or symmetrically. However, this study also shows limitations to providing people with information about their careers because some athletes' updating was inconsistent with normative theory. We identified three risk factors for incorrect updating: necessary optimism, reference group neglect, and affective information. If these factors are present, career information might even have the opposite of the intended effect, leading people to become further entrenched in their unrealistic expectations. Therefore, career counselors and athletic development practitioners need to continue developing creative ways to help people prepare for career transitions that do not rely on realistic expectations. For example, parallel career planning, where athletes explore a career inside and outside of sport simultaneously, helps players prepare for alternative careers without pressuring them to relinquish sport-based career goals.

We designed this study to provide recommendations that would benefit athletes and those that hope to see athletes succeed outside of sport. However, teams, coaches, and managers could use these findings to encourage unrealistic optimism among athletes. Players serving as administrators for an advocacy organization reviewed our results and pointed out that MLB and its affiliates structure the labor market and employment to promote unrealistic optimism. Although future research is needed to determine whether unrealistic expectations have negative outcomes for athletes, we recommend MLB provide accurate information for athletes if they ask for it. Lastly, the results of this study should not be interpreted as evidence that athletes are responsible for poor work conditions in minor league baseball. Many other actors are in the system, such as MLB, its affiliates, universities, high schools, lawmakers, and the MLB Players Association. Future research must consider each of these actors and their role in producing baseball's labor market conditions.

4.3. Limitations and future research

We used a career tree-based interview protocol to collect detailed data about players' career expectations and their updating behaviors; however, given the smaller sample size of this study, we cannot infer whether the behavior observed in this study is widespread in minor league baseball or other contexts. Moreover, it is possible that players who were more optimistic and harder working self-selected into this study, which would limit the applicability to other athletes. We used the C5.0 analytic method to create personalized career trees because it is more accurate than other methods; however, it still made errors (classifying out of sample data correctly 50% to 85% of the time). There is an inherent limitation in using an imperfectly accurate prediction method to provide updating information.

Latino players and Black players were underrepresented in this sample compared with the broader MLB labor market, and White players were overrepresented. Other researchers found Black athletes to have more unrealistic expectations than White athletes (Kennedy & Dimick, 1987; Sailes, 1998). Therefore, future research needs to consider the role of race, ethnicity, and country of origin in career expectations and updating behaviors. One of the reviewers of this study noted that personalized career information could have an emotional impact on players. We did not foresee or observe any impacts in this study; however, given that one of our themes was "affective information," it is plausible that other interventions could have emotional impacts. Future researchers could assess participants for emotional impact and provide mental health resources and career planning resources. This research was conducted in May 2020 after the minor league baseball season was postponed for COVID-19 and amidst talk of MLB clubs decreasing the number of affiliated minor league teams. Therefore, players might have been less optimistic than usual.

Two future research questions are crucial. First, do unrealistically optimistic expectations have overall positive or negative effects on career outcomes? This question is critical because athletes believe optimism is necessary for their career success. We are currently planning a longitudinal study to examine whether players with unrealistically optimistic expectations outperform predictions and enjoy other benefits from being optimistic. Other research is needed and should examine multiple pathways between optimism and career outcomes, given that optimism has multifaceted effects (e.g., mental health, motivation, unrealistic expectations). The second question is, how can researchers design effective information-based career interventions? We recommend examining two variables that may have limited the effectiveness of our study: information characteristics (e.g., is the information easy to interpret?) and sender characteristics (e.g., are the people giving the information trusted? Do they have authority to provide this information?). Future research might also build on our findings by manipulating reference group neglect. For example, Weinstein (1980) reduced reference group neglect by providing participants with lists created by other participants of personal success factors. Longitudinal and behavioral data are also needed to evaluate intervention effectiveness because the information might influence participants' decisions in the future, even if it does not change their expectations in the present.

CRediT authorship contribution statement

Christopher M. McLeod: Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **N. David Pifer:** Methodology, Software, Validation, Formal analysis, Writing – review & editing. **Emily P. Plunkett:** Validation, Writing – review & editing.

Declaration of competing interest

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References

Berengui, R., de los Fayos Ruiz, E. J. G., Ortin Montero, F. J., de la Vega Marcos, R., & Gullón, J. M. L. (2013). Optimism and burnout in competitive sport. *Scientific Research: Psychology, 4*, 13–18.

Bleichrodt, H., L'Haridon, O., & Van Ass, D. (2018). The risk attitudes of professional athletes: optimism and success are related. *Decision, 5*, 95–118.

Brown, S. D., Ryan Krane, N. E., Brecheisen, J., Castelino, P., Miller, M., & Edens, L. (2003). Critical ingredients of career choice interventions: more analyses and new hypotheses. *Journal of Vocational Behavior, 62*, 411–428.

Camerer, C., & Lovallo, D. (1999). Overconfidence and excess entry: an experimental approach. *The American Economic Review, 89*, 306–318.

Curry, L. A., Snyder, C. R., Cook, D. L., Ruby, B., & Rehm, M. (1997). Role of hope in academic and sport achievement. *Journal of Personality and Social Psychology, 73*, 1257–1267.

Eli, D., & Rao, J.-M. (2012). The good news-bad news effect: asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics, 3*, 114–138.

Epstein, L. G., Noor, J., & Sandroni, A. (2010). Non-Bayesian learning. *The BE Journal of Theoretical Economics, 10*, 1–18.

Eva, N., Newman, A., Jiang, Z., & Brouwer, M. (2020). Career optimism: a systematic review and agenda for future research. *Journal of Vocational Behavior, 116*, Article 103287. https://doi.org/10.1016/j.jvb.2019.02.011.

Gao, Y., & Eccles, J. (2020). Who lower their aspirations? The development and protective factors of college-associated career aspirations in adolescence. *Journal of Vocational Behavior, 116*, Article 103367. https://doi.org/10.1016/j.jvb.2019.103367.

Garrett, N., & Sharot, T. (2017). Optimistic update bias holds firm: Three tests of robustness following Shah et al. *Consciousness and Cognition, 50*, 12–22.

Grove, J. R., & Heard, N. P. (1997). Optimism and sport confidence as correlates of slump-related coping among athletes. *The Sport Psychologist, 11*, 400–410.

Hayes, A. F., & Krippendorff, K. (2007). Answering the call for a standard reliability measure for coding data. *Communication Methods and Measures, 1*, 77–89.

Ireland, G. W., & Lent, R. W. (2018). Career exploration and decision-making learning experiences: A test of the career self-management model. *Journal of Vocational Behavior, 106*, 37–47.
Johnson, D. D. P., & Fowler, H. F. (2011). The evolution of overconfidence. *Nature, 477*, 317–320.
Jones, S., Santos, R., & Xirinda, G. (2020). Misinformed, mismatched, or misled? Explaining the gap between expected and realized graduate earnings in Mozambique. In *WIDER working paper 2020/47*.
Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.
Kennedy, S. R., & Dimick, K. M. (1987). Career maturity and professional sports expectations of college football and basketball players. *Journal of College Student Personnel, 28*, 293–297.
Knights, S., Sherry, E., Ruddock-Hudson, M., & O'Halloran, P. (2019). The end of a professional sport career: Ensuring a positive transition. *Journal of Sport Management, 33*, 518–529.
Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling*. New York, NY: Springer.
Lent, R. W., & Brown, S. D. (2013). Social cognitive model of career self-management: Toward a unifying view of adaptive career behavior across the life span. *Journal of Counseling Psychology, 36*, 477–486.
Lent, R. W., & Brown, S. D. (2020). Career decision making, fast and slow: Toward an integrative model of intervention for sustainable career choice. *Journal of Vocational Behavior, 120*, Article 103448. https://doi.org/10.1016/j.jvb.2020.103448.
Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin, 2*, 267–286.
Massey, C., Simmons, J. P., & Armor, D. A. (2011). Hope over experience: Desirability and the persistence of optimism. *Psychological Science, 22*, 274–281.
McCann, M. A. (2006). It's not about the money: the role of preferences, cognitive biases, and heuristics among professional athletes. *Brooklyn Law Review, 71*, 1459–1528.
NCAA. (2019). GOALS study: Understanding the student-athlete experience. NCAA. https://ncaaorg.s3.amazonaws.com/research/goals/2020AWRES_GOALS2020con.pdf.
Nicholls, A. R., Polman, R., & C. J., L., A. (2008). Mental toughness, optimism, pessimism, and coping among athletes. *Personality and Individual Differences, 44*, 1182–1192.
Park, S., Lavallee, D., & Tod, D. (2012). Athletes' career transition out of sport. *International Review of Sport and Exercise Psychology, 6*, 22–53.
Peptitpas, A. J., Danish, S., McKlevain, R., & Murphy, S. (1990). A career assistance program for elite athletes. *Journal of Counseling and Development, 70*, 383–386.
Perna, F. M., Ahlgren, R. L., & Zaichkowsky, L. (1999). The influence of career planning, race, and athletic injury on life satisfaction among recently retired collegiate male athletes. *The Sport Psychologist, 13*, 144–156.
Peters, E., & Slovic, P. (2000). The springs of action: Affective and analytical information processing in choice. *Personality and Social Psychology, 26*, 1465–1475.
Pifer, N. D., McLeod, C. M., Travis, W. J., & Castleberry, C. R. (2020). Who should sign a professional baseball contract?: Quantifying the financial opportunity costs of major league draftees. *Journal of Sports Economics, 21*, 746–780.
Puri, M., & Robinson, D. (2007). Optimism and economic choice. *Journal of Financial Economics, 86*, 71–99.
Richardson, J., & McKenna, S. (2020). An exploration of career sustainability in and after professional sport. *Journal of Vocational Behavior, 177*, Article 103314. https://doi.org/10.1016/j.jvb.2019.06.002.
Rottinghaus, P. J., Day, S. X., & Borgen, F. (2005). The career futures inventory: a measure of career-related adaptability and optimism. *Journal of Career Assessment, 13*, 3–24.
Sailes, G. A. (1998). A comparison of professional sports career aspirations among college athletes. In G. A. Sailes (Ed.), *African Americans in sports: Contemporary themes* (pp. 261–269). New Brunswick, NJ: Transaction.
Sharot, K., Korn, C. W., & Dolan, R. J. (2011). How unrealistic optimism is maintained in the face of reality. *Nature, 14*, 1475–1479.
Sharot, T. (2011). The optimism bias. *Current Biology, 21*, 41–44.
Shepperd, J. A., Klein, W. M. P., Waters, E. A., & Weinstein, N. D. (2013). Taking stock of unrealistic optimism. *Perspectives on Psychological Science, 8*, 395–411.
Shepperd, J. A., Ouellette, J. A., & Fernandez, J. K. (1996). Abandoning unrealistic optimism: Performance estimates and temporal proximity of self-relevant feedback. *Journal of Personality and Social Psychology, 70*, 844–855.
Silver, N. (2012). *The signal and the noise*. New York, NY: The Penguin Press.
Sunstein, C. R. (2015). The ethics of nudging. *Yale Journal on Regulation, 32*, 413–450.
Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: A social psychological perspective on mental health. *103*(2), 193–210.
Taylor, S. E., & Brown, J. D. (1994). Positive illusions and well-being revisited: Separating fact from fiction. *Psychological Bulletin, 116*(1), 21–27.
Venne, S. A., Laguna, P., Walk, S., & Ravizza, K. (2006). Optimism levels among collegiate athletes and non-athletes. *International Journal of Sport and Exercise Psychology, 4*, 182–195.
Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology, 39*, 806–820.
Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology, 25*, 68–81.
Wiswall, M., & Zafar, B. (2015). How do college students respond to public information about earnings? *Journal of Human Capital, 9*, 117–169.