Design Patterns of Trading Apps and Their Effects on Investing Behaviors
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Smartphone apps such as Robinhood and Public that promise to "democratize investing" have risen in popularity over the past few years. These apps allow retail investors, typically with little prior investing experience, easy and inexpensive (often commission-free) access to trading stocks, options, and other securities. As such, it seems likely that these interaction patterns can significantly influence trading behaviors of users. However, there is little formal design guidance on how such apps should be designed. This paper draws on three bodies of related work: 1) findings from finance and economics literature on healthy investment practices, 2) the dual process theory from behavioral sciences, and 3) design metaphors used in interfaces with uncertain rewards to create a set of design guidelines that might encourage healthy investment habits. Using these guidelines, we qualitatively analyze the user interfaces of a couple of the most popular trading platforms. Our findings reveal that, unfortunately, popular trading apps follow few design patterns that encourage healthier trading habits. We discuss design implications and opportunities for future design.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; **Interaction design**.

Additional Key Words and Phrases: investment, financial wellness, behavioral finance, design guidelines

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1 INTRODUCTION

In recent years, smartphone applications that promise to "democratize investing" have shifted the stock market from being territory exclusive to institutional and wealthy investors and opened it up to less privileged individuals [59]. Zero-commission trading apps such as Robinhood and Public have become popular and received strong venture capital support [87, 88]. Unlike traditional brokerage firms, these apps require no minimum amount to be invested, potentially opening up investing to less wealthy "retail" investors. A retail investor is one who invests their own money and have no professional training in investing. Furthermore, while traditional brokerages charged investors every time they bought or sold an investment, newer apps do not charge commissions for most kinds of securities, making them more attractive to investors who seek to avoid the expenses of investing. So attractive are these offerings that even traditional brokerages are eliminating fees in order to remain competitive [98].

We argue that this transition from a traditional, high cost, and high barrier to entry interaction with financial market to a disruptive, zero-commission, and nearly effortless experience [9] constitutes a fundamental shift in one of the most consequential human behaviors - investing - and is thus worthy of close study by the design community. Not only has easy and free access to trading lured millions of people, especially first-time retail investors, to these platforms [72, 93],

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these apps also afford novice investors one-click access to invest in riskier securities such as cryptocurrencies and options [86]. As recent episodes with companies like GameStop demonstrate, these apps have also allowed inexperienced investors to adopt riskier strategies such as "short squeezing" [76]. Some estimates suggest that more than a quarter of Americans bought "meme" stocks in 2021, and a majority faced a loss [91]. For some, devastating losses have had catastrophic results [75]. In short, the rise of zero-commission trading apps has both vastly expanded the reach of investing and qualitatively changed its nature.

Given this background, it is easy to see the role that design might play in shaping investing behavior. Through its design, a trading platform can determine which actions and behaviors are easily available to users, and thus encouraged [63]. It could also discourage certain actions. To make an analogy, consider social networking apps. With its focus on ephemeral content and gesture-heavy user interface, Snapchat has a very different appeal compared to other platforms like Facebook and Reddit and encourages different kinds of content to be posted, even in a narrowly defined topic such as national elections [14]. Similarly, one could expect design decisions made by trading platforms to affect investing behavior.

More specifically, trading platforms can be considered as technical and social choice architectures that influence investing behavior. Extending research on digital choice architectures [39], one can expect that the design, structure, and features of trading apps can also enable and constrain specific behaviors in users. Certain design decisions can encourage investors to act on their instincts and possibly be less rational, while other alternative decisions might encourage systematic deliberation [13, 77]. For instance, absence of commissions for each trade in most popular trading apps can encourage more people to trade more frequently. Similarly, the use of "golden tickets", and confetti, and free stocks, as seen in Robinhood's interface (Figure 1) may blur the lines between a trading app and a gambling app [34, 93]. In sum, the design of smartphone trading platforms may prevent or encourage investors in making fully informed decisions [59]. In practice, these interactions may nudge investors to see investment as recreation.

Some evidence suggests that during the COVID-19 pandemic, people confined to their home repurposed the money they could no longer spend on recreation to speculations on these apps which were just a download away [55]. This contributed to the increased volume of trades in 2020, especially on these zero-commission trading apps [11]. Unfortunately, this more frequent trading has translated in poor financial outcomes for retail investors [8, 72].

Despite the large impact that design patterns can have on investing behaviors, research on this topic is unfortunately lacking. We note that there is a long history of research in the design community on how individuals, especially from vulnerable populations make budgeting decisions [43] and how design can induce prosocial habits in them [10, 23]. However, this prior literature does not address investing. There are three critical differences between putting one's money in safe instruments such as bank deposits, which has been studied in prior work, and investing in the stock market, which we focus on in this paper. First, saving and budgeting behaviors are strongly embedded in culture. For instance, immigrants to the United States in the early 20th century repurposed empty soup cans to earmark savings for different goals [95]. This practice is not altogether different from contemporary practices of spending and saving through different credits cards and bank accounts [43]. These cultural norms offer a guide for reasonable behavior (e.g. it makes raiding childrens' piggy banks to pay for an unexpected expense seem distasteful [95]). Unfortunately, except for discouraging speculation, there are few cultural practices around successful investing [21]. Second, further complicating the picture, successful saving and budgeting behaviors are often straightforward and intuitive to adults, but successful investing requires counterintuitive thinking. For instance, it is intuitive to most adults that it is better to save more in times of economic stability for a rainy day. It is less clear whether it is similarly better to purchase more stocks during a booming economy when stock prices may be inflated [12]. Third, and perhaps most important,

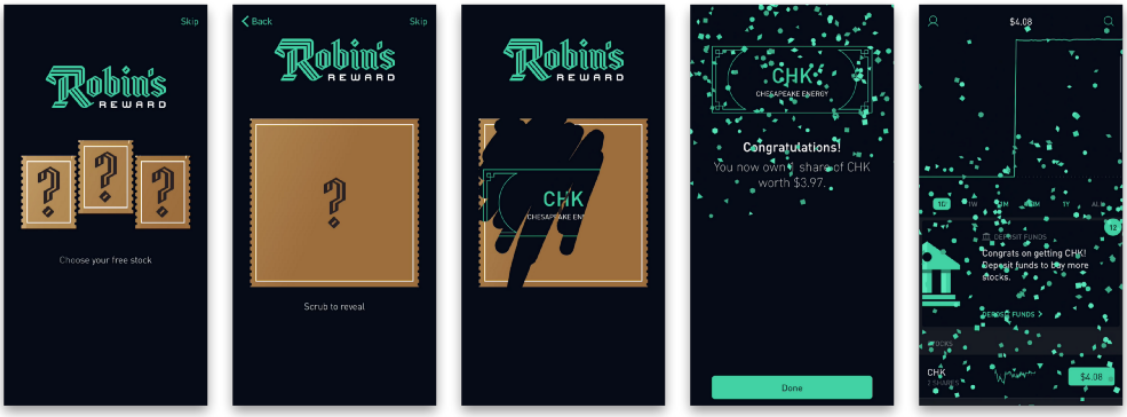


Fig. 1. Robinhood offers its users a free stock when joining the platform or referring a friend. This flow uses a lottery scratchcard interface. Such design patterns may lead users to conflate the idea of investing with gambling. Image from Tory Hobson/Pinch Pull Press (https://link.medium.com/uxXrSIPuCdb).

investing is inherently risky. While saving money in a bank account guarantees a risk-free return, investors also stand the chance to lose their capital and suffer ruinous losses. As such, the heuristics investors use to evaluate the trade-off between risks and potential rewards can play a big role in their success [8]. These critical differences between saving and investing suggest that design implications from studies on budgeting behaviors are unlikely to be sufficient to inform the design of investing interfaces.

This paper starts to fill this gap of design guidance. In doing so, we take inspiration from methods for creating design guidance in other fields without thick cultural practices, a need for counterintuitive thinking, and inherently uncertain outcomes. In particular, we draw inspiration from guidelines for designing interfaces for artificial intelligence (AI) applications that are based on fundamental findings from related domains such as psychology and law. Design guidelines for AI applications, while new, follow a decades-long intellectual tradition from human-computer interaction community: from Neilsen's heuristics for user interfaces [62] to Norman's principles of designs of everyday objects [64], guidelines have aided practitioners in designing interfaces and sparked future research.

This paper offers similar design guidelines for trading platforms based on fundamental insights from three bodies of related work: 1) findings from finance and economics literature on healthy investing, 2) the dual process theory from behavioral sciences, and 3) design metaphors used in interfaces with uncertain rewards. These disparate insights were clustered into eight actionable guidelines that can help encourage more successful investing behaviors among the users of these platforms. We validate the guidelines by using them to analyse two popular US trading apps, Robinhood and E-Trade. We end the paper by discussing design implications and opportunities for future design.

This paper makes three contributions: first, it demonstrates, based on fundamental research from related domains how trading apps might encourage certain kinds of trading habits. Second, it introduces a set of design guidelines for trading platforms that may encourage more successful investing behaviors. Finally, it identifies opportunities for design and research by highlighting gaps in current implementations of trading apps.

2 RELATED WORK

This paper tackles a topic that is inherently interdisciplinary. As such, it is informed by empirical observations that investment outcomes for retail investors are dominated by behavioral decisions, rather than information; theoretical models that explain these behaviors; and by previous approaches of designing guidelines.

2.1 Behavior of Retail Investors

If markets are perfectly efficient, retail investors should theoretically perform similarly to professional institutional investors such as banks and hedge funds. Yet, in practice, most retail investors under-perform their professional counterparts, even when they have the same information. Researchers have attributed this under-performance primarily to behavioral, rather than informational factors. Overconfidence in their investing decisions, poor risk evaluation [8, 31], overreacting to news events [54], and believing they can predict the market [46, 47] lead retail investors to realize fewer gains.

Because under-performance is caused by behavioral rather than informational factors, making trading easier or increasing access to information backfires. Indeed, it encourages investors to trade more actively and perform even worse [9, 65]. Some popular media accounts also contend that easier app-initiated trading nudges retail investors to take bigger risks [71, 72, 92, 93]. However, outside of accounts in popular media, research on how these apps influence investing behaviors is still lacking.

Overall, the empirical research on retail investor outcomes suggests that the design of our guidelines should be informed by behavioral findings on financial decision-making.

2.2 Heuristic Evaluation Processes

Many studies have shown that decision making under uncertainty, such as in financial markets, involves *heuristic processing* [70, 82]. Unlike *systematic processing* that involves careful and deliberate processing of the message, heuristic processing reduces cognitive effort by using simple decision rules to quickly analyze situations. While these simplifications, such as buying stocks based on a friend's recommendation, are often valuable in uncertain environments, they are also susceptible to predictable biases. For instance heuristic decisions are prone to persuasive techniques such as framing, anchoring, and social proof [22, 32, 52, 56, 82–84]. These effects are further intensified in digital settings [19, 51, 96]. Overall, this research suggests that design metaphors and decisions that affect heuristic processing can be leveraged to improve trading habits and thus outcomes for investors. We focus our attention next to such design metaphors.

2.3 Design Metaphors

User interface choices such as what elements are first visible, which stimuli are salient (e.g. choice of colors), and which settings are chosen as defaults, influence the heuristic decisions made by users [50]. Similarly, researchers have studied how design metaphors can make messages more persuasive [29, 56]. Others note that certain design patterns (dark patterns) can encourage heuristic processing and result in more instinctive decision making [13].

Most closely related to our work, Tanakaa and Kawabatab found the interface predictability can impact the kinds of bets people make [81]. To our knowledge, no prior work has directly studied how design metaphors influence trading habits. However, other researchers have studied the impact of design metaphors in contexts such as filing taxes [40], social lending [94], and voting [42]. We leverage these findings taken together in developing our guidelines.

2.4 Guidelines for Designing Human-Centered Technology

For several decades, the human-computer interaction community has proposed guidelines for ethical design of technology across many domains. For instance, Norman applied principles of designs from everyday objects to technology products [64]. Höök's concept of soma design shifted the perspective on interactive design to focus more on fundamental human values [35]. Horvitz's formative work on mixed-initiative systems [36], Brown's work on human-computer interfaces [17], and Amershi et al.'s work on human-AI interaction guidelines [4] are some example of sets of guidelines that serve as a useful resource for practioners working with consumer-focused technology. There is also a growing body of research on how and why to improve the fairness and explanability of AI systems [45, 49, 73, 85]. Several notable organizations such as Google [1], McKinsey & Company [18], and Partnership on AI [2] have also laid down their own principles for responsibly building AI products. Further, there has also been work on how to best operationalize these guidelines in industry [53, 58].

In general, the development of design guidelines follows a four-step process that we adopt in our own work: 1) a review of findings from fundamental research to suggest possible design decisions or metaphors, 2) clustering of related decisions and abstracting higher-level guidelines, 3) evaluation of guidelines to ensure they apply to practical design artifacts, and 4) refinement based on evaluation.

While guidelines are meant to distill theoretical rigor into practical suggestions, they are not meant to be rigid rules. Also, given the effort and time required to design new interfaces, it remains difficult in practice to evaluate if designers' decisions based on guidelines empirically improve user outcomes. Indeed, some of the most impactful guidelines such as Neilsen's heuristic evaluation method [62] or Amershi et al's guidelines for human-AI interaction [4] lacked such evaluation when they were first introduced. Our work has the same limitation.

Finally, we note that a theory-based approach is not the only feasible way to discover design guidelines. For instance, a service design approach has also been used in the area of financial literacy successfully [97], and it is possible such an approach might unearth new service expectations. Elsewhere, Odom et al. offer deep design guidance on "slow technology" using a *research through design* approach (e.g. [66, 67]). It is easy to see how such an approach might also be valuable around investing. Further afield, Irani and others take an ethnographic approach that critically examines power structures [38]. While our work is largely complementary to these methodologies, this prior work also highlights our own methodological limitations. For instance, we do not seek to question or reframe the goals of retail investing or to investigate the power structures inherent in app-initiated investing.

3 METHODS

We developed the guidelines in Table 2 using a four-phase process. In Phase I, we reviewed fundamental literature from behavioral finance, psychology, and design relevant to financial decision making and tried to extract recommendations that are actionable through interaction design interventions. In Phase 2, we consolidated these insights to propose an initial list of design guidelines for trading apps. In Phase 3, we applied these guidelines to one trading app (Robinhood) and one traditional investment platform (E-Trade) to evaluate their applicability, violations, and blindspots and asked other researchers in our organization with no prior experience designing investing interfaces to independently review the guidelines and their applications. These reviews led to improvements to enhance the clarity and scope of the guidelines in Phase 4.

4 PHASE 1: REVIEW OF FUNDAMENTAL THEORY

In Phase 1, we reviewed literature in three areas: 1) fundamental insights from finance and economics to understand the nature of investing, 2) behavioral science findings on how investors and other actors in uncertain situations make decisions, and 3) design metaphors for how these behavioral findings may be operationalized.

4.1 Investing, Uncertainty, and Diversification

Investing is the act of putting aside money with the hope of gaining more, while acknowledging that some money may be lost. This inherent risk associated with investing sets it apart from saving, which could be practically "risk-free" [25].

The returns on investments are generally understood to be determined by three factors: asset allocation (the kinds of things or assets that are invested in, such as stocks, real estate, etc.), security selection (the particular assets or securities chosen, such as specific companies, plots of land, etc.), and time horizon (the timeline of when these securities are bought and sold) [28]. The expected return from particular allocations, securities and timing are subject to risk. Risk is generally classified as either systematic or specific. Systematic risks such as recessions, interest rate changes, pandemics, etc. broadly affect all investing (e.g. most investments do poorly in a shrinking economy). Specific risks are related to a particular security or industry.

4.1.1 Diversification. Diversification is the process of investing in multiple kinds of assets and securities and with varying timing to reduce the specific risk assumed [60]. Investing and portfolio theory emphasizes diversification, but empirically there is a gap between these theoretical recommendations and how retail investors actually invest [8, 27]. While adequate diversification is possible even with 30 securities [78], retail investors typically only invest in 4 [8]. In addition, many retail investors trade speculatively rather than systematically and so increase risks related to timing. As a result of these actions, an average retail investor under-performs institutional investors such as university endowments by 4 to 8% every year [48], and even the market as a whole by approximately 1.5%.

4.1.2 Security Selection. While portfolio theory suggests choosing securities based on expectations of future earnings and growth potential, other factors are empirically more predictive of retail security selection. In particular, retail investors choose securities with a local bias and are overweight past performance.

Local bias is the tendency of investors to invest in stocks of businesses that they are psychologically or physically nearby, such as a local construction company, the industry that employs them, or a favorite chain restaurant. However, the increased familiarity with the selected securities does not predict increased future performance [27, 47]. Such concentrated portfolios can sometimes perform better than diverse portfolios but also carry more specific risk, and under-perform over the long term[8].

Kumar and Dhar found that a large number retail investors are sensitive to past price trends [46], such as focusing on stocks that are "rising" or a "steal" at current prices. Retail investors with high trend-tracking behavior were correlated with having portfolios with lower levels of diversification [27].

4.1.3 Market News and Timing. While news releases and earning events have some significance for future returns of an investment, retail investors tend to overreact to these events, believing they fundamentally change the value of their investments more than they actually do [54].

Barbera and Odean found that stocks retail investors bought tend to earn strong returns in the subsequent two weeks of the trade but underperform in the long run. This behavioral anomaly of selling investments that are doing well while

holding on to their losing investments is called the disposition effect [8]. We outline potential reasons for this bias in Section 4.2.

4.1.4 Sensation Seeking. Investing money in the stock market can result in a thrilling sensations akin to gambling. This is evidenced by the fact in periods with high lottery jackpots, the volume of trade is lower [31]. However, high-turnover in portfolios, whether caused by an overreaction to market news or sensation-seeking, decreases investing returns over time. Active retail investors underperform the market by 6.5% every year, as compared to 1.5% for investors who buy and hold [8].

4.1.5 Transaction Costs. While transaction costs such as brokerage commissions, taxes, and fees reduce the returns earned by investors, there is evidence that retail investors earn below market returns even before these costs are accounted for [8]. Phone based trading apps and new brokerages typically charge no commissions, and instead earn money through margin fees, cash balance interest, and compensation by other wholesaler firms that buy and sell securities [86]. As a result, investors now can trade securities for free. Such free trades have increased trading frequency [86]. These frequent trades have also likely reduced investor returns.

4.2 Heuristic Evaluation Processes

The heuristic-systematic model of information processing is a dual-process theory that suggests that human beings can process messages systematically and/or heuristically [20]. Systematic processing involves careful and deliberate processing of the message, whereas heuristic processing reduces cognitive effort by using simplifying decision rules to quickly analyze the message. For instance, heuristic processing might skip the complete processing of the content of the message and instead uses indicators such as credibility and expertise the person who is sending the message or endorsing it. This can occasionally lead to cognitive biases in the decision making process [82].

Investment decisions are made in the presence of heuristic processing [70]. Due to imperfect information in financial markets, inherent uncertainties, and volatility, investors can only rely on a handful of data points when making decisions. Heuristics, such as past performance of a stock or analysts rankings, simplify and speed up the decision-making process. Studies suggest that even financially literate investors are driven by behavioral factors and tend to trust their intuition while building their portfolios [26]. However, relying on some heuristics over others can result in biased judgments and poor financial decisions [3]. For instance, the level of under-diversification is affected by factors such as overconfidence, trend-tracking behavior, and local bias of the investor [27].

The two most important determinants of which processing route is used when processing a information are motivation and ability [69]. People are more likely to engage systematically with a persuasive message if they are more motivated to do so. This in turns depends on the personal relevance and response involvement of the message. Similarly, people's tendency to choose heuristic processing is higher when availability of cognitive resources is low. This includes lack of time, focus, or requisite knowledge or the presence of stress and other distractions [26]. Below, we discuss specific heuristics most relevant to investing, and how they affect financial decisions.

4.2.1 Representativeness Heuristic. Under uncertainty, such as while trading, people tend to rely on representativeness to make judgments. For instance, trend-tracking investors believe that a stock with a good returns in the past will continue to perform well in the future [7, 15]. This leads to the extrapolation bias and the tendency to make generalized impressions about the potential of stock after observing its performance for a short period of time. These analyses are

prone to be incorrect since the valuation of stocks are a function of market factors and not necessarily of their past performance.

4.2.2 Availability Heuristic. People assess the likelihood of events with the salience of the event, i.e. the ease at which similar instances can be brought to mind. Investment decisions can be biased by more vivid and memorable stock price movements, what other investors are purchasing, and similar salient events, rather than less salient information such as the history of dividends paid by the company. The availability heuristic also causes investors to blindly trust analysts' market recommendation revisions, even when they are not sound investments [44].

4.2.3 Hot Hand Fallacy and Gambler's Fallacy. The hot hand fallacy and gambler's fallacy are two widely studied cognitive biases that causes people to misinterpret sequences of essentially random market prices and affects their investment decision. The hot hand fallacy is the expectation that price trends will persist indefinitely, i.e. rising stocks will continue to rise and falling stocks will continue to fall. This leads to buying stocks that show an increasing trend and selling stocks that show a decreasing trend, together increasing the cost of investing. The gambler's fallacy is the expectation that investments will always revert to their previous price, without regard to fundamental changes such as technological innovation or obsolescence. This leads to people holding onto losing investments for too long and selling winning investments too soon. Huber et al. found that people who rely on the recommendations of experts were prone to the hot hand fallacy and people who acted individually were prone to the gambler's fallacy [37].

This disposition effect stems from the prospect theory, which posits that humans tend to be risk-averse when dealing with gains but risk-seeking when dealing with losses [41]. Factors such as involvement, choice, and familiarity can also lead investors to develop an illusion of control and makes them believe that they can control the outcome of chance situations [47].

4.2.4 Anchoring Heuristic. The anchoring heuristic is a behavioral bias in which, when under uncertainty, people estimate quantities using an initial benchmark and then adjusting it to make judgments [82]. One consequence of this is that people can anchor their estimates of what an investment is worth to the price they purchased it for, rather than to present market conditions. This can cause them to hold onto poor investments for too long [61, 70].

4.2.5 Confirmation Bias. Confirmation bias leads people to seek information that is consonant with their prior beliefs. It lead to investors maintaining unrealistically high expectations of performance of their current investments, and lower expectations of alternative investments, leading to lower overall returns [68]. Moreover, focusing too narrowly on ones current portfolio can also expose investors to high levels of specific risk.

4.3 Lottery Design Metaphors

Beyond fundamental psychological biases, decision-making is also influenced by design metaphors and decisions. Specifically, certain design decisions can prompt System 1 thinking processes, which are undemanding, instinctive, and possibly less rational than System 2 thinking processes as suggested by dual process theories [13, 77]. We outline some relevant decisions below.

4.3.1 Jackpot Metaphors and Ignoring Probabilities. Few investors make investment decisions after accounting for factors such as implied volatility, or adjusting returns for risk [57]. However, when deciding whether to invest in what is perceived as a "jackpot", decision-making is dominated by the magnitude of the potential winning, rather than its probability [30]. To the extent that trading apps highlight the massive returns of penny stocks and some options

contracts or use explicit visual imagery of jackpots or lotteries (Figure 1) they may encourage investment gains to be perceived as jackpots.

4.3.2 Commitment Leading to Entrapment. Entrapment is the tendency of people to commit to a goal that has not been realized beyond an economically rational point [16, 79]. Argyris found that cutting ones losses, in gambling and trading, is interpreted as embarrassing and also giving up on potential returns [6]. To the extent that apps and platforms allow users to share information about their trade, such as on a social feed, they may increase commitment, in turn leading to entrapment, despite mounting losses [90].

4.3.3 Gratification Delays, Reinforcement Schedules and Habit Formation. While latency in interfaces is generally detrimental [5], immediate payback of risky bets encourages more frequent plays and the tendency to regamble any winnings with little rational financial consideration [30]. For instance, when playing with scratchcards and slot machines, there is only a few seconds between the initial gamble and the payback. Instant settlement on trading apps can also potentially result in similar behavior.

How frequently and regularly rewards are obtained can play a significant role in engendering behaviors and habit formation. A variable-ratio reinforcement schedule, where rewards result after a varying number of attempts, such as with slot machines, lead to stronger habit formation [24]. Unfortunately, frequent trading, especially with little financial consideration, results in rewards with varying frequency, further reinforcing the risky habit.

5 PHASE 2: CLUSTERING OF GUIDELINES

From the literature review phase, we came up with a list of 25 factors that play a role in determining investors' success. Of these, 20 factors can be affected or encouraged through interface design. We labeled these factors as either visual, behavioral, or financial, depending on the community where the underlying research was conducted.

Next, one member of the team generated an initial set of design guidelines that operationalized these factors. The candidate guidelines were then clustered using affinity diagramming, such that guidelines that were related in possible implementations were clustered together. We limited cluster sizes such that guidelines did not become too abstract and distinguishing between applications and violations of the guidelines was difficult to identify.

This clustered set of guidelines went through multiple stages of iterations with the help of other authors of the paper. This involved reclustering, rephrasing, and dropping some guidelines. For instance, we realized that frequency and thoughtful trading were not necessarily correlated, so we split the "Discourage Infrequent and Thoughtful Trading" guideline into two. We also noticed that the "Do Not Charge Commissions" guideline emphasized a particular business decision, rather than a design decision. We rephrased this guideline to "Minimize Roundtrip Costs" to improve its applicability and flexibility. Other guidelines were rephrased to improve clarity. Still other guidelines were dropped entirely if they did not relate specifically to investment or trading, such as the "Use Clear Verbiage" guideline.

Some of harder to resolve conflicts come from inconsistencies across the different domains. As one notable example, though finance literature suggests transaction costs significantly bite into an investor's returns, behavioral finance literature suggests that the lack of commissions can encourage investors to trade more frequently. In this case, we decided to keep both the, potentially conflicting, guidelines. This was in recognition of the fact that technology design can involve difficult trade-offs. Our set of guidelines helps designers evaluate their design choices, and consider how problematic effects could be mitigated creatively. A list of the clusters and corresponding guidelines towards the end of this phase is shown in Table 1.

Table 1. Initial clusters of design guidelines for trading apps. Guidelines are inspired by research done by visual design (V), behavioral sciences (B), and finance (F) communities.

Factor	Guideline
[F] Diversification [F] Security Selection	Encourage Diversification
[B] Representativeness Heuristic [B] Anchoring Heuristic [B] Commitment Leading to Entrapment [F] Market Timing	Focus on the Long-Term Future
[B] Hot Hand Fallacy [B] Gambler's Fallacy [B] Confirmation Bias [B] Illusion of Control	Do Not Encourage Predicting Random Numbers
[V] Gratification Delays [V] Habit Formation [F] Sensation Seeking	Discourage Active Trading
[V] Jackpot Metaphors [V] Ignoring Probability [B] Availability Heuristic [F] Market News	Do Not Make Trading a Popularity Contest
[V] Reinforcement Schedules [B] Heuristic Processing	Encourage Thoughtful Trading
[F] Transaction Costs	Minimize Roundtrip Costs

6 PHASE 3: EVALUATION

In this phase, we evaluated our set of guidelines with five other researchers and designers to identify its applications, violations, and blind spots. Some evaluators ($n = 2$) had not used any trading app in the past. All of them are members of an interdisciplinary design and research institute at our university and are our frequent collaborators.

Our study was inspired by the modified heuristic evaluation done by Amershi et al. while devising their list of guidelines for human-AI interaction [4]. Amershi et al. ask evaluators to use their guidelines to assess existing interfaces and identify applications and violations of their guidelines. We extended their method and also asked evaluators to also provide feedback on any potential blind spots of the guidelines themselves. This helped us identify potential ways in which our guidelines could be extended to be more applicable.

For our evaluation, we decided to study the design patterns in two different trading platforms: Robinhood, one of the most popular zero-commission trading apps, and E-Trade, one of the "big four" brokerages in the United States. Between them, these platforms handle more than 5 million daily average revenue trades [74]. Moreover, these two platforms use significantly differently modalities (smartphone and website, respectively) and target investors with different amounts of investable capital, allowing us to inspect how our guidelines evaluates them differently. If the evaluator did not have an account on the platform, we provided them a comprehensive list of screenshots and flows of the application. Evaluators provided verbal feedback on how each platform compared against our set of guidelines and how easy and intuitive it was to apply the guidelines.

Evaluators were able to identify applications, violations, and blind spots of guidelines, despite not having prior experience designing trading platforms. The cumulative data is presented in Table 2. For brevity, the table displays the updated text of the guidelines from the end of Phase 4.

7 PHASE 4: REVIEW OF REVISIONS

In Phase 4, we incorporated evaluators' feedback by revising the guidelines. First, we rephrased the "Encourage Thoughtful Trading" guideline to "Encourage Deliberate Trading" to clarify the emphasis on deliberation and systematic processing. We also improved the order in which the guidelines were presented to make them easier to follow. They were numbered and labeled with the overarching research community they were inspired from (visual, behavioral, or financial) and sorted by type. We also ensured our final guidelines obeyed the phrasing conventions used by Amershi et al. [4]. These included limiting each guidelines to 10 words, without any conjunctions, and beginning with an action word. We also added a description to help clarify any potential ambiguities. This process resulted in the eight guidelines as seen in Table 2.

7.1 Limitations

The list of factors we were able to extract from Phase 1 is non-exhaustive. While our factors were the most prominent in the literature we reviewed, many other visual, behavioral, and financial factors may affect an investor's success in investing. Furthermore, the factors we extracted are limited to the extent we reviewed the literature. This is particularly challenging due to the interdisciplinary nature of investment and the many fields of expertise that may be relevant. Finally, some factors such as risk appetite and political inclination yield inconsistent or even contradictory guidance.

In evaluating our guidelines, we were only able to examine two investing apps that are popular in the US market. Unlike applications that are ready to use as soon as they are installed, trading platforms require providing sensitive personal information and making a financial commitment. Similarly, we were unable to assess our guidelines against non-American investing apps such as eToro (popular in UK and Israel) because we could not open trading accounts on these platforms from the US. Furthermore, while we conducted our evaluation with human-computer interaction researchers and designers knowledgeable about the design process in general, we were unable to recruit anyone from the financial services industry.

8 DESIGN IMPLICATIONS

8.1 New Interaction Models for Investing

The above guidelines may be useful not only for evaluating existing trading interactions but also new and emergent ones. For instance, consider Public, a trading app focused on making investing in the stock market "social". Public allows users to display their portfolio on their profile, and share their investment decisions with their friends (Figure 2a). It also curates lists of some of the most popular stocks among users of the app. These features capitalize on the availability heuristic and can potentially make investing a popularity contest; violating guidelines B2, B4, and B5. In contrast, Options AI includes data-driven visualizations of potential future values of a stock based in part on the prices of options sold on the stock (Figure 2b). Such an interface is in line with guidelines V1, V2, and B5.

Designers may also find guidelines useful in adopting ideas from other kinds of applications. For instance, mindfulness applications may offer multiple design patterns to encourage deliberate trading (B2), remove fixation on past performance (V1), and discourage overreactions to news (B5).

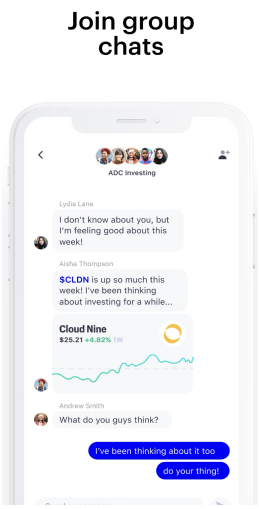
8.2 Applications Beyond Investing

While we developed our guidelines with the assumption that investments were in traditional asset classes such as stocks, bonds, and other regulated securities, they may apply equally well to newer, alternative investments. For

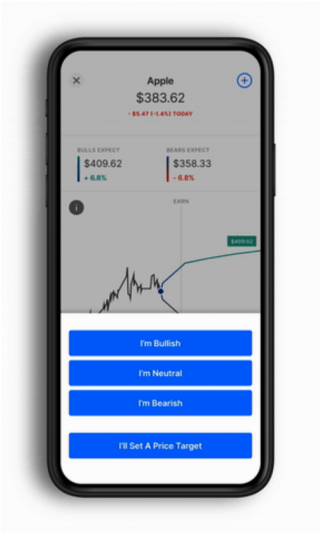
Table 2. Design guidelines for trading apps that encourage healthy investing behaviors. Guidelines are roughly split into visual design (V1 and V2), behavioral (B1 to B5), and financial (F1)

	Guideline	Robinhood	E-Trade
V1	**Focus on the Potential Instead of the Past** Display information that helps investors make investment decisions based on how the security will perform in the future, not how it has performed in the past.	Prominently features a performance charts while all information relevant to future performance is below the fold.	Easy access to metrics such as analyst recommendations, price targets, income statements, etc. in addition to past performance.
V2	**Expose Risks** Help the investors understand exactly what they stand to lose or gain with the investments they make.	Highlights the systematic risks of investing in the stock market but not specific risks for individual securities.	Provides tools to calculate probability of a security reaching a certain price by a certain date. Displays beta values.
B1	**Encourage Diversification** Help investors put their money in a variety of financial instruments and industries.	Each position mentions its position diversity. Overall asset composition data is buried in account settings.	Shows the asset composition of a portfolio and compares it to sample portfolios. Security selection metrics are missing.
B2	**Encourage Deliberate Trading** Make it easy for investors to make well-thought out trades based on knowledge of market fundamentals.	One-click access to trading allows making trades despite lack of time, focus, or background or in the presence of stress and other distractions.	The complexity and website modality forces investors to sit down, think, and take their time while making trades. Orders can be saved for later.
B3	**Encourage Long-Term Trading** Help investors think of trading as a long-term activity and discourage them from trying to catch minute-to-minute market movements.	Default time range in charts is one day, which can incentivize trying to catch the day-to-day market movements.	Default time range in charts is in the order of years. Gains are classified as long and short-term.
B4	**Discourage Active Trading** Limit investors' ability making frequent trades unless they understand risks associated with it.	Proceeds from sale are instantly immediately available to reinvest. Obeys SEC-mandated day trade restrictions.	Trades take upto 2 days to settle for cash accounts. Obeys SEC-mandated pattern day trade restriction for margin accounts.
B5	**Discourage Overreactions to Market News** Help investors interpret market news in a manner consistent with market fundamentals instead of acting on hype and behavioral factors.	Prominently features market news. Sends push notifications close to earning calls. Highlights securities whose price moved the most.	Market news and top movers list is available but not the centerpiece of the home screen.
F1	**Minimize Roundtrip Costs** Minimize the amount investors have to pay for each trade in transaction costs and ensure these are transparent to the user.	Does not charge commissions or transaction fees for any type of security.	Does not charge commissions or transaction fees for most securities. Some contracts have a flat fee.

instance, a cursory review of app stores for the Apple and Google's mobile platforms surfaces apps for speculating in cryptocurrencies such as Bitcoin (Figure 3a), equity crowdfunding, which allows low-cost investing in startup companies (Figure 3b), and even "democratized" investing in art that allows users to purchase fractions of famous pieces of artwork (Figure 3c). While the markets targeted are varied, guidelines based on fundamental findings may still be relevant.

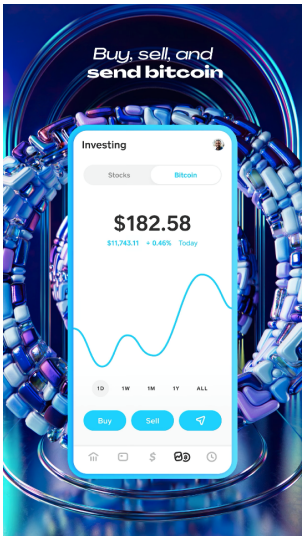


(a) Public turns the stock market into a social activity. Violates B2, B4, and B5.

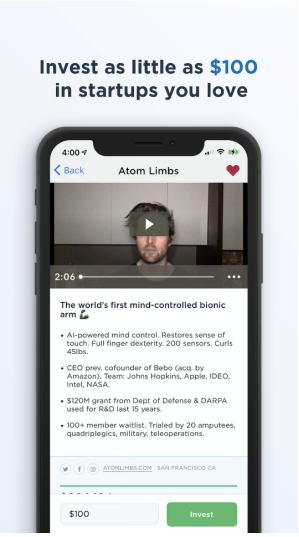


(b) Options AI offers data-driven charts of a security's potential to influence trades. Applies V1, V2, and B5.

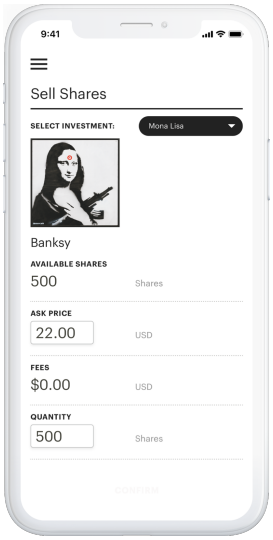
Fig. 2. Examples of some other trading apps and how they apply and violate our guidelines. Images from each platform's website and marketing materials.



(a) Cash App allows retail investing in Bitcoin.



(b) Wefunder allows small investments in non-public companies.



(c) Masterworks allows retail investing in artwork.

Fig. 3. Some alternative investment platforms where our guidelines may be applicable. Images from each platform's website and marketing materials.

9 CONCLUDING DISCUSSION

We reviewed fundamental literature from the fields of finance, psychology, and design to that resulted in eight actionable design guidelines for retail investing applications. These efforts, and their subsequent evaluation suggest that our guidelines can be useful in suggesting evaluating and suggest directions to improve design of these applications.

9.1 Non-prescriptive Guidelines

This research was inspired by media accounts of retail investors suffering catastrophic harm as a result of poor investments. As such, we hypothesized that simple design guidelines might prevent such failures. However, our research suggests that designers, even relying on the most robust theoretical findings, must make trade-offs. Consequently, our guidelines are non-prescriptive as well. Factors such as the age of the target user, their risk appetite, prior experience with losses in investing, etc. may guide practitioners in making these trade-offs.

We also recognize that our guidelines, while theoretically sound, might be difficult to realize into actual products due to practical business concerns. For instance, companies whose revenues are driven by active trading may find it difficult to discourage the practice. Similarly, though not charging commissions can minimize roundtrip costs, but requires platforms to turn to more creative revenue streams, which have had mixed success so far [89]. While these concerns are beyond the scope of this paper and our own expertise, developing sustainable business practices around these guidelines may be a productive area for future work.

9.2 Applicability to Vulnerable Populations

One side-effect of our approach is that our guidelines are likely less effective for vulnerable populations. This is because of persistent population biases in the literature that we draw from, especially psychology [33, 80]. Many fundamental results were studied with white, rich, educated, and independent people [33], and wealth, independence, and education may well affect investing decisions. As such, our guidelines are best seen as the first step in a longer process of making investing more democratic in actuality, not just in rhetoric.

9.3 Future Work

Future research could explore the uses and value of these guidelines at various stages of design, and for specific populations. We also see a need for triangulation of guidance from literature with more qualitative and ethnographic methods. For future practice, beyond the direct implications of our work, our guidelines may also serve as a useful starting point for discussions such as *how* trading apps can encourage deliberate trading. Finally, our work may suggest future policy that requires trading platforms to disclose not only whom they serve, such as the investors with high net worth as is current practice, but also interactional patterns of public interest, such as how long users hold securities, how frequently they trade in response to news events, and the degree of diversification. Similarly, data sharing around interactions like whether investors who received free stocks when joining the platform take greater risks may improve future design.

Overall, our work suggests that investing is an activity worthy of attention from designers and design researchers; and doing so is necessary to transform investing from an activity fraught with risks and reserved to those with privilege into one that is truly democratic.

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