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Decision-Making and Management of Self-Care in Persons with Traumatic Spinal Cord Injuries: A Preliminary Study

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Abstract

Patients and physicians understand the importance of self-care following spinal cord injury (SCI), yet many individuals with SCI do not adhere to recommended self-care activities despite logistical supports. Neurobehavioral determinants of SCI self-care behavior, such as impulsivity, are not widely studied, yet understanding them could inform efforts to improve SCI self-care. We explored associations between impulsivity and self-care in an observational study of 35 US adults age 18 - 50 who had traumatic SCI with paraplegia at least six months before assessment. The primary outcome measure was self-reported self-care. In LASSO regression models that included all neurobehavioral measures and demographics as predictors of self-care, dispositional measures of greater impulsivity (negative urgency, lack of premeditation, lack of perseverance), and reduced mindfulness were associated with reduced self-care. Outcome (magnitude) sensitivity, a latent decision-making parameter derived from computationally modeling successive choices in a gambling task, was also associated with self-care behavior. These results are preliminary; more research is needed to demonstrate the utility of these findings in clinical settings. Information about associations between impulsivity and poor self-care in people with SCI could guide the development of interventions to improve SCI self-care and help patients with elevated risks related to self-care and secondary health conditions.

Keywords

Spinal Cord Injury, Self-Care, Decision-Making, Paraplegia, Impulsive Behavior, Health Care

1. Introduction

The costs associated with spinal cord injury (SCI) are very high [1] [2] and include secondary health conditions (SHC), which can place individuals at significantly greater risk of early mortality [3] [4]. Importantly, both health and financial risks associated with SCI can be mitigated [5] [6] [7]. Risk factors and secondary health conditions are not only managed by the healthcare team, but also by the person with SCI in the form of "self-care" [8]. Self-care behavior consists of activities specifically intended to manage ongoing medical conditions, prevent future disease, and generally improve health outcomes. These activities are self-initiated, with frequencies determined by a decision-making process [9]. Of interest here is understanding the psychology underlying individual differences in volitional self-care engagement, as a first step toward helping providers and psychoeducation campaigns offer more effective messaging to patients with SCI.

Researchers have begun to determine how self-care following SCI might mitigate secondary health conditions by quantitatively measuring self-care behavior [10] [11] [12] [13], where some have related individual differences in self-care scores to the incidence or severity of SHC outcomes [14] [15]. Although there can be significant logistical and practical barriers to engaging in self-care in many patients, and psychoeducation for self-care itself can vary across patients as a function of access to quality SCI care [16], individual attitudinal factors can also be important determinants of the differences in proactive health behavior. However, motivational patterns related to self-care are not straightforward. Self-care was not associated with general self-efficacy for people with SCI [17] which suggests that exploration of other, more nuanced individual differences may be needed to understand self-care behavior.

One understudied temperamental trait that may critically impact SCI self-care is impulsivity. Impulsivity can be thought of as a dispositional trait of "acting *without* awareness" and its antipode could be mindfulness, "acting *with* awareness" [18]. Self-care behavior following SCI requires creating and maintaining a routine [19] and impulsive people appear to have greater trouble with routines [20]. Thus, dispositional impulsivity may be a key individual difference underlying suboptimal SCI self-care. However, associations between these dispositions and SCI self-care are essentially unknown. Somewhat related research has found that individuals with SCI are more extraverted and sensation-seeking compared to community controls, and individuals with SCI with low neuroticism have lower binge drinking and better psychosocial adjustment to the injury [21]. In addition, mindful awareness can both moderate drinking behavior and mitigate negative consequences of drinking when it occurs [22]. It stands to reason that mindful individuals with SCI are well attuned to the totality of their surroundings and senses (including their body position and skin condition) and so may engage in more frequent self-care behavior.

Impulsive decision-making, however, may be especially critical as an established risk factor for a variety of maladaptive health behaviors [23]. Unlike trait impulsivity, decision-based impulsivity is prone to momentary fluctuations, including mood states [24]. As individuals decide which, if any, self-care behaviors to engage in at any moment, they likely engage in cost-benefit calculations on at least a cursory level. Behavioral economics may help explain how decision-based impulsivity could be involved when individuals with SCI do not engage in adequate self-care, even if barriers to self-care are minimal. Successful SCI self-care requires frequent expenditure of time and energy in the *present*, such as pressure relief maneuvers or intermittent catheterization, to prevent a potential *future* problem such as a pressure injury or urinary tract infection. People typically subjectively discount the value of future rewards at a hyperbolic rate, meaning that the subjective value of a prospective reward markedly decreases at the prospect of any delay, then decreases gradually with longer delays [25]. Potential future secondary health conditions stemming from inadequate self-care can also be seen as *uncertain* outcomes, which can be devalued in comparison to those seen as *certain* [26]. Individuals with exaggerated discounting of future and/or uncertain outcomes may be especially prone to opting to forego self-care behaviors.

Individuals with infrequent self-care may also show idiosyncratic motivational biases about potential gains and losses with ambiguous probabilities-biases that could be leveraged by providers in how they communicate with patients about self-care. Measures of such cost/benefit decision-making can be obtained using laboratory behavioral probes such as the Iowa Gambling Task (IGT) [27]. The IGT requires participants to sample computerized face-down card decks to win hypothetical money where success depends on deducing the optimal (*i.e.*, less risky) decks to select across trials for a net gain in dollars. Decision-making in the IGT is commonly quantified by the proportion of selections from the riskier decks. However, theory-driven computational models can be used to estimate more nuanced aspects of decision-making in the IGT based on observed patterns of deck choices following experienced rewards and losses. Reinforcement learning models based on behavioral economics consider the expected utility (*i.e.*, value) of decisions based on recent trial-wise outcomes. Reinforcement learning models of decision-making in the IGT [28] [29] [30] [31] [32] estimate model parameters that describe aspects of motivation in decision-making, such as outcome sensitivity and loss aversion, in addition to learning rates and perseverance.

Understanding how positive and negative feedback affects decision-making could directly inform how individuals with SCI could best be motivated to change behavior, such as with recent contingency management-like interventions to apply rewards based on sensor-driven feedback to encourage pressure relief activities [33]. Specifically, IGT model parameters account for non-linear associations between subjective value and actual (mathematical) expected value. An example would be the tendency for people to place more value than expected on rewards that occur frequently [34] and to devalue losses that occur frequently [35]. Expectations change with experience, and the degree to which decisions are biased by outcome magnitude and frequency can be described as *outcome sensitivity*, a utility shape parameter captured by some reinforcement learning algorithms that model IGT decisions [36]. For example, an outcome sensitivity value < 1 implies that an individual's behavior is shaped more by the frequency of rewards than the magnitude of rewards, wherein for example, finding a $1 bill on the sidewalk five times would have more total motivational impact than finding a $5 bill once.

The current study was designed to test the associations between levels of SCI self-care and these different facets of trait- and decision-based impulsivity by applying diverse assessments in individuals with paraplegia that resulted from traumatic SCI and relating scores to self-reported SCI self-care. These decision-making parameters included delay discounting rate, probability discounting rate, and risky choice ratio, as well as decision-making computational parameters (including loss aversion and outcome sensitivity) estimated from the IGT using reinforcement learning models. In light of previous linkages between poor health behavior and propensity to discount delayed rewards most severely in the laboratory [37], we hypothesized that impulsivity and decision-making guided by sensitivity to rewards and ambivalence to potential ambiguous losses would each be associated with reduced SCI self-care.

2. Methods

This research was conducted in accordance with the Helsinki Declaration and approved by institutional review boards (IRBs) at the Richmond Veterans Affairs Medical Center and Virginia Commonwealth University.

2.1. Participants

Prior to conducting informed consent, potential participants were pre-screened by telephone, including structured questions regarding substance use. Following consent, substance use information was collected verbally for all participants and through biological screening for in-person participants (see Supplemental Material). We recruited 35 adults aged 18 - 50 who experienced traumatic SCI at least six months prior to testing and had impairment of the lower body but retained finger functionality. Our sample was restricted to traumatic SCI to maximize the potential range of impulsivity values to include persons with substance use-related accidents. Participants were recruited at a Veterans Affairs Medical Center (n = 5) and at its affiliated university and its medical center (n = 30). Recruitment procedures were conducted in collaboration with community organizations in addition to the two hospitals. Injury information for all participants recruited from hospitals, and most recruited from the community, was obtained from medical records (n = 29). Four community participants provided self-reported injury information. To limit cognitive confounds resulting from recent/current prescription or illegal substance use and brain injury, potential participants were ineligible if they 1) were currently prescribed prescription opioid medication or 2) reported current or previous problematic substance use other than nicotine, alcohol, or cannabis.

Participants reported race/ethnicity as Black or African American ($n = 7$), Native Hawaiian or Other Pacific Islander ($n = 1$), White ($n = 23$), and Other or Chose Not to Report ($n = 4$). There were more men ($n = 25$) than women ($n = 10$) and the median age was 30 ($M = 32.43$, $SD = 7.68$). Injury levels ranged from sensory C4 to L3 and the most common level was T11 (**Table 1**). Of participants with injury information, 74% (26 of 33) had complete injuries. The most common cause of injury was a motor vehicle accident ($n = 16$) and other causes included gunshot and fall (each $n = 5$). Two participants had primary causes that were progressive. About half of the participants ($n = 17$) frequently and regularly used nicotine, alcohol, or cannabis; the other half reported no regular substance use ($n = 18$). We used medical records to identify TBI in six participants (one severe, two moderate, three mild), a loss of consciousness at injury without TBI in two others. Three participants self-reported a head injury. Most participants did not have a TBI in their medical records or report a head injury ($n = 22$). Nine participants had a psychiatric diagnosis in medical records and the most common was depression ($n = 5$).

Table 1. Tallied here are the vertebral levels of spinal cord injury among study participants, as obtained from medical records review and self-report.

Injury Level	Count
C4 (T1 motor)	1
C6	1
C7	1
C8	2
T1	1
T2	1
T3	3
T4	5
T6	2
T8	3
T9	1
T10	2
T11	6
T12	1
L2	1
L3	1
Unknown (not reported)	2
Unknown (reported)	1

2.2. Procedures

Due to COVID-19 social distancing precautions imposed amid the study timeline, assessment procedures transitioned from face-to-face laptop PC based-assessments (n = 23) in the laboratory or the patient's home to coached remote self-administered assessments on the participant's own device (n = 12). Collection of informed consent and testing of the initial in-person assessments was conducted by a research assistant using a Windows PC laptop, USB keyboard/mouse, and Inquisit 5 Lab neurobehavioral testing software (Millisecond Software LLC) either in the laboratory or in the participant's home. Subsequent remote participants tested during COVID-19 lockdowns were instructed by staff to download the Inquisit 5 Web app onto their device as well as the task testing scripts using a custom hyperlink transmitted by email or text message. The core task script was identical between the lab and web platforms. After cognitive testing, participants completed an interview with the research assistant (either in-person or by phone) and responded to self-report questionnaires assessing impulsivity, dispositional mindfulness, and SCI self-care. Participants were paid $60 for their testing session.

2.3. Measures

Missing self-report items were mean-imputed when more than 50% of the items for a score had a valid response. See Supplemental Material for more detail on assessments.

2.3.1. Spinal Cord Injury Lifestyle Scale (SCILS)

To quantify intensity of different self-care activities in people with SCI, we administered the Spinal Cord Injury Lifestyle Scale [12]. SCILS scores have correlated negatively with secondary SCI health conditions [15], suggesting that its item content is germane to deleterious secondary health outcomes. We focused on the total self-care score (N = 35, total coefficient α = 0.71).

2.3.2. Self-Reported Impulsivity (UPPS-P) and Mindfulness

To capture trait-like impulsive behaviors that we expected to be negatively correlated with frequency or intensity of self-care, we administered the Urgency, Perseverance, Premeditation, Sensation-Seeking (UPPS) Scale to quantify these four distinct types of impulsive disposition [38]. We also included Positive Urgency (P) to complement the original [negative] Urgency subscale [39]. The coefficient α for each subscale of the UPPS-P (N = 33) was greater than 0.80. Conversely, to capture potential positive correlations between mindfulness and self-care, we administered the Mindful Attention and Awareness Scale (MAAS: N = 34, α = 0.92) to quantify an individual's dispositional mindfulness, or tendency to act with awareness and attend to the present moment [40].

2.3.3. Delay Discounting Task (DDT)

To determine individual differences in future-orientation or myopic mindset, we used a computerized adjusting delay discounting task [25] to assess the severity of subjective devaluation of delayed (hypothetical monetary) rewards, which we expected to be negatively correlated with self-care. Participants chose between a standard amount ($50 or $5000) that they could receive at varying timepoints in the future, or a smaller amount that they could receive now. A titrating algorithm adjusted the amount of each immediate offer based on previous responses, to arrive at indifference points wherein the smaller immediate reward was equally as desirable as the larger future reward. The area under the curve (AUC) formed by a plot of indifference points at each delay was calculated separately for each of the $50 and the $5000 standard amount blocks, where lower AUCs indicate more severe discounting of the subjective value of rewards with delay (*i.e.* greater impulsivity).

2.3.4. Probability Discounting Questionnaire (PDQ)

To determine the degree to which an individual devalues, or discounts, the value of rewards as a function of reduced probability or *likelihood* of their delivery, we administered the probability discounting questionnaire (PDQ) [41]. The PDQ presents three blocks of choices between a smaller but certain (hypothetical monetary) reward vs a larger but uncertain reward (with explicitly stated odds). PDQ choices can be used to calculate two common metrics: *h (*the probability discounting rate) and *risky choice ratio* [42], which we averaged across the three blocks.

2.3.5. Iowa Gambling Task (IGT)

We administered the IGT to probe decision-making processes under conditions of uncertainty [43]. IGT performance has typically been indexed by the tally of advantageous choices relative to the tally of disadvantageous choices [44]. To instead obtain more detailed metrics of task behavior and motivation, we used hierarchical Bayesian modeling with the hBayesDM package [36] to computationally model IGT behavior using reinforcement learning principles. Observed IGT decision-making data were successfully captured with two models, one based on prospect theory and one based on objective outcome values. We also tried to fit the Prospect Valence Learning-Delta model, following the Rescorla-Wagner rule. This model did not converge; therefore, the parameter estimates were considered unreliable and not examined. The Prospect Valence Learning-Decay (PVL-Decay) model [30] allowed us to estimate individual differences in learning decay, outcome sensitivity, and loss aversion. The Outcome-Representational Learning (ORL) model [31] allowed us to estimate individual differences in reward learning rate, punishment learning rate, perseverance decay, outcome frequency sensitivity, and perseverance weight. Each individual difference parameter represented a latent behavioral economics decision-making construct.

2.3.6. Stop-Signal Task (SST)

We also measured acute motor behavior control in a stop signal task (SST) as one index of motor impulsivity. The SST measures aptitude for response *cancellation*, defined as the ability of individuals to terminate mid-process motor responses that were elicited by a target signal to initiate the response [45]. Underlying the SST is the assumption that a cue to initiate behavior begins a process which culminates in an action. Similarly, a cue to inhibit behavior begins a parallel process which would inhibit the action. In a "horse race" model, the process which concludes first determines whether the behavior is ultimately completed or inhibited. The primary parameter calculated from behavior in the SST is the "stop-signal reaction time" (SSRT), which is an estimate of response-inhibition latency (*i.e.*, how long it takes a person to stop a motor response). We followed the procedures described in a recent consensus guide [46] to estimate the SSRT.

2.4. Analysis Plan

First, we examined whether there were differences in key variables based on staff-administered vs self-administered testing mode. Then, to examine cross sectional associations, we tested zero-order correlations between SCILS total scores and each measure of impulsivity. Finally, to determine if any neurobehavioral metrics were predictors of self-care behavior when entered into a model simultaneously with demographic information, we used least absolute shrinkage and selection operator (LASSO) regression procedures [47]. LASSO regression is a procedure which systematically adjusts the regression coefficients of potentially inter-correlating predictors and can reduce coefficients to 0 in order to remove less predictive variables from the model. Potential predictors in this LASSO regression model included all dispositional variables, all behavioral metrics (e.g., discounting rate AUC and SSRT), all computationally modeled latent decision-making parameters (e.g., outcome sensitivity, loss aversion), age, and four binary variables indicating substance use, traumatic brain injury (TBI), sex (man/woman) and race (not white/white). Participants with missing data were excluded pairwise in correlations ($33 \le n \le 35$) and listwise in LASSO regression ($n = 32$).

3. Results

We did not find a statistically significant difference between staff-administered and remote self-administered testing modes for any of the key metrics (Supplemental Table 1). Due to violation of normality typical in discounting choice task results, we used the log of the probability discounting rate parameter h in analyses.

3.1. Dispositional and Decisional Correlates of SCI Self-Care Behavior

In simple bivariate analysis, SCI self-care total scores were negatively correlated with three dispositional metrics: negative urgency, (lack of) premeditation, and (lack of) perseverance from the UPPS-P, and positively correlated with mindfulness (**Table 2**). SCI self-care total scores were negatively associated with one behavioral task metric: outcome sensitivity from the PVL decay RL model applied to IGT choices (**Table 2**), such that individuals with poor self-care showed more sensitivity to IGT trial outcome magnitudes. Exploratory correlations between SCILS subscale scores and impulsivity metrics are available in Supplemental Material.

Table 2. Correlations between measures of impulsivity and self-care.

Variable	*M*	*SD*	SCILS	NURG	PURG	PREM	PERS	SS	MASS	AUC50	AUC5K	logH	RCR	A	alpha	cons	lambda	Apun	Arew	betaF	betaP	K	SSRT
1. SCILS *N = 35*	69.16	10.52		0.018	0.457	0.020	0.027	0.879	0.027	0.480	0.358	0.579	0.527	0.942	0.002	0.140	0.177	0.418	0.694	0.636	0.194	>0.999	0.419
2. NURG *N = 33*	24.94	5.56	−0.41* [−0.66, −0.08]		0.001	0.043	<0.001	0.538	<0.001	0.052	0.006	0.836	0.928	0.837	0.040	0.673	0.621	0.400	0.277	0.940	0.275	0.579	0.781
3. PURG *N = 33*	24.94	7.78	−0.13 [−0.46, 0.22]	0.53** [0.23, 0.74]		0.174	0.086	0.606	0.194	0.288	0.369	0.984	0.661	0.554	0.045	0.907	0.846	0.937	0.593	0.814	0.911	0.436	0.161
4. PREM *N = 33*	21.42	5.70	−0.40* [−0.66, −0.07]	0.35* [0.01, 0.62]	0.24 [−0.11, 0.54]		0.166	0.028	0.131	0.622	0.305	0.835	0.924	0.315	0.119	0.661	0.907	0.805	0.116	0.166	0.629	0.382	0.721
5. PERS *N = 33*	17.79	4.57	−0.39* [−0.64, −0.05]	0.61** [0.33, 0.79]	0.30 [−0.04, 0.59]	0.25 [−0.11, 0.54]		0.809	<0.001	0.338	0.162	0.677	0.728	0.826	0.503	0.919	0.387	0.845	0.439	0.967	0.872	0.653	0.242
6. SS *N = 33*	35.82	7.09	−0.03 [−0.37, 0.32]	−0.11 [−0.44, 0.24]	0.09 [−0.26, 0.42]	0.38* [0.04, 0.64]	−0.04 [−0.38, 0.30]		0.287	0.251	0.512	0.388	0.566	0.498	0.852	0.880	0.409	0.416	0.015	0.974	0.623	0.268	0.974
7. MASS *N = 34*	4.44	0.94	0.38* [0.05, 0.64]	−0.59** [−0.78, −0.31]	−0.23 [−0.53, 0.12]	−0.27 [−0.56, 0.08]	−0.69** [−0.83, −0.45]	0.19 [−0.16, 0.50]		0.764	0.365	0.433	0.516	0.947	0.127	0.892	0.875	0.820	0.730	0.931	0.688	0.286	0.198
8. AUC50 *N = 34*	219.16	69.29	0.13 [−0.22, 0.44]	−0.35 [−0.62, 0.00]	−0.19 [−0.51, 0.17]	−0.09 [−0.43, 0.27]	−0.17 [−0.49, 0.18]	0.21 [−0.15, 0.52]	−0.05 [−0.39, 0.29]		<0.001	0.131	0.220	0.412	0.194	0.372	0.224	0.253	0.950	0.103	0.581	0.191	0.741
9. AUC5K *N = 34*	27005.97	6230.36	0.16 [−0.19, 0.47]	−0.47** [−0.71, −0.15]	−0.16 [−0.49, 0.20]	−0.19 [−0.50, 0.17]	−0.25 [−0.55, 0.10]	0.12 [−0.24, 0.45]	0.16 [−0.19, 0.48]	0.65** [0.39, 0.81]		0.266	0.204	0.558	0.038	0.407	0.169	0.036	0.940	0.157	0.467	0.410	0.724
10. logH *N = 35*	0.51	1.05	−0.10 [−0.42, 0.24]	0.04 [−0.31, 0.38]	−0.00 [−0.35, 0.34]	−0.04 [−0.38, 0.31]	−0.08 [−0.41, 0.28]	−0.16 [−0.47, 0.20]	0.14 [−0.21, 0.46]	−0.26 [−0.55, 0.08]	−0.20 [−0.50, 0.15]		<0.001	0.736	0.632	0.276	0.223	0.458	0.629	0.716	0.763	0.188	0.959
11. RCR *N = 35*	0.52	0.23	0.11 [−0.23, 0.43]	−0.02 [−0.36, 0.33]	0.08 [−0.27, 0.41]	0.02 [−0.33, 0.36]	0.06 [−0.29, 0.40]	0.10 [−0.25, 0.43]	−0.12 [−0.44, 0.23]	0.22 [−0.13, 0.52]	0.22 [−0.12, 0.52]	−0.96** [−0.98, −0.91]		0.670	0.722	0.190	0.228	0.319	0.661	0.631	0.575	0.066	0.880
PVL-decay																							
12. A *N = 35*	0.55	0.22	−0.01 [−0.34, 0.32]	−0.04 [−0.38, 0.31]	−0.11 [−0.43, 0.25]	−0.18 [−0.49, 0.17]	0.04 [−0.31, 0.38]	0.12 [−0.23, 0.45]	0.01 [−0.33, 0.35]	0.15 [−0.20, 0.46]	0.10 [−0.24, 0.43]	−0.06 [−0.38, 0.28]	0.07 [−0.27, 0.40]		0.454	0.001	0.165	0.397	0.209	<0.001	<0.001	0.013	0.606
13. alpha *N = 35*	0.21	0.01	−0.50** [−0.71, −0.20]	0.36* [0.02, 0.63]	0.35* [0.01, 0.62]	0.28 [−0.07, 0.57]	0.12 [−0.23, 0.45]	0.03 [−0.31, 0.37]	−0.27 [−0.55, 0.08]	−0.23 [−0.53, 0.12]	−0.36* [−0.62, −0.02]	0.08 [−0.26, 0.41]	−0.06 [−0.39, 0.28]	0.13 [−0.21, 0.44]		0.005	0.011	0.440	0.718	0.809	0.004	0.078	0.071
14. cons *N = 35*	0.58	0.39	0.25 [−0.09, 0.54]	−0.08 [−0.41, 0.27]	−0.02 [−0.36, 0.32]	−0.08 [−0.41, 0.27]	−0.02 [−0.36, 0.33]	−0.03 [−0.37, 0.32]	−0.02 [−0.36, 0.32]	0.16 [−0.19, 0.47]	0.15 [−0.20, 0.46]	0.19 [−0.15, 0.49]	−0.23 [−0.52, 0.11]	−0.53** [−0.73, −0.24]	−0.46** [−0.69, −0.15]		<0.001	0.174	0.048	0.814	<0.001	<0.001	0.765
15. lambda *N = 35*	1.53	1.58	−0.23 [−0.53, 0.11]	0.09 [−0.26, 0.42]	0.04 [−0.31, 0.37]	0.02 [−0.32, 0.36]	−0.16 [−0.47, 0.20]	−0.15 [−0.47, 0.21]	−0.03 [−0.36, 0.31]	−0.21 [−0.51, 0.13]	−0.24 [−0.54, 0.11]	−0.21 [−0.51, 0.13]	0.21 [−0.13, 0.51]	0.24 [−0.10, 0.53]	0.43* [0.11, 0.67]	−0.57** [−0.76, −0.29]		0.019	0.404	0.603	<0.001	<0.001	0.691
ORL																							
16. Apun *N = 35*	0.10	0.04	−0.14 [−0.45, 0.20]	0.15 [−0.20, 0.47]	−0.01 [−0.36, 0.33]	−0.04 [−0.38, 0.30]	−0.04 [−0.37, 0.31]	−0.15 [−0.47, 0.21]	−0.04 [−0.37, 0.30]	−0.20 [−0.51, 0.15]	−0.36* [−0.62, −0.03]	0.13 [−0.21, 0.44]	−0.17 [−0.48, 0.17]	−0.15 [−0.46, 0.19]	0.13 [−0.21, 0.45]	0.24 [−0.11, 0.53]	0.39* [0.07, 0.64]		0.003	0.654	0.358	0.854	0.559
17. Arew *N = 35*	0.51	0.21	0.07 [−0.27, 0.39]	−0.19 [−0.50, 0.16]	−0.10 [−0.43, 0.26]	−0.28 [−0.57, 0.07]	−0.14 [−0.46, 0.21]	−0.42* [−0.67, −0.09]	0.06 [−0.28, 0.39]	−0.01 [−0.35, 0.33]	0.01 [−0.33, 0.35]	0.08 [−0.26, 0.41]	−0.08 [−0.40, 0.26]	−0.22 [−0.51, 0.12]	0.06 [−0.28, 0.39]	0.34* [0.00, 0.60]	0.15 [−0.20, 0.46]	0.49** [0.19, 0.71]		0.776	0.757	0.581	0.534

Continued

18. betaF	2.07	2.03	0.08	−0.01	−0.04	−0.25	0.01	0.01	−0.02	0.28	0.25	0.06	−0.08	0.69**	−0.04	0.04	0.09	0.08	0.05		0.013	0.366	0.403
N = 35			[−0.26, 0.40]	[−0.36, 0.33]	[−0.38, 0.31]	[−0.54, 0.11]	[−0.34, 0.35]	[−0.34, 0.35]	[−0.35, 0.32]	[−0.06, 0.57]	[−0.10, 0.54]	[−0.28, 0.39]	[−0.41, 0.26]	[0.47, 0.83]	[−0.37, 0.30]	[−0.30, 0.37]	[−0.25, 0.41]	[−0.26, 0.40]	[−0.29, 0.38]				
19. betaP	−1.32	5.01	0.22	−0.20	0.02	0.09	0.03	0.09	−0.07	0.10	0.13	0.05	−0.10	−0.67**	−0.48**	0.74**	−0.62**	−0.16	0.05	−0.42*		<0.001	0.642
N = 35			[−0.12, 0.52]	[−0.51, 0.16]	[−0.33, 0.36]	[−0.26, 0.42]	[−0.32, 0.37]	[−0.26, 0.42]	[−0.40, 0.27]	[−0.25, 0.42]	[−0.22, 0.45]	[−0.29, 0.38]	[−0.42, 0.24]	[−0.82, −0.43]	[−0.70, −0.17]	[0.54, 0.86]	[−0.79, −0.36]	[−0.47, 0.18]	[−0.28, 0.38]	[−0.66, −0.10]			
20. K	0.70	0.36	−0.00	−0.10	−0.14	0.16	0.08	0.20	−0.19	0.23	0.15	0.23	−0.31	−0.42*	−0.30	0.68**	−0.58**	0.03	0.10	−0.16	0.71**		0.543
N = 35			[−0.33, 0.33]	[−0.43, 0.25]	[−0.46, 0.21]	[−0.20, 0.48]	[−0.27, 0.41]	[−0.16, 0.51]	[−0.50, 0.16]	[−0.12, 0.53]	[−0.20, 0.46]	[−0.11, 0.52]	[−0.59, 0.02]	[−0.66, −0.10]	[−0.58, 0.04]	[0.45, 0.83]	[−0.76, −0.30]	[−0.30, 0.36]	[−0.24, 0.42]	[−0.47, 0.19]	[0.49, 0.84]		
21. SSRT	254.93	252.93	−0.14	0.05	0.25	−0.06	0.21	0.01	−0.23	0.06	−0.06	0.01	−0.03	0.09	0.31	0.05	−0.07	0.10	0.11	0.15	−0.08	0.11	
N = 35			[−0.45, 0.20]	[−0.30, 0.39]	[−0.10, 0.55]	[−0.40, 0.28]	[−0.14, 0.52]	[−0.34, 0.35]	[−0.52, 0.12]	[−0.28, 0.39]	[−0.39, 0.28]	[−0.33, 0.34]	[−0.36, 0.31]	[−0.25, 0.41]	[−0.03, 0.58]	[−0.29, 0.38]	[−0.39, 0.27]	[−0.24, 0.42]	[−0.23, 0.43]	[−0.20, 0.46]	[−0.40, 0.26]	[−0.24, 0.42]	

Note. SCILS = Spinal Cord Injury Lifestyle Scale, NURG = negative urgency, PURG = positive urgency, PREM = (lack of) premeditation, PERS = (lack of) perseverance, SS = sensation seeking, MAAS = Mindful Attention and Awareness Scale, AUC50 = subjective value of rewards in the $50 block of the delay discounting task. AUC5K = subjective value of rewards in the $5000 block of the delay discounting task, logH = log of probability discounting rate parameter, RCR = risky choice ratio, A = recency parameter from PVL-decay model, alpha = outcome sensitivity parameter from PVL-decay model, cons = response consistency parameter from PVL-decay model, lambda = loss aversion parameter from PVL-decay model, Apun = punishment learning rate from ORL model, Arew = reward learning rate from ORL model, betaF = outcome frequency weight from ORL model, betaP = perseverance weight from ORL model, K = perseverance decay from ORL model, SSRT = stop signal reaction time. * indicates $p < 0.05$. ** indicates $p < 0.01$. 95% confidence intervals are shown below each r value. Exact p values are shown on the upper half of the matrix.

3.2. Unique Predictors of SCI Self-Care Using LASSO Regression

After examining zero-order correlations, we conducted LASSO regression with all variables in Table 2, two binary variables indicating TBI status and substance use, plus basic demographic variables (age, white/not white, man/woman), to ascertain whether any measures of impulsive disposition or decision-making predicted total self-care scores. All five metrics that were significantly correlated with self-care were retained as predictors in the LASSO model. The coefficient estimates for all other variables were reduced to zero and considered not significant predictors. Among the retained predictors, outcome sensitivity from the PVL decay RL model had the strongest association with self-care ($\beta = -2.58$). Holding the other predictors constant, for each one standard deviation higher on outcome sensitivity, self-care ($M = 69.16$, $SD = 10.52$) scores were 2.58 points lower. The largest standardized coefficient estimate for a dispositional impulsivity metric was (lack of) premeditation ($\beta = -1.36$), followed by negative urgency ($\beta = -1.12$), (lack of) perseverance ($\beta = -0.80$), and mindfulness ($\beta = 0.18$). There were no meaningful changes in correlations or LASSO regression results when data from the one participant with a severe TBI were excluded, or when those data plus data from the two participants with moderate TBIs were excluded.

4. Discussion

In adults with traumatic SCI, we found significant correlations between frequency of self-care and each of three dispositional facets of impulsivity (*i.e.*, negative urgency, lack of perseverance, and lack of premeditation) as well as dispositional mindfulness. Although each of these metrics was a promising predictor in LASSO regression, a computationally modeled decision-making parameter had the strongest association with self-care. These results suggest that, when it comes to self-care, decision-making and dispositional impulsivity may be more important than motor behavior impulsivity and some demographic factors.

Notably, greater outcome sensitivity (Alpha) was associated with lower self-care scores. In this sample, the mean outcome sensitivity (Alpha) parameter value (0.21) was less than 1, indicating that in general, participants preferred decks that win more frequently over decks that deliver the same overall reward tally but win less frequently. However, across the range of these frequency-preferring Alpha scores, participants with the lowest self-care engagement had the highest Alpha scores, indicating a greater ambivalence toward the frequency of the rewards, and relatively more value placed on their magnitude. If replicated in a larger study, this would suggest that self-care in persons with SCI could generally be best motivated with frequent smaller rewards (to capture that general preference in most persons), but where periodic lottery-like large-magnitude bonuses may be particularly salient and motivating for the most at-risk persons whose self-care behaviors are most infrequent.

These preliminary findings suggest that, in addition to self-reported dispositional impulsivity, computational modeling latent decisional impulsivity parameters could be an effective way to classify SCI patients who may be at risk of poor self-care. Changes in decision-making could then be explored during self-care interventions, as has been done with weight loss [48]. Even without changing a patient's decision-making, however, procedures such as contingency management [49] or sensor-driven feedback [33] could theoretically be adjusted on a case-by-case basis, using information about an individual's decision-making preferences to optimize the motivational power of reward magnitude and frequency.

These intriguing preliminary findings should be tempered by consideration of study limitations. First, due to the modest sample size (truncated by COVID-19), these findings should be replicated in a larger sample—potentially enabled by the novel all-remote testing capacity. Second, although self-care behavior was similar between in-person and remote testing, there may nevertheless be subtle effects of the different administration modes which could be avoided in future studies that use only remote procedures. In addition, the sample was limited to people age 18 to 50, so more research would be needed before generalizing these findings to older adults or to children. To balance recruitment feasibility with potential cognitive confounds with chronic use of "harder" substances, we excluded people who were prescribed opioids or reported problematic substance use other than nicotine, alcohol, and cannabis, and we only used a single binary substance use variable in the models. Future research with larger samples could explore whether substance use moderates or mediates associations between impulsivity and self-care.

Third, more subtle disability may have interfered with behavioral results. For example, multiple factors increase the risk of cognitive impairment in SCI patients [50] such as premorbid or comorbid TBI, especially in veterans [51], where TBI has been associated with impairments in decision making [52]. We note, however, that our results did not change when participants with severe (n = 1) and severe or moderate (n = 3) TBI were excluded from the analyses. Relatedly, participants in this study had a range of injury levels and severities of impairment, but every participant had at least some ability to move their arms, hands, and fingers. Despite screening for hand dexterity, more subtle influences, such as original injury effects, carpal tunnel syndrome from wheelchair use, or other secondary conditions may have introduced variance in reaction-time-dependent metrics like the SSRT. Fourth, to minimize participant burden, we only utilized one assessment of self-care, the SCILS, and the relationships we describe are purely cross-sectional. Future work would benefit from exploring additional understandings of SCI self-care, such as a more recent approach to measuring SCI self-care which distinguishes aspects of self-care related to maintenance, monitoring, management, and efficacy [11].

Finally, we note that the association between the computationally modeled individual differences in outcome sensitivity and self-care was not examined over time. Repeated administrations of the IGT would be necessary to examine the stability of this association. Similarly, to better understand the implications of changes in self-reported self-care, the predictive strength and validity of SCI self-care measures should be tested in longitudinal studies.

5. Conclusion

To our knowledge, this is the first attempt to link computationally modeled covert motivational preferences to intensity of self-care behavior in persons with SCI. Despite the modest sample size, anticipated relationships between aspects of impulsivity and self-care were detected. Indeed, researchers have suggested that computationally modelled discounting parameters are critical to understanding unhealthy behavior [37] and others are actively studying covert motivational preferences in other domains, such as among healthy adults pursuing fitness goals [53]. As these findings are preliminary, we suggest caution in inferring clinical implications, yet it is tempting to speculate. If interventions were to reduce an individual's dispositional impulsivity, increase mindfulness, or reduce the sensitivity to outcomes in the IGT, we expect that they could also promote self-care. For example, if patients tend to ignore small negative consequences until they develop into larger problems, interventions that increase the value of small negative (or positive) consequences hold the potential to influence self-care. Future research could use these results to guide programmatic studies of the associations between impulsive decision-making and self-care, including replication of these results in a more representative sample including longitudinal interventions targeting behavioral economic decision-making, or mindfulness. Furthermore, existing procedures such as contingency management or sensor-driven feedback might be more effective if incentive delivery schedules account for an individual's decision-making preferences, specifically those obtained through computational modeling.

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Data Availability

The data of this study are available from the corresponding authors upon reasonable request.

Code Availability

Analysis code is available on OSF (Analyses were conducted using R 4.2.2 [54] and scripts are available at https://osf.io/ebzau/?view_only=cf5a90286eb94e0fa1f7e5b77adda6cb).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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